Essays on Financial Markets Predictability

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Chapter 1

Introduction

The current study is all about the elusive nature of market predictability. This topic has captured huge attention because of its intrinsic economic value and because it is intimately related to financial theory. Indeed, accordingly, to the neoclassical theory of finance market are unpredictable beyond the risk premia. Still, in recent years, the efficient market hypothesis and the related random-walk assumption of financial markets felt under rising pressure, and evidence is mounting that financial markets are far from being completely efficient. This new evidence is closely linked with the recent spur in the field of artificial intelligence and a more mature understanding of the behavioral dynamics of financial markets.

The first part of this work involves the study of the famous sentiment index proposed by Baker and Wurgler [2006] (B-W from now on). Indeed, while a big literature proposes alternative measures of sentiment, we still lack a precise understanding of what ultimately sentiment is. The empirical analyses performed show how the B-W sentiment index is effective only in detecting situations of abnormally low levels of risk pricing but fails in detecting abnormally high levels of risk pricing consequently the B-W index can be better understood as an index of greed. Interestingly, the results show how the B-W sentiment index is tightly linked with uncertainty (defined as the dispersion in investors' views) and is Granger caused by the changes in the most optimistic views in the investors' spectrum. These results point in favor of an understanding of financial markets in which during bull markets, prices are driven by the most optimistic (less risk-averse) investors. Furthermore, our results point in favor of an understanding of financial markets in which a dichotomy exists between the asset prices estimated by the representative investor, which reflects the investors value-weighted average views, and market asset prices (marginal investor prices in the text), which reflect the investors constrained value-weighted average among all investors views. Indeed, in the real world investors are constrained by many legal and regulatory constraints that deter them from implementing their views. The dichotomy holds in equity markets and explains why the B-W index, which is extrapolated from equity-based measures, can detect only abnormally low levels of risk pricing. After that, we propose a fear proxy, which is complementary in terms of time series and cross-sectional predictive power to the B-W index. Our measure is indeed effective in detecting abnormally high levels of risk pricing only. Our measure of fear is based on a measure of illiquidity and skewness coming from the risk-neutral distribution extrapolated from options. Indeed, options markets are largely driven by hedging needs and are intrinsically forward-looking and consequently are well suited to detect abnormally high levels of risk aversion. Importantly, our results hold well in forecasting the $S\&P500$, both in-sample and out-of-sample. Subsequently, we find that our fear measure is specular to the B-W sentiment index even at the cross-sectional level completing with the ability to time the short leg of the anomalies the results of Stambaugh et al. [2012] which proved how the B-W sentiment index was effective in timing the long leg of the anomalies. Finally, the results found at the cross-sectional level shows how conditionally on a high level of fear the expected return per unit of risk is higher than on average while the opposite holds for the B-W sentiment proxy.

The second part of this research studies the three key ingredients of out-of-sample predictability: predictive models, predictors, and the function of market uncertainty that we aim at predicting. At first, we merge machine learning and model selection approaches to achieve superior predictive accuracy using as inputs the well-known predictors of Welch and Goyal [2008]. The results show how combining more and more powerful predictive approaches is possible to raise the predictive accuracy out-of-sample for the returns of the $S\&P500$ and that our results hold even for the most recent years. After that, we employ as predictors the spread returns of the eleven anomalies employed by Stambaugh et al. [2012], and we observe how these predictors exhibit a record high predictive power in terms of R^2_{OS} and Δ Utility with regards to the $S\&P500$ even when employed in univariate linear regressions. Finally, the approach proposed by Bakshi and Madan [2000] is studied under the lenses of out-of-sample predictability. Our results show how the returns of the moments' contracts introduced by Bakshi and Madan [2000], which are built through a linear combination of call and put options, exhibit R^2_{OS} and Δ Utility values well above the ones traditionally recorded for the $S\&P500$. Consequently, given the flexibility of the approach proposed by Bakshi and Madan [2000] it becomes possible to synthesize new securities with highly predictable returns revering the traditional issue of market predictability: instead of working on highly sophisticated models to predict hard to forecast securities, it becomes possible to create and trade new complex securities which are easier to forecast.

The third part of this work studies the dynamics of predictability itself. The starting point is the understanding that the time series of the R^2_{OS} coming from different models and-or predictors can provide a valuable source of information on the genesis of predictability. After that, the analyses focus on understanding whether predictability stems from changes in economic fundamentals or investors' sentiment. From a theoretical point of view, this study is linked to the ongoing debate between behavioral and neoclassical finance. Indeed, the theory on asset pricing is divided into two main conflicting schools of thought: the neoclassical approach, which states that higher expected returns are a consequence of higher risks and the behavioral approach, which explains how human biases lead investors to deviate from full rationality. Empirical results show how the interaction among risks and the pricing of risks is at the very base of predictability, and consequently, both behavioral and neoclassical theories provide useful tools in understanding financial markets. After that, our results combined suggest how different typologies of market predictors have a changing predictive power accordingly to the prevailing market regime. More in detail, fundamentals are the main drivers and are more precisely incorporated into prices during bear markets, while during bullish markets, the dynamics of risk pricing are more relevant, and non-fundamental (technical, trend following, behavioral) signals have a higher impact. Finally, we study the causality dynamics among behavioral and fundamentals variables, and we document how, on average, are changes in fundamentals (risks) that trigger changes in behavioral variables (risk premia). These relations are stronger (in terms of magnitude, statistical power, and the number of statistically significant predictors) during the bear than during the bull regime. This helps to explain the dominant role played by fundamentals in forecasting market returns during recessions. Our results reject the theory advanced by Julien and Michael [2017], who explains the higher probability detected during economic recessions through the existence of an uncertainty risk premium. Indeed, all our analyses confirm how the level of uncertainty has no explanatory power for predictability dynamics in bear markets. In bull markets, on the other hand, the impact of fundamentals is weaker, and the dynamics of uncertainty, which drive risk premia, have a larger impact in explaining predictability. From a theoretical perspective the habit theory introduced by Campbell and Cochrane [1999], which explains market time-varying risk premia through a utility function which discounts more risks in bad than in good times, is largely consistent with our empirical evidence: prices are driven by changes in current fundamentals (risks) which trigger changes in behavioral variables (risks pricing).

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Chapter 2

Greed and Fear

2.1 Introduction

In the last decade, financial economists have devoted huge efforts to study the impact of sentiment on financial markets. Surprisingly, while an extensive list of studies employs sentiment proxies[1], it is still not clear what sentiment really is. With this study, we aim at providing an empirically based answer. To achieve it, we explore the links among uncertainty, sentiment, and fear. These findings allow us to reconcile, inside a unified framework, the puzzling evidence coming from the research on options[2] and on the relative underlying stocks[3].
We build on the existing literature on uncertainty[4] to understand the main drivers of sentiment and fear. The empirical evidence emerging from our analysis suggests that the currently employed proxies for sentiment are driven by both uncertainty and the most optimistic investors while the proxies for fear are driven by uncertainty and the most pessimist views. Our results show that sentiment and fear proxies are complementary in their out of sample predictive ability, with sentiment (fear) indexes especially powerful in predicting negative (positive) returns. Consequently, these indexes are effective in detecting abnormally low (sentiment) or high (fear) levels of risk aversion but not both of them jointly. After that, we show how conditioning on the presence or absence of high levels of fear or sentiment

[1] See, e.g., Baker and Wurgler [2006]; Baker et al. [2012]; Stambaugh et al. [2012]; Israel and Moskowitz [2013]

[2] Andersen et al. [2015] and Bollerslev et al. [2015] show how factors driving the left tail of the risk-neutral distribution can predict the market while the same does not apply for the factors coming from the right tail

[3] The impact of sentiment and fear on cross-sectional returns has been recently addressed by Stambaugh et al. [2015], and Farago and Tédongap [2018]

[4] Among the studies which influenced our subsequent analysis we especially highlight Diether et al. [2002], Buraschi and Jiltsov [2006],and Yu [2011] and Barinov [2013]

the out-of-sample predictability and the risk-return relation for the most relevant anomalies detected in the empirical literature varies dramatically. Depending on the prevailing market conditions, we observe subsequent high or low return per unit of risk. Consequently, we prove how the same indicators which are complementary in timing the aggregate market are even complementary in timing the anomalies: a unique logic drive returns both at a market wide and at a cross-sectional level.
The empirical analysis makes use of an extensive amount of indexes of uncertainty[5] and fear[6] coming from the existing literature and it is further augmented by newly proposed indexes of fear following Barone-Adesi et al. [2008] and Barone-Adesi [2016]. This paper enrich the existing literature building simple, yet powerful, measures of fear coming from the left tail and the skewness of the option risk-neutral distribution. These measures exploit the forward-looking nature of options to detect abnormally high levels of risk aversion (fear). We show how the differences between option implied percentiles have a remarkable predictive power out-of-sample. To the best of our knowledge, this is the first study that makes use of option implied information to time cross-sectional returns (the so-called 'anomalies') both in sample and out of sample.
Acting as one of the main driver of the paper, we introduce the conceptual dichotomy between the marginal and the representative investor which provides a theoretical rationale for our empirical analysis. Prices reflect the views of the optimistic investors (the marginal ones) and these views can diverge from mean views (the representative investor's ones). The divergence occurs because in many cases legal and regulatory constraints do not allow for short selling. Consequently, from stocks, it is only possible to infer proxies that detect excessive low risk aversion (overbought or greed) while options are needed to infer the complementary measures which detect excessive high risk aversion (oversold). On the ground of the stated dichotomy, this work addresses inside a coherent framework, some of the issues that are still left open by the previous literature.
The first issue concerns the relationship between sentiment and uncertainty. In their work Stambaugh et al. [2012] do not assign a role for a time varying cross-sectional dispersion of views. They simply hypothesize that the views of the most optimistic investors in the cross-section are more likely to be too optimistic when the measure of investor sentiment is high than when it is low. That can occur for different reasons. As the sentiment measure rises, the cross-sectional mean of investors views can remain near to a reasonable valuation level while the cross-sectional dispersion of views increases. Alternatively, as the sentiment measure

[5] E.g. the analysits dispersion of the views of Yu [2011] and the macroeconomic and financial uncertainty indexes of Jurado et al. [2015]. See the section 2 on Data for the full list

[6] E.g. the VIX index, the Variance Risk Premium, the Crash Confidence Index, the tail measure of Bollerslev et al. [2015], the pricing kernel tail measure of Almeida et al. [2017]. See the section 2 on Data for the full list.

increases, the dispersion of opinions can remain relatively constant, or even fall, while the mean of investors views increases significantly above a rational valuation level. This paper addresses this critical dilemma, and analyzes the link between uncertainty and sentiment. In our empirical analysis, we show how sentiment and uncertainty are closely linked and how sentiment is driven by the most optimist views which are Granger caused by uncertainty.
The second issue comes from Andersen et al. [2015]. The authors find that the left tail factor extrapolated from the risk-neutral distribution of options predicts both the equity and the variance risk premia. Their finding are consistent with Bollerslev and Todorov [2011] who find that the equity and variance risk premia embed a common component stemming from the compensation of left tail jump risk. The fact that both the equity and variance risk premia depend on the left tail risk factor, coupled with the significant persistence of the latter, rationalizes the predictive power of the variance risk premium for future excess returns, documented in Bollerslev et al. [2009]. Crucially the authors document a substantial time variation in the pricing of market risks and provide strong evidence that the factors driving risks and risk premia differ systematically. The fact that the option implied left tail factor can forecast equity and variance risk premia without being able to predict the risk is a puzzle which we address. We find that fear and financial uncertainty are linked and that fear proxies capture abnormally high levels of risk aversion, which result in subsequent positive returns.
The third issue regards the apparent conflict between two series of empirical studies related to uncertainty and return predictability. One set of studies, started by Diether et al. [2002] and continued by Chen et al. [2002] and Yu [2011], shows how an increase in uncertainty predicts negative returns. To justify their findings, the authors refers to the seminal work of Miller [1977] which shows how the mixture of uncertainty and short-term constraints create an upward bias in prices. The second path of studies introduces the concept of risk premium for uncertainty (Buraschi and Jiltsov [2006], Buraschi et al. [2014]) and shows how an increase in uncertainty brings to a concomitant fall in prices and predicts positive returns. Our empirical results point against the existence of an uncertainty risk premium. We observe how uncertainty rises before extreme market movements. The presence of a risk premium would call for a rise in market uncertainty during market crashes and a concomitant rising in the related risk premium. Our results prove that high uncertainty predicts subsequent higher volatility, but it has no predictive power on the subsequent direction of the market. An intimately connected result involves the rationale underpinning the existence of higher predictability during bear markets. The recent literature explains this predictability through the existence of an uncertainty risk premium (Cujean and Hasler [2017]), but our results imply that a different explanation is needed. We argue that high levels of

fear, or excessively high levels of risk aversion, are at the base of the high level of predictability detected.
The fourth issue regards the connection between fear and the cross-section of stocks returns. Fear, like sentiment, should prevent arbitrageurs to enter the market and should magnify the anomalies. After that, the long leg of each long-short anomaly strategy should have high returns (greater profits) following high fear periods than following low fear ones. To the extent that an anomaly represents mispricing, the profits in the long leg should reflect relatively greater underpricing than the stocks in the short leg. In this setting, underpricing should be the prevalent form of mispricing. Our option-based measures of fear capture exactly this phenomenon. Our analysis also allows us empirical results show the existence of a link between the work of Andersen et al. [2015], based on the predictive power of the left tail factor driving the risk-neutral distribution, and the study of Farago and Tédongap [2018], which explains how fear is reflected in the cross-section of stock returns. Our analysis also allows us to gain novel insight into the rationale underpinning the temporary movements in aggregate stock markets driven by movements in the equity risk premium[7].
The fifth issue involves the relationship between risk and returns for different factors-anomalies. The literature on empirical asset pricing is divided into two opposite interpretations, some authors explain the extra profits in terms of related additional risks[8] while others authors believe that the phenomenon arises because of behavioural biases unrelated to actual risks[9]. In this paper, we will investigate the risk-return relationship for the anomalies and factors detected by the literature[10]. Our empirical analysis shows how, conditioning on a high (low) level of fear the risk-return relationship breaks up: we observe subsequent high (low) returns per unit of risk. The reverse holds for sentiment.
Perhaps the studies most closely related to ours ones are these of Baker and Wurgler [2006], Stambaugh et al. [2012] and Andersen et al. [2015]. The first study proposes a measure of market-wide sentiment and explains how it exerts a stronger impact on stocks that are difficult to value and hard to arbitrage. In their study, the authors examine returns on stocks judged most likely to possess both characteristics. They prove that sentiment is associated with cross-sectional return

[7] Campbell et al. [2010] show how the cash flows of stocks are particularly sensitive to temporary movements in aggregate stock prices driven by changes in the equity risk premium. With our work we study the drivers and analyze the dynamics at the base of changes in the risk premium

[8] Fama and French [1993] motivate the finding that small stocks over perform big ones through differences in default probabilities.

[9] See Lakonishok et al. [1994] for an empirical analysis and Daniel and Titman [1997] for a theoretical one

[10] We employ the eleven anomalies introduced by Stambaugh et al. [2012] and Stambaugh and Yuan [2017]

differences that are consistent with stocks' characteristics. We explore the components of the Baker and Wurgler index of sentiment and its predictive power to gain a better understanding of what it captures. The second study explains how anomalies are stronger in periods of higher sentiment and how the profitability of long-short portfolios relies heavily on the short part of it and on the stocks which are more difficult to arbitrage (higher IVOL). These results suggest that sentiment and the related overpricing are largely at the base of many of the anomalies detected in the existing literature but ignore the related issue of under-pricing. We proposes measures of fear which fulfil the under-pricing gap finding results specular to the ones presented by Stambaugh et al. [2012]. Finally, the third study introduces a new left tail driver of the risk-neutral surface and shows how this tail factor predicts subsequent positive returns for the underlying index not matched by higher subsequent risks. We build on this idea and we show how the risk return trade-off changes conditionally on fear, sentiment or uncertainty.

While the three works just cited are probably among the closest to our work, our study is also related to other studies on behavioural asset pricing. The first study which proves how stocks exhibit excessive volatility in comparison with the volatility of fundamentals dates back to Shiller [1980]. For our analysis, this article is critical because it proves that not only risks but even the pricing of the risks affects stocks. Consequently, sentiment indexes which capture risk pricing become an essential element of analysis in asset pricing. Subsequently, remarkable studies have proposed a way to decompose market returns on the base of changes in expected dividend and expected returns (Campbell and Shiller [1988]) and a related approach to decompose the variance of returns (Campbell [1991], Campbell and Ammer [1993]). These seminal works, showing the relevant role played by the pricing of risks, provide a sound theoretical ground for our analysis of sentiment and fear. After that, a number of studies have investigated whether we can explain the cross-sectional variation of stocks' returns on the ground of a risk-based explanation[11] or a behavioural one [12] reaching opposite conclusions. Our analysis provides novel elements to the ongoing debate showing how conditioning on fear and sentiment proxies, which are complementary in capturing the pricing of risk, it is possible to time the risk-return trade-off of both factors and anomalies. Another promising line of research, close to our study, introduces the concepts of a behavioral pricing kernel (Shefrin [2008]; Barone-Adesi et al. [2012, 2016]), a Behavioural Capital Asset Pricing Theory (Shefrin and Statman [1994]) and a related Behavioural Portfolio Theory (Shefrin and Statman [2000]). Recently, the work of Stambaugh and Yuan [2017] sheds new light on the commonalities among

[11] Extremely insightful studies on the role of risks as drivers of cross-sectional returns comes from Vuolteenaho [2002], Campbell and Vuolteenaho [2004] and Campbell et al. [2010]

[12] A characteristic based explanation has been proposed in the empirical works of Lakonishok et al. [1994], Daniel and Titman [1997] and Hong et al. [2000]

anomalies while the study of Greenwood and Shleifer [2014] investigates the relationship between sentiment and market predictability finding a negative relation. Our findings confirm the results coming from these studies. While the sentiment proxies employed in our analysis follow the approaches proposed by Baker and Wurgler [2006], and Huang et al. [2015] other works extend these findings: Baker et al. [2012] introduce the concept of global and local sentiment while Kumar and Lee [2006] and Da et al. [2015] provide further evidence of the relevance of sentiment in financial markets.
The rest of the paper is organized as follows. Section 2 presents the data used and introduces our novel fear proxies. Section 3 introduces the dichotomy between the representative and the marginal investor providing a conceptual justification for our study. Section 4 analyzes sentiment and fear proxies and their relation with uncertainty. Section 5 studies the risk-return relations at the cross-sectional level conditionally on high (low) level of sentiment, fear or uncertainty. Section 6 concludes.
An online appendix reports all the empirical analysis and details which, for seek of brevity, are unreported in the main text.

2.2 Data

The following pages detail all the data and indexes employed for the current analysis. We report further details in the online appendix.

2.2.1 Sentiment

To build proxies for sentiment, we follow Baker and Wurgler [2006] and Huang et al. [2015]. These approaches are the most commonly employed in the empirical literature and are a natural benchmark for our analysis. Consequently, when we argue that we explain sentiment, we mean that we explain what these indexes capture. The monthly time series span the period from 07-1965 to 12-2016. The indexes are built using the following monthly data[13]:

- Close-end fund discount rate (cefd): value-weighted average difference between the net asset values of closed-end stock mutual fund shares and their market prices.

- Share turnover (turn): log of the raw turnover ratio detrended by the past 5-year average. Here the raw turnover ratio is the ratio of reported share volume to average shares listed from the NYSE Fact Book.

[13] Professor Guofu Zhou website, http://apps.olin.wustl.edu/faculty/zhou/

- Number of IPOs (nipo): number of monthly initial public offerings

- First-day returns of IPOs (ripo): monthly average first-day returns of initial public offerings.

- Dividend premium (pdnd): log difference of the value-weighted average market-to-book ratios of dividend payers and nonpayers.

- Equity share in new issues (s): gross monthly equity issuance divided by gross monthly equity plus debt issuance.

The methodologies employed to build the sentiment indexes are the ones detailed by Baker and Wurgler [2006] and by Huang et al. [2015]. The first approach makes use of the first principal component (PC6) to synthesize the information coming from the six proxies of sentiment listed above while the second approach makes use of the partial least squares (PLS6) to summarize the information coming from the same six proxies of sentiment. A single equation succinctly summarizes this procedure:

$$S^{PLS} = XJ_NX'J_TR(R'J_TXJ_NX'J_TR)^{-1}R'J_TR \tag{2.1}$$

where where X denotes the T x N matrix of individual investor sentiment measures, $X = (x'_1, x'_2, ..., x'_T)$, and R denotes the T x 1 vector of excess stock returns as $R = (R_2, ..., R_{T+1})'$.The matrices J_T and J_N, $J_T = I_T - \frac{1}{T}i_Ti'_T$ and $J_N = I_N - \frac{1}{T}i_Ni'_N$ enter the formula because each regression is run with a constant. I_T is a T-dimensional identity matrix and i_T is a T-vector of ones.

2.2.2 Fear

Specular to sentiment, fear is a key variable in our analyses. To best capture fear we employ a large set of different indexes. We divide these indexes into three main groups: one based on surveys, one based on macroeconomic and equity measures and one based on option-based measures. Some of the latter measures are new, and we detail them in section 2.3 and 2.4.
In the surveys based indexes we list:

- Crash Confidence Index (CRASH). Data comes from the Yale School of Management website[14]. The time series considered ranges from 01-1990 to 12-2016.

[14]https://som.yale.edu/faculty-research/our-centers-initiatives/international-center-finance/data/stock-market-confidence-indices

- The Anxious Index (ANX). Data come from the Federal Reserve Bank of Philadelphia[15]. In this study, we consider the forecast for the second quarter after the quarter in which the survey takes place. Data spans the period from 01-1990 to 12-2016.

- Bull-Bear spread (Bull-Bear). These indicators come from the American Association of Individual Investors[16]. The time series available starts the 07-1988 and ends in the 12-2016.

- The difference: (Upper view-Mean view) - (Mean view-Lower view) (UM-MD). Data come from the IBES database and spans the period 07/1988-12/2016.

- Livingston six months ahead Skewness (LIV skew). This index is built computing the average skewness of the six months ahead forecasts using a list of economic variables coming from the Livingston survey[17]. The time series used involves the period 07/1988-12/2016.

- Livingston RGDPX (RGDPX skew) six month ahead Skewness. The time series used involves the period 07/1988-12/2016[18].

The list of macroeconomic and equity-based indexes is so composed:

- The tail risk measure of Kelly and Jiang [2014] (KJ). Data comes row from the authors[19] and spans the period 01-1973/12-2010.

- The Economic uncertainty measure of Bali et al. [2014] (Macro). Data comes from the authors[20] and includes the period 01-1993/08-2013.

- The CATFIN measure of aggregate systemic risk proposed by Allen et al. [2012]. Data comes from the authors[21] and includes the period 01-1973/12-2010

- The tail-risk measure (TAIL) based on the risk-neutral excess expected shortfall of a cross-section of stock returns proposed by Almeida et al. [2017]. The available time series include the period 01-1973/12-2010[22].

[15]https://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/anxious-index
[16]http://www.aaii.com/sentimentsurvey
[17]https://www.philadelphiafed.org/research-and-data/real-time-center/livingston-survey
[18]https://www.philadelphiafed.org/research-and-data/real-time-center/livingston-survey
[19]We thank the authors for sharing the data
[20]We thank the authors for sharing the data
[21]We thank the authors for sharing the data
[22]We warmly thank the authors for sharing their codes and data

The list of option-based fear indexes is so composed:

- The VIX index. The time series employed come from the Federal Reserve of Philadelphia and spans the period from 01-1990/12-2016.

- The Variance Risk Premium (VRP) Zhou [2017]. Data come from the website of the author[23]. The available data spans the period from 01-1990 to 12-2016.

- The left tail risk proxy of Bollerslev et al. [2015] (BTX). The available data spans the period 01-1996/08-2013[24].

2.2.3 First new measure of Fear: GARCH-FHS approach

Our first option proxy of fear, called Fear FHS (henceforth: FFHS), exploits and extends the semi-parametric GARCH-FHS approach of Barone-Adesi et al. [2008]. Consequently, at first, we briefly summarize Barone-Adesi et al. [2008], recalling how to extrapolate a time-varying risk-neutral distribution from a panel of options, and subsequently, we introduce our novel measure of fear which is based on the skewness of the distribution.
For each month[25] in the period 01-2002/08-2015 we fit two asymmetric GJR GARCH models (Glosten et al. [1993]). To describe the index dynamic under the historical distribution, a first GJR GARCH model is fitted to the historical daily returns of the S&P 500. The estimation is obtained via Gaussian Pseudo Maximum Likelihood. Subsequently, to capture the dynamic under the risk-neutral distribution, and using the just estimated historical parameters as a starting point for the optimization, another GJR GARCH model is calibrated to the cross section of out-of-the-money (OTM) put and call options written on the S&P 500. The calibration is achieved minimizing the sum of squared pricing errors with respect to the GARCH parameters. Starting from the just estimated risk-neutral parameters, the risk-neutral distribution is estimated numerically by Monte Carlo Simulation. Using the Empirical Martingale Simulation method of Duan and Simonato [1998], we simulate 50,000 trajectories of the S&P 500 from t to $t + \tau$, where e.g. τ is the desired time-to-maturity. Key for the estimation and for our analysis, the distributions of the innovations are estimated non parametrically following the filtered historical simulation (FHS) approach of Barone-Adesi et al. [1999][26].
Starting from the time series of monthly risk-neutral densities, our measure of fear FFHS, is defined as the spread between the values of the underlying for the 95^{th}

[23] https://sites.google.com/site/haozhouspersonalhomepage/
[24] We thank Professor Todorov for the support in replicating the model
[25] Precisely each last Wednesday of the month.
[26] Further details needed for the replication can be found in the original paper

and 5^{th} percentiles:

$$\text{FFHS} = \text{UV}_{95} - UV_5 \tag{2.2}$$

where UV_{95} and UV_5 represent the underlying value at the 95^{th} and 5^{th} percentile of the risk-neutral distribution. To prevent possible liquidity and mispricing issues both percentiles are estimated discarding the first and using the second shortest maturity available. While we report only the difference between the 95^{th} and the 5^{th} percentiles, the differences between other percentiles (90^{th}-10^{th} and 85^{th}-15^{th}) give rise to qualitatively similar results[27].

2.2.4 Second new measure of Fear: the Option implied VaR approach

Our second proxy of fear, called Fear VaR (henceforth: FVaR), exploits and extends the non-parametric approach of Barone-Adesi [2016] and Barone-Adesi et al. [2018]. The key idea of the model is that extracting the VaR from the option surface converts the mathematical nature of statistically-based risk measures into economic-grounded risk measures. The VaR is in fact just a quantile, a single numeric value determined at a specific threshold over the cumulative distribution of the profit and loss distribution. Under the Arrow-Debreu representation and following Breeden and Litzenberger [1978], the first derivative of a put price, $p = e^{-rT} \int_0^K (K-S) f(S) dS$ over its strike price, K is:

$$\begin{aligned}
x &= \frac{dp_{t,T}}{dK} && (2.3)\\
&= \frac{d[e^{-r_{t,T}T} \int_0^K (K-S_T) f(S_{t,T}) dS_{t,T}]}{dK} && (2.4)\\
&= e^{-r_{t,T}T} \int_0^K f(S_T) dS_{t,T} && (2.5)\\
&= e^{-r_{t,T}T} F(K) && (2.6)\\
&= e^{-r_{t,T}T} \alpha && (2.7)
\end{aligned}$$

where $r_{t,T}$ represent the risk-free rate, the lower bound of the integral has been changed with no loss of generality from $-\infty$ to 0[28] and α represents the chosen risk level. For all values, $_{t,T}$ identifies the today value with respect to a forward-looking future value T. The option-implied $VaR^{\alpha}_{t,T}$ is then the difference between the time t portfolio value minus the strike price of a European put option at level $K^{\alpha}_{t,T}$:

$$VaR^{\alpha}_{t,T} = S_t - K^{\alpha}_{t,T} \tag{2.8}$$

[27]Results are available upon request.

[28]This corresponds to the natural assumption of holding a portfolio with limited liability.

Being alpha proportional to the probability that the portfolio value will be below $K^{\alpha}_{t,T}$, the obtained risk measure is naturally forward-looking and directly linked to the perceived future market's beliefs. The use of put options links the analysis to the left tail of the distribution. By the same token, the use of call options leads to the same results, but linked to the right tail of the distribution. After that, the CVaR measure follows naturally:

$$CVaR^{\alpha}_{t,T} = VaR^{\alpha}_{t,T} + e^{r_{t,T}T}\frac{p^{\alpha}_{t,T}}{\alpha_{t,T}} \tag{2.9}$$

where p^{α} represents the put option contract at the risk level α. Just relying on the option market data, the option-implied CVaR is the sum of the VaR and an additional term. This extra term is the compounded put price divided by the probability of the underlying being smaller than the selected strike .

The approach just introduced allows us to estimate the percentiles of the risk-neutral distribution using calls or puts only. The intuition of our measure of fear is the following: the 15th percentile (left tail) coming from the risk-neutral distribution estimated employing puts only give us a measure of the risk aversion of pessimist investors while the 15th percentiles (left tail) of the risk-neutral distribution estimated using calls only gives us a measure of the risk aversion of the optimistic investors. The difference between the two percentiles provides a measure which captures abnormal levels of risk aversion or fear. Consequently, it is now straightforward to define the FVaR index as:

$$\text{FVaR} = \text{VaR}_{\text{Call}}\ 15 - \text{VaR}_{\text{Put}}\ 15 \tag{2.10}$$

where the VaR_{Call} 15 and VaR_{Put} 15 are the values-at-risk extrapolated from call and put options and based on the 15^{th} percentile. Indeed, whether the primary function of index options is the transfer of unspanned crash risk (Johnson et al. [2018] and Chen et al. [2018]), the demand for options will be especially high during and immediately after major market falls and, in these circumstances, the left tail of the risk-neutral distribution would provide a sound proxy of fear. Our intuition is further confirmed by the recent study of Cheng [2018] where the newly introduced VIX premium exhibits dynamics aligned with the FVaR ones.

As did for the FFHS, we report only the difference between the 15^{th} percentiles, the differences between other percentiles ($\text{VaR}_{\text{Call}}\ 10 - \text{VaR}_{\text{Put}}\ 10$ and $\text{VaR}_{\text{Call}}\ 20 - \text{VaR}_{\text{Put}}\ 20$) give rise to similar results[29]. As a natural extension, we also propose the FCVaR measure, which is obtained in the same way of the VaR $L15 - L15$ but employing CVaR measures instead of VaR ones.

[29] Results are available upon request

2.2.5 Uncertainty

To model uncertainty, we propose three separate approaches. The first one relies on modeling the aggregate volatility of analyst forecasts about firms' earnings (Yu [2011]). The second one is based on the dispersion of the economists' forecast about different economic variables (Buraschi and Jiltsov [2006]). The third one is based on the uncertainty indexes proposed by Jurado et al. [2015].

The first approach was originally introduced by Diether et al. [2002]. The authors employed one (fiscal) year earnings estimates (coming from the I-B-E-S database) for stocks which are covered by two or more analysts, and which have a price greater than five dollars. Unfortunately, the one-year earning forecasts are strongly influenced by the management of the firm under scrutiny. Consequently, Yu [2011] employs the long earning per share long-term $I-B-E-S$ growth rate for stocks which are covered by two or more analysts. This measure of uncertainty is shown to be less affected by the managers. In conclusion, we employ this more robust methodology using the number of views each firm receive to weight the standard deviation of the views (DEVST). Our analysis run from December 1981 to December 2016. As extension, we further decompose this measure of uncertainty in two part: upward (downward) uncertainty measured as the difference between the highest (lowest) views and the mean ones: UP-UNC (DOWN-UNC).

The second measure of uncertainty comes from the work of Jurado et al. [2015]. The authors distinguish between two uncertainty measures: a financial one (UF) and a macroeconomic one (UM). Our analysis runs from 7/1960 to 12/2016 and uses monthly data[30].

The third and final measure of uncertainty employs the forecasts dispersion coming from different professional surveys. A similar approach has been successfully employed by Buraschi and Jiltsov [2006] and Colacito et al. [2016]. Following the studies just cited we employ :

- The Survey of Professional Forecasters (SPF).
- The Livingston Survey (LIV).

The detailed methodologies used for building these indicators are detailed in the appendix while the resulting time series span the period 01-1982/12-2016.

2.2.6 Anomalies

In this section, we detail the factors and anomalies employed in this study. An anomaly is a statistically significant difference in cross-sectional average returns that persist after the adjustment for exposures to the Fama and French [1993]

[30] Data comes from the website of Professor Sydney https://www.sydneyludvigson.com/.

three factors model. Our empirical analysis makes use of i) the eleven anomalies proposed by Stambaugh et al. [2015], ii) the four factors of the extended Fama and French [2015] model, iii) three widely accepted ratios of economic variables on prices (dividend yield, price-earnings, and cash flow price). All data are monthly and span the period from 01-1965 to 12-2016 except the net operating assets, the accruals, the return on assets and the distress anomaly for which data are available respectively only from 8-1965, 1-1970, 5-1976, and 1-1977. The considered anomalies are:

- Anomalies 1 and 2: Financial distress. Campbell et al. [2008] show that firms with high failure probability have lower, not higher, subsequent returns (anomaly 1). Another closely related measure of distress is the Ohlson [1980] O-score (anomaly 2).

- Anomalies 3 and 4: Net stock issues and composite equity issues. Loughran and Ritter [1995] show that, in post-issue years, equity issuers under-perform non-issuers with similar characteristics (anomaly 3). Daniel and Titman [2006] propose an alternative measure, composite equity issuance (anomaly 4), defined as the amount of equity issued (or retired by a firm) in exchange for cash or services.

- Anomaly 5: Total accruals. Sloan [1996] demonstrates that firms with high accruals earn abnormal lower returns on average than firms with low accruals.

- Anomaly 6: Net operating assets. Hirshleifer et al. [2004] find that net operating assets, computed as the difference on the balance sheet between all operating assets and all operating liabilities divided by total assets is a negative predictor of long-run stock returns.

- Anomaly 7: Momentum. The momentum effect, proposed by Jegadeesh and Titman [1993] is one of the most widespread anomalies in asset pricing literature.

- Anomaly 8: Gross profitability premium. Novy-Marx [2013] shows that sorting on gross-profit-to-assets creates abnormal benchmark-adjusted returns, with more profitable firms having higher returns than less profitable ones.

- Anomaly 9: Asset growth. Cooper et al. [2008] show how companies that grow their total assets more earn lower subsequent returns.

- Anomaly 10: Return on assets. Chen et al. [2011] show that firms with higher past return on assets gain higher subsequent returns.

- Anomaly 11: Investment-to-assets. Titman et al. [2003] show that higher past investment predicts abnormally lower future returns.
- Anomaly 12, 13, 14, and 15: the four factors proposed by the extended model of Fama and French [2015].
- Anomaly 16, 17 and 18: motivated by Gerakos and Linnainmaa [2018] we focus on three of the most notorious financial ratios: dividend yield, earning price and cash-flow price.

Further details are listed in the online appendix.

2.3 The dichotomy between the Representative and the Marginal investor

This paper proposes complementary measures of risk aversion coming from stocks and options markets. In what follows we explain how the existence of a dichotomy between the representative and the marginal investor motivates the need to use indicators coming from both the stock and the option markets. Empirically, stock-based indicators are especially successful in detecting abnormally low levels of risk aversion while the specular holds for option-based indicators. The dichotomy arises because legal constraints and the relatively high cost of shorting stocks are impediments for broad classes of investors (mutual funds, pension funds, and insurances) which account for a relevant share of the overall market. When these investors are optimists about a particular stock, they can easily buy it, but when they are pessimists, they cannot so easily short sell it. This asymmetry implies that the representative investor (or the weighted sum of investors' expectations) probability distribution of expected returns diverges from the marginal investor one (which is a constrained version of the previous). Indeed, the prices seen on the market are defined by marginal investors or the investors who not only have given views on the market at a given moment but also investors who can effectively implement their views. This fundamental mismatch is at the base of a number of puzzling asymmetries detected by the literature on stocks[31] and options[32]. Stock prices reflect mainly optimistic views and, from them, it is possible to build measures which detect abnormally low levels of risk aversion but not abnormally high levels of risk aversion. This occurs because the views of the most pessimist investors

[31] The works of Miller [1977], Hong and Stein [2003] and Edmans et al. [2015] are fundamental in explaining how short-selling constraints affect the informativeness of prices.

[32] The recent studies of Bollerslev et al. [2015] and Andersen et al. [2015] show how the left tail of the risk-neutral distribution is informative of future movements of the underlying S&P500 index but the same does not hold for the right tail.

are not incorporated into stock prices (Chen et al. [2012]). Options, on the other hand, are widely used instruments to hedge risks. Being mostly used by sophisticated investors with weaker regulatory and legal constraints, options market data can naturally reflect the views of the most pessimist investors[33] and allow for the construction of measures which capture abnormally high levels of risk aversion.
To study empirically the implications of this theoretically grounded dichotomy we start by looking at the interaction between changes in volumes and stock returns. Uncertainty is the dispersion of the investors' views around the representative investor one, and a higher dispersion in belief leads to higher stock volatility and trading volumes[34]. Consequently, increasing volumes likely imply a high level of uncertainty. We study the impact of the joint dynamics of prices and volumes on subsequent returns to gain a first empirical assessment of the relevance of the dichotomy in bullish and bearish markets.
We start our empirical analysis in the simplest way: we take monthly returns and volumes data for the S&P500 for the period 01-1982/12-2015, we detrend volumes to account for the structural increase in volumes through the period considered and we divide our data into four sets, one for each possible combination between the dynamics of prices and volumes (positive/negative returns and rising/declining volumes). After that for each of the four monthly categories in which we have divided our sample, we compute the average return recorded by the S&P500 one month, three months and six months after the starting month. To provide an even more comprehensive picture, we also provide the cumulated returns spanning from month t+1 to month t+3, from month t+1 to month t+6 and from month t+4 to month t+6.

Insert Table 2.1

Table 2.1 provides a first representation of the impact of the dichotomy on the US financial markets. It is immediate to see the different impact of the rising volumes in bullish and bearish markets in predicting subsequent market returns. We observe how rising volumes, joined with negative returns, are evidence of a strong bearish movement which is likely to continue while rising volumes, joined with positive returns, are followed on average by subsequent high returns. Consequently, the impact of a high level of uncertainty on subsequent market returns depends on the prevailing market regime. Declining volumes matched by negative returns are evidence of a bearish market which is likely to revert and we report how they over perform, in terms of average returns, increasing volumes matched by negative returns for all the subsequent considered horizons. When bullish markets are considered, we observe how at month t+1 the average return of the S&P500

[33] Han [2008] shows how options prices timely reflect investor sentiment

[34] This idea is first introduced in the seminal work of Diether et al. [2002] and further developed both theoretically and empirically by Adem and Suleyman [2018]

following a month t characterized by rising volumes and positive returns is close to the performance following a month t characterized by declining volumes and positive returns. Crucially, when average returns at month t+3 are considered average returns are higher after a month t associated with positive returns and declining volumes than after a month t associated with positive returns and rising volumes, while the reverse applies for average returns at month t+6.

Our results imply that the dynamics of volumes and prices need to be scrutinized jointly because the existence of the dichotomy implies that uncertainty has a different informative content in bullish and bearish markets. Months characterized by negative returns and growing volumes are "fire sales" months (Shleifer and Vishny [2011]) and, because of liquidity spirals, (Brunnermeier and Pedersen [2009]) and cash flow based momentum (Vayanos and Woolley [2013]) are likely to be followed by months characterized by poor returns. On the other hand, months with negative returns and declining volumes imply that the bearish movement is ending or that is not robust enough to trigger liquidity spirals or massive fire sales: this implies that positive returns are likely to follow.

Even more interesting is the pattern which emerges when returns at time t are positive. At medium-short time horizons (months t+3), the average return of the following months (time t) characterized by declining volumes and positive returns over perform the average return following months characterized by rising volumes and positive returns, but the pattern reverse at longer horizons (t+6). This evidence seems to point to a "calm before the storm" explanation (Akbas [2016]). Indeed, when many investors enter the market in the same period (bullish market, rising volumes), a relevant share of investors expect markets to continue to rise. Even more importantly loss aversion[35] explains why it is unlikely for these investors to close their position in the following months if a negative shock arises. This reduces the possibility of a major drawdown. On the other hand, after months of rising prices and declining volumes, it is more common for investors who entered before the low volumes months to cash in the gains as soon as negative returns materialize. Indeed, the most optimist investors are usually fully invested in the market: if these investors are mutual funds, they cannot employ leverage, while if they can employ leverage, they are already marking full use of it. Consequently, when the market declines leveraged investors cannot buy much more. Another possible interpretation is that unusually low trading volumes during bull markets signals negative information since, under short-selling constraints, informed agents with bad news stay by the sidelines[36].

These results are coherent with the existing literature. Gervais et al. [2001] show

[35]The Prospect theory (Kahneman and Tversky [1979]) and the related disposition effect (Shefrin and Statman [1985]) provide a solid rationale to these findings

[36]See, e.g., Miller [1977] and Akbas [2016]

how stocks which experience unusually high trading volumes over a day or a week tend to appreciate over the course of the following month. The specular applies for stocks which experience unusually low trading volumes. Differently from them, we consider aggregate market volumes and he discriminate between rising or declining de-trended volumes not very high (low) ones. Consequently, what we analyze is a different aspect of the issue while agreeing on the main point: because a lot of investors cannot go short when they are bearish, they simply do not invest in the market reducing the volumes. Finally, Kaniel et al. [2008] prove that individuals tend to buy stocks following declines in the previous month and sell following price increases. The latter result is coherent with our understanding that, when a lot of investors has just bought stocks they are reluctant to sell and to realize losses in case negative returns occurs. Furthermore the authors also show how, in agreement with our findings, stocks register positive excess returns in the month following strong buying by individuals and negative excess returns after individuals strong sell.

2.4 Greed and Fear

In this section we study the empirical performance of the sentiment and fear proxies to understand what these indexes capture. At first, we examine their predictive power both in and out-of-sample. Then, we analyze which are the drivers of sentiment and fear and how they relate to uncertainty.
The first objects of study are sentiment proxies. To address what these indexes reflect we study how they interact with uncertainty. We aim at verifying whether rising sentiment relates to an increasing dispersion in the views (uncertainty). To study this relation, we make use of correlation, Granger causality, and lasso analysis among uncertainty proxies and sentiment indexes. After that, we analyze the existence of an uncertainty risk premium, and we consider the predictive power of uncertainty. Before proceeding with the formal analysis, we plot the time series of interest to gain first qualitative insights into the variables under study.
In Figure 2.1, upper part, we introduce the proxies considered in this study for sentiment while in the same Figure, lower part, we provide a first visualization of the relationship between sentiment and uncertainty.

Insert Figure 2.1

From Figure 1 emerges how all the sentiment proxies exhibit a procyclical dynamic: they pick at the end of prolonged bull markets, and bottom after market crashes. Interestingly, after the financial crisis of 2008, the PC 6 sentiment proxy remains well below its long-term average despite an extremely prolonged period of rising markets. In the same period, all other sentiment proxies stayed in a more conservative range and close to their historical average. The lower part of Figure 2.1 shows us how sentiment and uncertainty proxies are closely related: they exhibit similar patterns both during bull and bear markets. Consequently, Figure 2.1 seems to suggest that the dispersion of investors views is linked to sentiment. We also report a surprising fact: sentiment indicators proposed by the existing literature (PC 6 and PLS 6) appear to spike right in the middle of some of the most violent market downturns of the last decades. These findings lead us to consider carefully the role played by the constituents from which the sentiment indexes are estimated. A deep investigation tells us that two (turnover and number of IPOs) of the six proxies initially employed are biased proxies of sentiment. First, share turnover is very high both in bull and in bear markets and, accordingly to our analysis of the previous section, the dynamics of volumes should be analysed jointly with the market dynamics to be insightful about future expected returns. Second, the 'number of IPOs' is largely driven by historical dynamics, like the dot.com wave or the development of a specific country or sector. Consequently, we argue that the number of IPOs is a biased proxy for sentiment. In the online appendix (Figure 2.3), we provide a visualization of our intuition: we plot the time series of turnover and of the number of IPOs with the sentiment proxy estimated using the Principal Component methodology and the remaining four sentiment indicators initially proposed by Baker and Wurgler. We observe how after the IPOs wave of the late nineties, the last few years of the sample which are characterized by extraordinarily high returns are matched by a relatively low number of IPOs in the US. In conclusion, we propose to estimate the sentiment indexes making use of only four of the six sentiment proxies originally proposed by Baker and Wurgler: these new indexes (PC4 and PLS4) are both plotted in Figure 2.1 next to the original ones (PC6 and PLS6).

The second object of study regards the fear proxies. As previously stated, the dichotomy between representative and marginal investor implies that it is not possible to accurately extrapolate fear from the stock market: the most optimistic investors can in fact express themselves directly on stock markets buying stocks, but the same does not apply to the most pessimistic ones. On the other hand, the opaqueness of over the counter markets foreshadows the possibility to extrapolate reliable information from that side. To circumvent these limitations, we rely on surveys which explicitly address the concerns of the investors and on the options market which is both transparent and liquid. The nature of the options market and the composition of the pool of investors who work on it make the option market perfectly suitable for those analyses that are not feasible on the stock exchange. The existence of liquid put and call options with different maturities and moneynesses, allows traders to express their views without the constraints at the base of the dichotomy between marginal and representative investors. As a consequence the left tail of the risk-neutral distribution emerges as a natural candidate for better understanding the nature of fear and its relation with downward uncertainty about fundamentals. Johnson et al. [2018] analyze the demand for options in the market and conclude that the primary function of index options is the transfer of unspanned crash risk. A vast literature[37] finds that while the left tail of the distribution has a strong predictive content the same is not true for the right tail of the risk-neutral distribution. The asymmetry occurs because the optimist investors can freely express themselves on the stock market and they do not need to make use of options to speculate on optimistic views. After that, the percentage of investors which is short on the market is a low fraction of the total, and consequently, the need to hedge against markets upside movements is limited. As done previously for sentiment, we start our analysis of fear indexes from visual inspection. Figure 2.2, upper part, shows how fear proxies interact with volatility and with the lower bound of the analysts'views. The lower part of the same Figure, shows how fear proxies relate to uncertainty measures.

Insert Figure 2.2

Figure 2.2 shows how, while linked, volatility and fear are two separate phenomena. It also show how the lower bound of the EPS long term growth views (LOW in the Figure) follows a path close to the fear measures ones. Furthermore, the lower plot reports how the downward uncertainty proxy is closely linked to the FVaR proxy while the financial uncertainty proxy (UF, in the Figure) is closely matched by the Crash Confidence Index measure of fear.
To better define the relation among measures of sentiment, fear, and uncertainty we analyze the correlation between sentiment and uncertainty variables and between fear and uncertainty ones (Table 2.2).

Insert Table 2.2

From the upper panel of Table 2.2 emerges how all sentiment indexes exhibit a strong positive correlation among themselves. Secondly, it is immediately clear how the weighted standard deviation of the forecast (DEVST) is more positively correlated with the upper bound of the forecasts than negatively correlated with the lower bound of the forecasts. Consequently, the upper bound of the views appears to affect the dispersion of the views more than the lower bound. After that, we observe how correlations between sentiment indexes and uncertainty proxies are positive (UF, UM, SPF, LIV) or close to zero (DEVST, UP-UNC, DOWN-UNC). Finally, the uncertainty proxies, as expected, are positively correlated among themselves.

[37] See, e.g., Andersen et al. [2015], Bollerslev et al. [2015] Christoffersen et al. [2012], Amaya et al. [2015]

Three main findings emerge from the lower panel of Table 2.2. First, option-based measures of fear are positively correlated among themselves (VaR L15-L15, BTX, FFHS, VRP, VIX). Second, the correlations between our newly proposed fear proxies (FFHS, VaR L15-L15, TAIL) and the lower bound of analysts forecast are higher than the correlations between the same fear proxies and the upper bound of analysts forecasts. The asymmetry is clear evidence that the most optimist and the most pessimist investors react differently to changes in the aggregate market risk aversion, a result coherent with what we found in our previous analysis of sentiment where our results are specular (upper panel of Table 2.2). Third, the correlations between fear proxies (Bull-Bear, CRASH, FVaR, FFHS) and uncertainty ones (UM, UF, DEVST) are negative or close to zero, and the results are stronger conditionally on a decline of the FVaR measure[38].
To unveil what our sentiment, fear and uncertainty proxies capture we start studying their predictive performance out of sample using the R^2_{os} and delta utility metrics. The former metric is further decomposed to disentangle the capability of the proxy to forecast positive and negative returns only (Bull and Bear in Table 2.3). For the analysis, the out-of-sample performance metrics considered are:

- The R^2_{os} statistic proposed by Campbell and Thompson [2008]

$$R^2_{os} = 1 - \frac{\sum_{t=1}^{T}(r_t - \hat{r}_t)^2}{\sum_{t=1}^{T}(r_t - \bar{r}_t)^2} \tag{2.11}$$

  R^2_{os} measures the percent reduction in mean squared forecast error (MSFE) between the forecasts generated by the chosen predictive model, $\hat{r}$, and the historical average benchmark forecast, $\bar{r}$. To assess the statistical significance of R^2_{os} we employ the p-values coming from the Clark and West (2007) MSFE-adjusted statistic. This indicator tests the null hypothesis that the historical average MSFE is less than or equal to the forecasting method MSFE against the alternative that the historical average MSFE is greater than the forecasting method MSFE (corresponding to $H_0 : R^2_{os} \leqslant 0$ against $H_1 : R^2_{os} > 0$).

- The Delta Utility measure proposed by Campbell and Thompson (2008) Campbell and Thompson [2008]. Following the original paper, we estimate the variance using a ten-year rolling window of returns. We consider a mean-variance investor who forecasts the equity premium using the historical averages. She will decide at the end of period t to allocate the following share

[38] The tables which report conditional correlation are reported in the online appendix (Table 2.19 and 2.25).

of her portfolio to equity in the subsequent period t+1:

$$w_{0,t} = \frac{1}{\gamma}\frac{\bar{r}_{t+1}}{\hat{\sigma}_{t+1}} \tag{2.12}$$

where $\hat{\sigma}_{t+1}$ is the rolling-window estimate of the variance of stock returns. Over the out-of-sample period, she will obtain an average utility of:

$$\hat{v}_0 = \hat{\mu}_0 - \frac{1}{2}\gamma\hat{\sigma}_0^2 \tag{2.13}$$

where $\hat{\mu}_0$ and $\hat{\sigma}_0^2$ are the sample mean and variance, over the out-of-sample period for the return on the benchmark portfolio formed using forecasts of the equity premium based on the historical average. Then we compute the average utility for the same investor when she forecasts the equity premium using one of the predictive approaches proposed in this paper. In this case, the investor will choose an equity share of:

$$w_{j,t} = \frac{1}{\gamma}\frac{\hat{r}_{t+1}}{\hat{\sigma}_{t+1}} \tag{2.14}$$

and she will realize an average utility level of:

$$\hat{v}_j = \hat{\mu}_j - \frac{1}{2}\gamma\hat{\sigma}_j^2 \tag{2.15}$$

where $\hat{\mu}$ and $\hat{\sigma}_{t+1}$ are the sample mean and variance, over the out-of-sample period for the return on the portfolio formed using forecasts of the equity premium based on one of the methodologies proposed. In this paper, we measure the utility gain as the difference between $\hat{v}_j$ and $\hat{v}_0$, and we multiply this difference by 100 to express it in average annualized percentage return. In our analysis, following the existing literature[39], we report results for $\gamma = 3$.

To make our results comparable, in light of the heterogeneity of the length of the different time series considered, we apply the same percentages to split each time series into an in sample, hold out and out-of-sample period: 40%, 10% and 50% respectively.

Insert Table 2.3

The results of the out-of-sample predictive performance are extremely insightful. Table 2.3 shows how, overall, the most powerful predictor among sentiment proxies

[39] Among the most cited works on the subject Campbell and Thompson [2008] and Rapach et al. [2010] impose the same level of risk aversion

employs six inputs and the PLS approach (R^2_{OS}=2.11). Interestingly, disaggregating the overall predictive ability (Tot) in the capability to forecast positive (Bull) or negative (Bear) returns only, other results emerge. At first, it appears how original sentiment proxy of Baker and Wurgler [2006] (PC6) is more effective in forecasting positive (R^2_{OS}=0.80) than negative returns (R^2_{OS}=-0.03). Similarly, the turnover variable is powerful in predicting positive returns (R^2_{OS}=2.31) and weak in predicting negative ones (R^2_{OS}=-1.30). The omission of this variable[40] makes the PC 4 and PLS 4 sentiment proxies good predictors for bear markets and weak predictors for bull ones. Consequently, the capability to forecast correctly bear markets but not bull ones means that the PC 4 and PLS 4 indexes capture overbought situations or situations of abnormally low risk aversion. The PLS 6 sentiment proxy presents a similar performance (Bull R^2_{OS}=0.42, Bear R^2_{OS}=3.47) and this implies that the employment of a more powerful statistical procedure (PLS) is a viable alternative in effectively synthesizing the predictive power of the six original proxies for sentiment into an effective overbought indicator.

Then we analyze the predictive power of uncertainty proxies. The obtained results are aligned and clear: while overall their predictive performance is weak, all the financial and macroeconomic uncertainty indexes are effective in forecasting negative returns but not positive ones. The evidence that the overall predictive performance is weak is in line with our previous finding that high uncertainty precedes both positive and negative returns depending on the prevailing market conditions. Moreover, the capability to forecast negative but not positive returns is in line with the predictive ability of the PC 4, PLS 4 and PLS 6 proxies for sentiment and confirms the strong links between sentiment and uncertainty proxies.

We now study fear proxies. Here the most powerful predictors are option-based: FVaR (R^2_{OS}=9.54), FCVaR (R^2_{OS}=18.79), and VRP (R^2_{OS}=6.06). When we disentangle the overall predictive performance in the capability to forecast positive and negative returns, we observe how a clear pattern emerges. The indexes which make use of surveys (UM-MD, the LIV Skew, the RGDPX Skew, CRASH) and the indexes that make use of option implied information (FFHS, FVaR, FCVaR) achieve a robust predictive performance in forecasting positive returns and a weak performance in predicting negative ones. On the other hand, stock based indexes (TAIL, KJ, CATFIN), the MACRO uncertainty proxy, and the Anxious index (ANX) are all better able to forecast negative than positive returns. Finally, the VIX index shows no sign of having a predictive power, while the variance risk premium (VRP) has an overall positive and statistically significant predictive power coming from its ability to forecast both negative and positive returns. Overall, the predictive performances out-of-sample of the indexes considered lead us to classify them in two categories: indexes of uncertainty, which concentrate their predictive

[40] The number of IPOs sentiment proxy has a different impact in different historical periods.

power in forecasting negative results only; and indexes of fear, which have an overall statistically significant predictive power that comes mostly from their ability to forecast positive results.

Analyzing the predictive power of the same proxies at longer horizons, other interesting patterns emerge[41]. At short time horizons (t+2, t+3) the option implied measures of fear that perform better are the VRP and the VaR-based ones. Differently, at intermediate horizons (t+6) the most potent predictors are the BTX and the FFHS measures. The different performances of the indexes at different horizons can be explained understanding how the various measures are built. The FVaR and CVaR indicators are built using options with monthly maturity and, not surprisingly, have reliable predictive power at short horizons. On the other hand, the FFHS measures are built with a panel of options with maturities in the range between 8 and 365 days, and consequently, their predictive performance grows at intermediate time horizons. Interestingly, while option-based measures of fear have a robust out-of-sample predictive performance there is no trace of predictive ability for the VIX index. These results jointly confirm that volatility and fear are two separate concepts.

Having studied the out-of-sample predictive performances of sentiment, fear and uncertainty proxies, we now investigate whether the in-sample results confirm the out-of-sample ones. We consider the in-sample linear relationship between excess returns, and standard deviation, of the S&P500 at month t+1 and the level of the previously reviewed predictors at month t. The standard deviation is computed through a forty months rolling window. All t statistics (and the R^2 values) are based on the heteroscedasticity-consistent standard errors of White (1980). The methodology employed is based on univariate linear regressions estimated through GMM.

$$Y_{t+1} = \alpha + \beta X_t + \epsilon_t \tag{2.16}$$

where Y_{t+1} are next month excess returns or standard deviations of the S&P500 and X_t is the level of the chosen regressor this month.

Insert Table 2.4

The obtained results confirm our previous findings for the out-of-sample analysis. Three strong findings emerge. First, the level of sentiment is negatively related to subsequent S&P500 excess returns. Second, uncertainty predicts subsequent high volatility while it has a weak predictive power on subsequent excess returns. Third, short-term option-based measures of fear (VRP, FVaR) predict subsequent high excess returns. Extending the analysis at longer horizons (t+3, t+6, t+12) the predictive power of the intermediate-term option-based measures of fear (FFHS,

[41] Results are documented in Tables 2.18, 2.22, and 2.28 in the online appendix

BTX) on excess returns, match their performance out-of-sample[42].
The previous findings led us to investigate the existence of a risk premium for uncertainty. Our first visual inspection pointed against it (Figure 2.1); our empirical results indicate in the same direction (Tables 2.3 and 2.4). Whether an uncertainty risk premium exists a spike in uncertainty should be linked with a contemporaneous price drop and a related increase in expected returns. To test the existence of this risk premium, we consider the 30 best and worst returns for the S&P500 for the period 01-1992/12-2016, and we compute the average percentile the month before the occurrence of the extreme return. The percentiles are computed with regard to the distribution of the level of the chosen index in the previous ten years.

Insert Table 2.5

We observe how, on average, the month before a major market fall the uncertainty indexes are already high: the weighted standard deviation of the views (DEVST) is at its ten-year 82^{nd} percentile, the financial uncertainty index at its 78^{th} percentile and the macroeconomic uncertainty indexes are all between their 70^{th} and 60^{th} percentile. Consequently, we argue that uncertainty was already high **before** major market drops. A careful investigation of timing of the falls implies that is unlikely that an uncertainty risk premium might exists. Interestingly, even before significant market rises the level of the uncertainty indexes was high: the financial uncertainty index was in its 77^{th} percentile while the weighted standard deviation of the views was in its 84^{th} percentile. The reported results imply that, when uncertainty is high, the probability of a major market movement is high, and the market movement could be positive or negative. We argue that when uncertainty is high, the arrival of new information can trigger a sharper reaction than when there is broad consensus on the future market direction. These results are consistent with the work of Zhang [2006] which, in the cross-sectional contest, shows how greater information uncertainty should produce relatively higher expected returns following good news and relatively lower expected returns following bad news.

Having found that sentiment indexes capture abnormally low levels of risk aversion and that they are tightly linked with uncertainty proxies we now study which are the main drivers of sentiment indexes. To achieve this goal we make use of the Granger causality test and the lasso approach. Our approach for the Granger causality test considers two time series per time and tells us if one leads the other (or more precisely whether one moves before and in the same direction of the other). Out tests are designed in the following way:

- At first, 4 legs are chosen as default initial size and the AIC criteria is employed to identify the best number of lags.

[42] Results are reported in the online appendix Tables 2.23 and 2.29

- Once the correct number of legs is identified we compute the value of the F-statistic and the related critical value from the F-distribution at the 5 % significance level.

- If F > critical value, we reject the null hypothesis that y does not Granger cause x.

As in Rapach et al. [2013] the role of the Lasso model selection methodology is to confirm the robustness of the results of the Granger causality and involves the following minimization problem:

$$\min_{\beta_0,\beta}\left(\frac{1}{2N}\sum_{i=1}^{N}(y_i-\beta_0-x_i'\beta)^2+\lambda\sum_{j=1}^{p}|\beta_j|\right) \tag{2.17}$$

where N is the number of observations, y_i is the response observation, x_i is a vector (of length p) of values at observation i, λ is a non-negative regularization parameter, parameters β_0 and β are a scalar and a vector of length p. The algorithm calculates the largest value of lambda that gives a non-null model and after that the smallest alpha value is found imposing that the ratio of the smallest lambda value divided by the highest equals 1e-4. The remaining lambda values are found employing a geometric sequence. We report the parameters related to the 60^{th} (and 90^{th}) lambdas values because they provide restrictive (and very restrictive) selections of the most powerful predictors.

Insert Table 2.6

The first remarkable result relates to sentiment indexes. Here we observe a clear difference between the PC6 sentiment proxy and the others sentiment indexes: the former appears to be driven by the weighted mean view (the representative investor one) while the others sentiment proxies are led by upper view and by macroeconomic uncertainty. The results that emerge lead us to confirm our understanding of sentiment indexes as indicators of overbought because the most optimistic investors drive them (UP), but the most pessimist ones do not (LOW)[43].
Also the results coming from the lasso approach confirm this intuition: the upper view is selected for the PLS6, PLS4 and PC4 sentiment proxies at the 90% percentile of the distribution of the lambda parameter. We then consider the interaction between sentiment and uncertainty indexes. At first, we report how sentiment and uncertainty indexes are cointegrated[44] and that macroeconomic uncertainty (DEVST, UP-UNC) drives the most optimist views (Table 2.6).

[43] The full sample of Granger tests is in the online appendix, Table 2.21

[44] Johansen tests on cointegration are reported in the online appendix, Table 2.20

In summary, being a powerful predictor of negative returns and being Granger-caused by the upper bound of the views we interpret sentiment as an indicator of overbought driven by upside uncertainty about fundamentals. More precisely, a high level of sentiment captures situations in which a minority of over-optimists investors push prices far from the representative investor valuations (weighted mean expectation of the investors). In conclusion, when sentiment is high, prices reflect the risk aversion of optimist investors leading to sharp corrections when exogenous news does not confirm the existing trend.

Insert Table 2.7

The next empirical analysis studies fear proxies (Table 2.7). The first remarkable result is that the option based measures of fear (FVaR, FFHS, VRP) neither Granger cause nor are Granger-caused by the VIX index and the two phenomena appear to be distinct. Indeed, the VIX appears to be linked mostly with uncertainty and its most powerful driver, among the ones considered, is the financial uncertainty measure of Jurado et al. (2015). After that, we observe how the upper bound of the views (UP) appears to be Granger-caused by uncertainty indexes (DEVST) but to Granger cause volatility (VIX). Interestingly, the lower bound of the views (LOW) follows a different pattern: it is Granger caused not only by uncertainty (DEVST) but also by fear indexes (TAIL, BTX, CRASH, Bull-Bear, ANX) and by the VIX index. The result just stated is a further evidence of the existence of an asymmetry between optimistic and pessimistic views: optimistic views have a direct impact on the market, while pessimistic views do not own such a property.

We also study the relationship between uncertainty and fear. At first, we document how option-based fear indexes (FVaR, VRP, FFHS, BTX) are cointegrated with uncertainty proxies (DEVST, UF, UM)[45]. Secondly, we document how our short-term option implied proxy of fear (FVaR) appears to be driven by financial uncertainty (UF) and by the representative investor view (MEAN). As a consequence this index reflects the average market view that is unable to express itself directly on stocks prices. Finally, we report how the indexes of fear coming from long-term maturity options (FFHS) are Granger-caused by indexes of fear coming from short-term maturity options (FVaR) and how indexes of fear based on surveys on the expected dynamics of the stock market (CRASH CI) are Granger caused both by option based indexes of fear (FVaR, BTX) and by volatility (VIX). The picture that emerges from this analysis is clear: the causality dynamics among indexes are consequence of the time needed by the different indexes to reflect the views of the investors. When financial uncertainty is high, options, being used by a set of sophisticated investors, are the first one to reflect expectations on fu-

[45]Results on cointegration are reported in the online appendix, Table 2.22

ture markets falls through the left tail of the risk-neutral distribution. After that, uncertainty about a possible adverse event is reflected in the views of analysts (LOW, UM-UD) and the economists (LIV skew, RGDPX skew). Only later, when the negative returns are already occurring, and volatility is rising, the views of investors (CRASH CI, Bull-Bear) indicate abnormally high level of risk aversion[46]. In conclusion, we have seen how uncertainty is tightly linked not only with sentiment but even with fear. Fear indexes have a predictive power that is specular to sentiment ones because it comes from the capability to forecast positive returns while the predictive performance of sentiment indexes is linked to their ability to predict negative returns. Consequently, while sentiment indexes, built using equity-based indicators capture situations of excessive optimism (low-risk aversion), option-based fear indexes, detect situations of excessive pessimism (high-risk aversion). In a nutshell while upward uncertainty about fundamentals drives sentiment, downward financial uncertainty leads fear.

2.5 Timing Cross-sectional risks and returns

In their seminal paper, Stambaugh et al. [2012] prove that anomalies, to the extent they reflect mispricing, should be stronger following high sentiment. Moreover, if the primary form of mispricing is overpricing, then mispricing should be more prevalent when sentiment is high. In the previous section, we have shown that sentiment can effectively identify only situations characterized by abnormally low levels of risk aversion. In this analysis, we show that having identified sound proxies for fear, which is specular to sentiment, the reverse applies: anomalies are stronger even following high levels of fear and, in such case, the primary source of mispricing is underpricing. This means that while conditioning on a high sentiment level the main driver of the factors and anomalies is the short leg, conditioning on a high level of fear the main driver of returns is the long leg. We also show how, conditionally on a high level of sentiment or fear, the risk-return relationship breaks up: we observe respectively low or high excess returns per unit of risk. Finally, we link our results to the ones coming from the recent literature on the topic.

Insert Table 2.8

We start representing the summary statistics of monthly returns in Table 2.8. In the upper part we report the correlations among the long-short benchmark-adjusted returns, which in this paper we define as return net of what is attributable to the three factors of Fama and French [1993]. Consequently, the benchmark-

[46]The full table of Granger causality is in the online appendix Table 2.23

adjusted return is the sum of a_i and the fitted value of $\varepsilon_{i,t}$ in the regression:

$$R_{i,t} = a_i + bMKT_t + cSMB_t + dHML_t + \varepsilon_{i,t} \tag{2.18}$$

The lower part of Table 2.8 reports the averages excess monthly returns (returns in excess of the monthly Treasury bill rate) for the long and short legs and the long-short return spread. In the lower panel of the table, we report the second, third and fourth moments, the Sharpe ratio and the Cornish-Fisher ratio[47] for long and short legs and the long-short return spread. The first interesting result is the difference between the excess returns of anomalies (1-11), built following the approach detailed by Stambaugh and Yuan [2017], and factors (12-18), coming from the French data library. The excess returns coming from the short leg of the first set is negative while it is positive for the second set. The spread of the monthly excess returns ranges from a minimum of 43 basis points for the yield ratio to a maximum of 210 for the default probability anomaly. The skewness of the long leg of the anomalies-factors appears to be on average more negative for the long leg than for the short leg while the reverse applies for kurtosis. No remarkable differences are discernible between the long leg and the short leg regarding standard deviation. Finally, looking at the Sharpe and Corner-Fisher ratios we notice how the results provided by these two indicators are aligned: the highest values come from the investment factor the composite equity issue anomaly, the failure probability anomaly and the investment to assets anomaly.
The first step of our empirical analysis studies the performance of the anomalies at month t+1 conditionally on having at month t a high (low) level of sentiment, uncertainty or fear. A month t with high (low) level of sentiment, uncertainty or fear is one in which the value of the chosen index is above (below) its median value for the whole sample period. This procedure, originally introduced by Stambaugh et al. [2012] for sentiment indexes, is employed by us to analyze the impact of the level of uncertainty and fear indexes on the subsequent risk-return dynamics of the long and short leg of the anomalies. Differently, from Stambaugh et al. [2012] we do not consider only excess returns but also conditional Sharpe ratios for all the eleven anomalies and the seven factors-ratios considered. In the online appendix, we report even conditional standard deviations, skewness, kurtoses, and Cornish-Fisher ratios. The proposed approach allows us to assess the conditional risk-return profile of the anomalies studied. To further analyze the proxies we introduce a combination strategy that invests equally in all the 18 factor-anomalies. Such an approach provides a useful summary indicator of the overall conditional behavior of all the anomalies-factors considered.

Insert Table 2.9

[47] Average return minus risk-free divided by the Cornish-Fisher 99^{th} percentile VaR

We start considering the performance of the anomalies-factors conditionally on a high (low) level of sentiment or uncertainty. The chosen proxy for sentiment is the PLS 6 sentiment index of Huang et al. [2015] while the chosen proxy for uncertainty is the macroeconomic uncertainty (UM) of Jurado et al. [2015]. We have chosen the PLS 6 proxy for sentiment because it is the sentiment index with the strongest predictive power out-of-sample in timing the aggregate market and it has the strongest predictive performance even regarding the timing of the anomalies. The employment of the other sentiment measures (PLS 4, PC 6 and PC 4) give rise to the same qualitative results[48]. The UM metric is chosen in light of its close relationship with the sentiment indexes and because it is tightly linked with all other measures of uncertainty. Also here, the employment of others uncertainty proxies (UF, LIV, SPF) gives rise to the same qualitative results[49]. The findings, conditioning on high (low) levels of sentiment (Table 2.9), Stambaugh et al. [2012]. After months of high sentiment, the returns for both the long and the short leg are lower than after months of weak sentiment. The combination strategy shows how the long leg has an average return of 12 basis points after month of high sentiment but 96 basis points after low sentiment months. Similarly, the short leg of the combination strategy switches from minus 58 basis point after months of high sentiment to plus 58 basis point after months of low sentiment. Interestingly, the returns after months of high sentiments are strongly negative for all the anomalies of the long leg and all the anomalies, two factors and the combination strategy for the short leg. Moreover, the standard deviations of the anomalies-factors are higher after high sentiment than after low sentiment months. These two results jointly imply that after high levels of sentiment lower (and often negative) returns are matched by higher risks while after a low level of sentiment the reverse applies. We also observe how for all the anomalies-factors (long-short in the table) the excess returns are higher after a high level of sentiment than after a low level of sentiment: a result driven by the short leg.

A possible explanation for the mismatch between conditional excess return and standard deviation, is that standard deviation is an incomplete measure of risk which could manifest itself otherwise through skewness or kurtosis. To address this concern, we analyze conditional skewness and kurtosis, and we make use of the ratio of excess returns on the 99% Cornish-Fisher VaR estimated with the four conditional moments of the considered returns (results reported in Table 2.30 in the online appendix). Our results on the skewness are even more striking: after low sentiment, skewness is positive while turns strongly negative after high sentiment months. Finally, the performance of Sharpe ratios is exactly matched by the performance of Cornish-Fisher ratios. The obtained results confirm that

[48] Results are available upon request

[49] Results are available upon request

sentiment is a crucial driver of the performances of both anomalies and factors, but we add the critical insight that, conditionally on a high (low) level of sentiment, we observe subsequent low (high) excess returns per unit of risk.

Insert Table 2.10

As a next step we consider the behavior of anomalies conditionally on a high (low) level of macroeconomic uncertainty. Conditionally on a high level of uncertainty the excess returns are lower, the standard deviations higher (and the skewness are more negative)[50], than conditionally on a low level of uncertainty. Overall the results from uncertainty are similar to the results coming from sentiment, but they are weaker. Indeed, they are valid on average (combination strategy) but, differently from sentiment, they do not hold for all the anomalies-factors considered. The similarity between sentiment and uncertainty with respect to their predictive ability in timing the anomalies is consistent with our previous results on their predictive strength in timing the aggregate market: the results are precisely aligned.

Insert Table 2.11 *Table* 2.12

We now study the risk-return profile conditioning on the VIX index and the Variance Risk Premium (VRP). The results are fascinating: conditioning on a high level of the VIX index we observe higher excess returns than conditioning on a low level of the index (for the combination strategy 84 and 33 bps against 43 and minus 2 bps for the long and short leg respectively), but the higher returns are matched by higher risks both in terms of standard deviation and skewness. Consequently, the differences between Sharpe ratios (and Cornish-Fisher ratios)[51], conditionally on a high-low level of the VIX are remarkably low. Precisely, the differences in terms of Sharpe ratios between months following high volatility and months following low volatility are respectively equal to 0.38 for the long leg and to 4 for the short leg of the combination strategy.
The results conditioning on the VRP are different: here, similarly to the previous case, a high-level of the index is linked to higher subsequent excess returns and standard deviations than in the case of a low-level of the index. The crucial difference is that the risk-return proportions are now different: the Sharpe ratios conditionally on a high level of VRP are much higher than conditionally on a low level of the VRP (20.2 against 2.2 for the long leg and 10.1 against -6.6 for the short leg of the combination strategy). Our results are coherent with Feunou et al. [2017] who show how the downside variance risk premium is the dominant component of the VRP and consequently the VRP can be interpreted as a proxy for

[50] As documented in Table 2.31 of the online appendix

[51] Table 2.32 in the online appendix

fear.

Insert Table 2.13 and Table 2.14

Finally, we consider the performance of the anomalies conditionally on our newly proposed measures of fear (FVaR and FCVaR). The results are striking: conditionally on a high level of fear the subsequent excess returns are higher and the risks (in term of standard deviation)[52] are lower than conditioning on a low level of fear.Indeed, we document how for the combination strategy, conditionally on a high level of the FVaR index, the subsequent average returns are 84 bps for the long leg and 61 bps for the short leg against minus 13 bps and minus 31 bps conditionally on a low level of the index. Interestingly, now the abnormal performance of the anomalies-factor is driven by the long leg: a result precisely specular to the one find for sentiment indexes. It also emerges how conditionally on a high level of the FCVaR proxy, factor-anomalies are on average (combination strategy) 21 basis point higher than conditionally on a low level of the FCVaR proxy (the same applies for the VRP measure). Consequently, a high fear level, by detecting under pricing, forecasts a subsequent higher average performance of the considered factors-anomalies. In conclusion, our fear proxies are complementary to the sentiment indexes in timing the anomalies, and this allows us to complete the picture proposed by Stambaugh et al. [2012]. Our new understanding of the complementarity of sentiment and fear enables us to time the mispricing reflected in the returns of anomalies and factors. This applies both in the case when overpricing is the dominant mispricing component (high sentiment) and when under-pricing is the dominant component (high fear).
To gain further insight into the dynamics previously detected we perform an in-sample analysis of the relation between sentiment, uncertainty and fear proxies at month t and excess returns and standard deviation at month t+1 (Table 2.15). At first, we compute the volatility of the long and short legs of the anomalies through the standard deviation of a rolling window of forty months. Then, we regress the level of the selected variables at month t on excess returns; and the newly computed standard deviations at month t+1.

Insert Table 2.15

At first, it emerges how the negative relationship between the level of sentiment and subsequent excess return is matched by a positive relationship between sentiment and standard deviation. Consequently, and coherently with our previous results, a high level of sentiment implies subsequent lower returns and higher volatility. All the coefficient are statistically significant, thus confirming the robustness of the findings. We also observe that uncertainty predicts future higher volatility while

[52]In Tables 2.34 and 2.36 of the online Appendix we document how differences in conditional skewness are marginal, while conditional kurtoses are lower after high fear months.

the betas of the regressions on future excess returns are almost unanimously negative but not statistically significant. This result is coherent with our understanding of uncertainty as a valuable predictor of future volatility but not of future excess returns. Aligned with our previous findings it emerges how the relationships between the VIX and subsequent excess returns and volatility are positive. Finally, our measure of fear exhibits a positive relationship with future excess returns and a negative one with future subsequent volatility. In a nutshell, a high level of fear (sentiment) implies that stocks are underpriced (overpriced).
To strength the analysis, we consider the out-of-sample performance generated by a portfolio exercise that uses as inputs the above analyzed elements. At each time t, the portfolio allocation is divided between the risk-free security and a risky investment. The risky investment is one leg of the anomalies or one leg of the combination strategy. At first, a univariate regression is employed to forecast returns at time t+1 using one of the chosen predictors. After that, on the base of the forecast, an optimization is performed, and the two portfolios weights are identified (one for the risky and one for the risk-free security). To avoid results driven by extreme and unrealistic allocations we follow the literature[53] and impose the following bounds to the weight of the risky asset: -1[54] and +1.5. Considering the different length of the available time series and to make the results comparable we implement the out-of-sample performance in the following way: 25% of the available data for each time series is used to estimate the univariate linear regression in sample, 15% is used as holdout period, and the remaining 60% is employed for the out-of-sample performance analysis. We focus on the capability of the chosen predictors to forecast the long and the short leg of the combination strategy: this approach provides a succinct summary of their predictive power for the long and the short leg of the individual factors-anomalies[55].

Insert Table 2.17

As expected the predictive power of sentiment indexes and fear ones is specular: sentiment measures are powerful in forecasting the short leg while fear ones are powerful in predicting the long leg. Previously we found that sentiment indexes are indicators of overbought. Here we report how they are indeed especially powerful in predicting the short leg that is coherently driven by overbought. On the other hand, we have seen how fear indexes are oversold indicators. Here we report how they are mostly effective in predicting the long leg of the anomalies.

[53]See, e.g, Campbell and Thompson [2008], Rapach et al. [2010], and Pettenuzzo et al. [2014] who impose similar bounds

[54]Reducing further the bound would rise the profitability of the strategies at the expense of making the dynamic asset allocation more unrealistic.

[55]Details for all the individual anomalies are reported in the online appendix in Table 2.38 and 2.39

Looking at the predictive performance of the uncertainty indicators, we observe how these indicators, like the sentiment proxies, are better suited in predicting the short than the long leg of the factor-anomalies. Once more, the predictive power of sentiment and uncertainty for anomalies matches the their predictive power for the aggregate market.

Finally, we observe how the one-week Bull-Bear spread, the Tail index, and CATFIN measure are the strongest predictors for both the legs of the combination strategy. In conclusion, both in-sample and out-of-sample analysis confirm that the predictive complementarity between sentiment and fear indexes, previously detected for the aggregate market (proxied by the S&P500), holds strong even at the cross-sectional level.

To conclude we put the obtained result in perspective, linking our findings with the ones coming from the existing literature. In an influential paper, Campbell and Shiller [1988] show how unexpected returns are equivalent to the revision in expectation about future dividends minus the revision in expected returns. Cohen et al. [2003] and Vuolteenaho [2002] adapt the same logic to decompose the Value Spread. The authors show how, analogously to the Campbell-Shiller model, the book-to-market ratio can be (temporarily) low if future cash flows are high and/or future excess stock returns are low. Crucially for a better understanding of our results, the same authors prove how news about expected returns are highly correlated across firms while cash flows news can largely be diversified away in large portfolios. More recently, Gerakos and Linnainmaa [2018] explain that corporations move between growth and value because of changes in either size or book value of equity and that the value premium is specific to variation in book-to-market that emanates from size changes only. All these findings jointly imply that the value spread is driven by changes in the expectations about returns and that these changes are relevant only when they affect the relative level of prices. What stated is equivalent to saying that it is the risk aversion that drives the value spread and it confirms our understanding of sentiment and fear proxies as two complementary sets of predictors for timing the dynamics of the anomalies. Even more interestingly, the empirical evidence that conditionally on sentiment and fear proxies the anomalies exhibit a similar behavior, suggests that the recent understanding of the dynamics underpinning the profitability of the value spread could be extended to all the other anomalies and factors.

Consequently, having seen that fear and sentiment predict the returns both at an aggregate market level and at a cross-sectional level, it is possible to conclude that risk aversion is a key driver of the markets. Because sentiment and fear, or broadly speaking risk aversion, drive the cross-sectional returns, it comes with little surprise that it is possible to extract from cross-sectional returns (anomalies and factors) powerful predictors for the aggregate market (Kelly and Pruitt [2015]

and Maio [2016]). The results of the last cited authors imply that the same risk aversion, which drives the anomalies, can be extracted from the cross section of returns and used to successfully forecast the dynamics of the aggregate market.
Our results also relate to Daniel and Titman [1997], Campbell et al. [2010] and Kozak et al. [2018]. The first paper argues that characteristics, not market-wide risk factors are responsible for factors' returns. The second paper shows how the systematic risks of stocks with similar accounting characteristics are driven by the systematic risks of their fundamentals, and consequently, fundamentals explain the genesis of the anomalies. Finally, the third paper argues that independently on the source of variation (sentiment or risk) a risk-return balance must arise if arbitrageurs are present.
This paper adds new insight into the literature showing how, conditionally on having a high level of sentiment or fear, the risk-return relationship breaks up: we observe low or high excess returns per unit of risk. Our empirical results suggest that risk aversion (of which fear and sentiment are two manifestations) is anchored to fundamental rationales and it is not a manifestation of irrationality. Still, risk aversion can be successfully timed and this implies that markets tend to overreact to economic news allowing investors the possibility to gain returns unbalanced by risk or to take risks unbalanced by returns. Indeed, not necessarily arbitrageurs can intervene or are willing to do it in a risky environment (Shleifer and Vishny [1997] and Hong et al. [2012]).

2.6 Conclusion

While sentiment and fear are two widely employed concepts in empirical financial economics, there is a visible shortage of studies that analyze what these measures ultimately are. With this study, we provide a first empirically rooted answer: sentiment and fear are two complementary measures of risk aversion that are linked with uncertainty. The two measures are specular regarding their predictive power both for the aggregate market and for the cross-sectional dispersion of returns (anomalies-factors).
All the analyses performed are based on the key insight that there is a distinction between the representative and the marginal investor, or that the prices reflect the views of the optimistic investors while the views of the pessimist ones are reflected on the options market. In light of this fundamental insight, we started developing our analysis.
At first, we show how volumes are a bad proxy for sentiment because their dynamic has a different relationship with future returns conditionally on being in bullish or bearish markets. After that, IPOs occur in waves linked to specific historical situations. When we remove the number of IPOs and volumes from the list of six

sentiment proxies at the base of the estimation of the Principal Components and Partial Least Squares sentiment indexes, we observe how these new indexes concentrate their predictive capability in forecasting negative returns. Consequently, they are authentic indicators of an excessively low level of risk aversion (they are indicators of overbought or greed).
After that, we concentrate on the relationship between sentiment and uncertainty, and we show how uncertainty is closely linked with sentiment. Indeed, we observe how the upper bound of the analyst's EPS (Earning Per Share) long-term growth Granger cause sentiment, and this implies that sentiment is driven by the most optimist investors or the marginal ones. Even more strikingly we find that extreme negative and positive returns occur when uncertainty indexes are already high, and consequently, there is no evidence of an uncertainty risk premium: high uncertainty predicts subsequent high volatility but it has no significant predictive power on subsequent returns.
Subsequently, we study the relationship between fear and uncertainty. We employ indexes coming from surveys, and we propose new measures inferred from the percentiles of the option implied risk-neutral distributions. We observe how financial uncertainty is closely linked with fear proxies and we document how fear indexes have a strong predictive power for positive returns only, and consequently, they can be interpreted as indexes of excessively high-risk aversion (or indicators of oversold).
Finally, we consider the impact of sentiment and fear proxies on the cross-section of returns (anomalies and factors), and we find that they can properly time both the legs of the anomalies. Remarkably, the risk-return relationship breaks up: conditionally on a high (low) level of fear at month t we observe a high (low) return per unit of risk in month t+1. The specular applies for sentiment.
Overall, our results show how the dynamics of risk aversion captured by sentiment and fear drive financial markets both at the aggregate and at the cross-sectional level. Our findings are coherent with the view that macroeconomic shocks impact simultaneously both risks and the prices of risks (Campbell and Cochrane [1999]), but subsequently their dynamics diverge (Moreira and Muir [2017]) allowing for a timing of the expected risk-return trade off.

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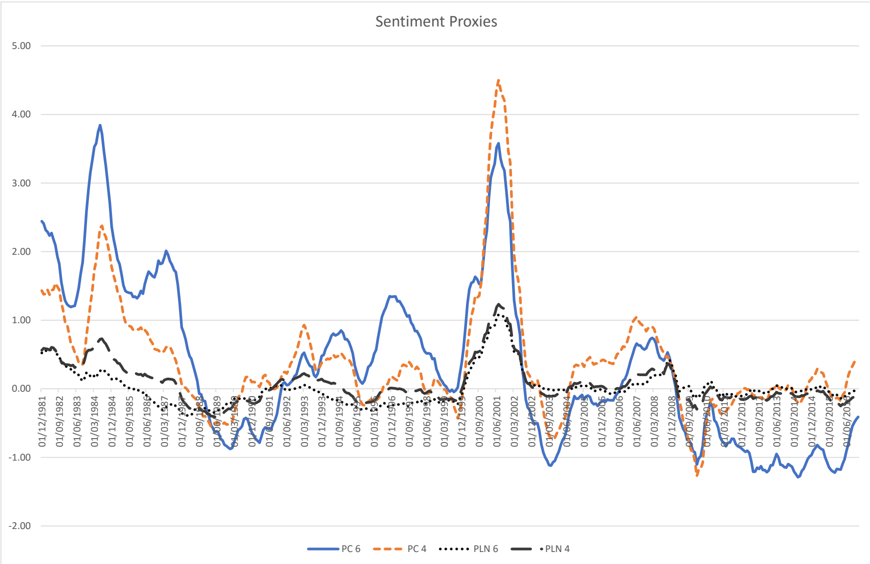
2.7 Tables and Figures

Figure 2.1: The upper figure depicts the monthly time series of the sentiment proposed Baker and Wurgler (PC) and by Huang et al. (PLS). Both the indexes are computed with 6 (Close-end fund discount rate, Share Turnover, Number of IPOs, First day return of IPOs, Dividend premium, Equity share in new issues) and 4 proxies (Close-end fund discount rate, First day return of IPOs, Dividend premium, Equity share in new issues). The lower figure shows the PLS 6 sentiment proxy with the financial uncertainty (UF) measure of Jurado et al. (2015) and the view weighted standard deviation of the long-term EPS growth forecasts (DEVST). All the indexes in the figure are standardized and span the period from 12-1981 to 12-2016



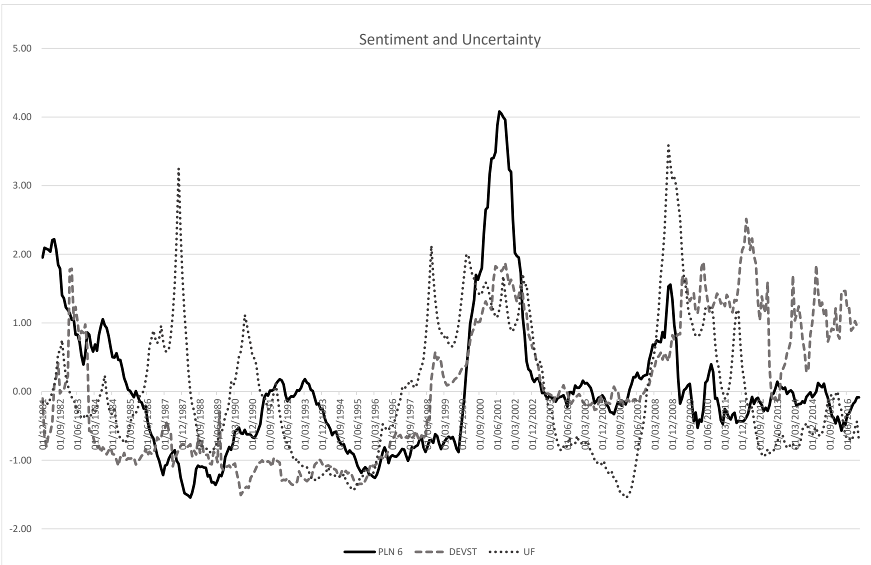
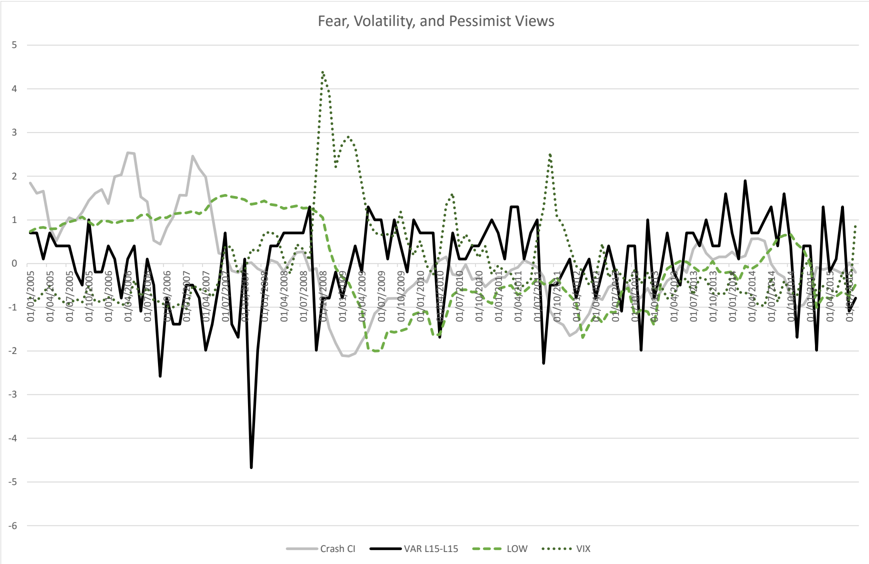


Figure 2.2: The upper figure, shows the time series of the crash confidence index (Crash CI), the VaR L15-L15 proxy, the VIX index and the lower bound of the analysts' EPS long-term growth forecasts (LOW).
The lower plot presents the same two fear proxies with the financial uncertainty measure of Jurado et al.(UF) and the downward uncertainty measure (DOWN-UNC) defined as the number of view weighted mean EPS long term growth minus lower bound of the EPS long term growth. All the indexes in the figure are monthly, standardized and span the period 01-2005/08-2015.



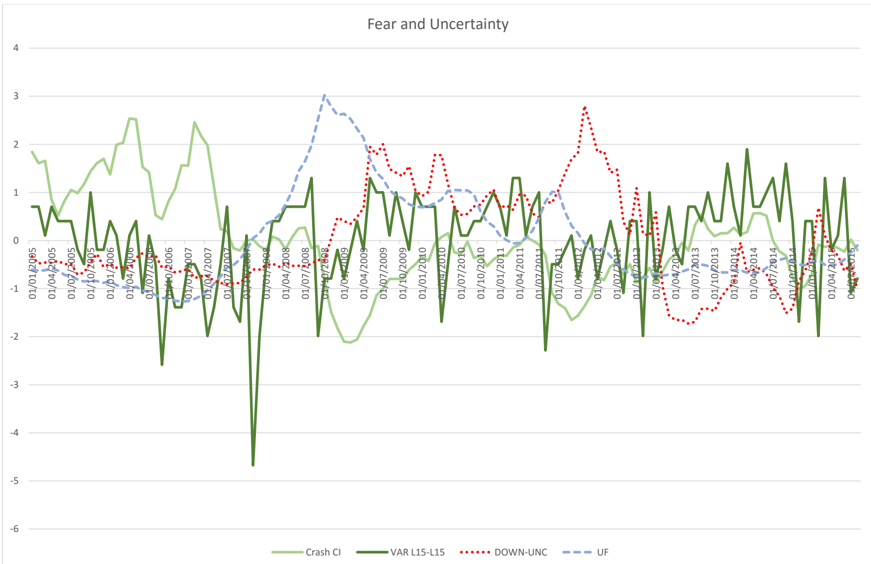


Table 2.1: The joint dynamics of volumes and prices and subsequent returns. The first three panels show the number of observations, the cumulated and the average returns at months t+1, t+3 and t+6 conditionally on being, at time t, in one of the following four conditions: positive (negative) return in month t and rising (declining) detrended volumes. The mean used to detrend the growth in volumes is built using all observations available up to time t. In the last three panels we present the returns of a trading strategy that buys at the beginning of time t+1 or t+4 conditionally on being in time t in one of the 4 possible return volumes combinations and hold the stock until the end of month t+3 or t+6 (t+1:t+3, t+1:t+6 and t+4:t+6 in the table respectively).

1982-2015 Monthly	positive returns rising volatility	positive returns declining volatility	negative returns rise volatility	negative returns declining volatility
t+1				
N observations	111	146	77	84
Cumulated return	0.89	0.94	0.22	1.11
Average Return	**0.008**	**0.006**	**0.003**	**0.013**
t+3				
N observations	110	145	77	84
Cumulated return	0.69	1.48	0.30	0.67
Average Return	**0.006**	**0.010**	**0.004**	**0.008**
t+6				
N observations	109	145	76	83
Cumulated return	1.19	0.43	0.26	1.27
Average Return	**0.011**	**0.003**	**0.003**	**0.015**
t+1:t+3				
N observations	110	145	77	84
Cumulated return	2.40	3.86	1.11	2.03
Average Return	**0.022**	**0.026**	**0.014**	**0.024**
t+4:t+6				
N observations	109	145	76	83
Cumulated return	5.46	6.54	2.43	4.43
Average Return	**0.028**	**0.018**	**0.017**	**0.029**
t+1:t+6				
N observations	109	145	76	83
Cumulated return	5.46	6.54	2.43	4.43
Average Return	**0.049**	**0.045**	**0.032**	**0.053**

Table 2.2: Monthly Correlations of the deltas and Summary Statistics of the levels. In the upper panel we report results for sentiment and uncertainty proxies while in the lower panel we present results for fear and uncertainty proxies. For each statistic we use all the data available for that proxy (summary statistics) or each pair of proxies (correlations). Detail on the length of each time series are listed in section 2 on Data. We present summary statistics and correlation for the deltas of the sentiment, fear and uncertainty proxies employed in this study.

Correlations	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
PC 6 (1)	1.00																				
PC 4 (2)	0.85	1.00																			
PLS 6 (3)	0.65	0.70	1.00																		
PLS 4 (4)	0.85	0.80	0.94	1.00																	
cefd (5)	**-0.28**	**-0.37**	**-0.19**	**-0.34**	1.00																
turn (6)	0.44	0.22	0.08	0.17	**-0.01**	1.00															
nipo (7)	0.44	0.01	**-0.11**	0.18	**-0.05**	0.08	1.00														
ripo (8)	0.73	0.81	0.72	0.75	0.01	0.22	0.10	1.00													
pdnd (9)	**-0.67**	**-0.83**	**-0.44**	**-0.53**	0.25	**-0.17**	0.12	**-0.42**	1.00												
s (10)	0.16	**-0.14**	0.47	0.42	0.14	**-0.05**	0.21	**-0.09**	0.10	1.00											
DEVST (11)	**-0.03**	**-0.01**	**-0.01**	**-0.02**	**-0.04**	**-0.01**	**-0.06**	**-0.05**	**-0.02**	**0.00**	1.00										
UP-UNC (12)	**-0.04**	**-0.04**	**-0.03**	**-0.03**	**-0.06**	0.01	**-0.05**	**-0.09**	0.00	0.02	0.86	1.00									
DOWN-UNC (13)	**0.00**	0.01	**-0.04**	**-0.03**	0.00	0.06	**-0.02**	0.01	**-0.01**	**-0.07**	0.82	0.64	1.00								
MEAN (14)	0.26	0.24	0.21	0.27	**-0.16**	0.03	0.12	0.20	**-0.16**	0.05	0.17	0.31	**-0.03**	1.00							
MEDIAN (15)	0.30	0.28	0.22	0.28	**-0.14**	0.06	0.15	0.26	**-0.18**	0.02	0.05	0.12	**-0.02**	0.94	1.00						
UP (16)	0.07	0.07	0.07	0.08	**-0.11**	0.02	0.01	0.01	**-0.07**	0.04	0.75	0.92	0.50	0.66	0.48	1.00					
LOW (17)	0.16	0.15	0.16	0.19	**-0.10**	**-0.02**	0.09	0.12	**-0.09**	0.09	**-0.51**	**-0.30**	**-0.78**	0.65	0.60	0.03	1.00				
UF (18)	0.16	0.07	0.15	0.18	**-0.11**	0.11	0.12	0.08	0.00	0.14	**0.00**	0.05	0.00	0.10	0.09	0.08	0.06	1.00			
UM (19)	0.12	0.12	0.22	0.18	0.04	0.05	**-0.08**	0.13	**-0.11**	0.16	0.00	0.01	0.01	0.01	0.02	0.01	0.00	0.45	1.00		
SPF (20)	**-0.02**	0.03	0.06	0.01	0.07	0.05	**-0.15**	0.05	**-0.03**	**-0.01**	**-0.01**	**-0.02**	**-0.05**	**-0.03**	**-0.05**	**-0.03**	0.02	0.03	0.14	1.00	
LIV (21)	0.05	0.12	0.12	0.07	0.04	0.13	**-0.22**	0.05	**-0.19**	0.02	0.05	0.04	0.07	**0.00**	**0.00**	0.03	**-0.06**	0.11	0.24	0.09	1.00

Summary Statistics	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
MEAN	0.34	0.40	0.01	0.07	-0.30	-0.03	0.18	0.02	-0.36	-0.31	4.38	6.12	5.11	15.14	14.87	21.25	10.02	0.94	0.79	0.11	0.95
MEDIAN	0.14	0.23	-0.02	-0.01	-0.14	0.35	-0.27	-0.25	-0.27	-0.53	4.28	5.87	4.95	14.59	14.26	20.60	9.79	0.91	0.78	0.10	0.90
STDEV	1.19	0.88	0.26	0.30	0.60	1.09	1.00	0.93	0.64	0.90	0.83	1.11	0.75	2.09	2.04	2.81	1.88	0.14	0.08	0.04	0.20
SKEW	0.79	2.12	1.70	1.45	-0.26	-0.74	0.80	3.01	-0.58	1.87	0.38	1.16	0.84	1.12	1.12	1.23	0.63	0.84	1.98	1.51	1.23
KURT	3.07	9.31	6.78	5.46	1.91	2.78	2.66	12.27	4.51	6.84	1.90	4.16	2.98	3.60	3.54	3.97	2.82	3.43	8.40	5.15	4.58
MAX	3.84	4.50	1.08	1.23	1.08	2.19	2.74	4.40	1.42	3.21	6.47	10.50	7.31	21.19	20.79	29.65	14.94	1.43	1.17	0.28	1.63
MIN	-1.29	-1.27	-0.40	-0.41	-1.62	-2.60	-1.18	-0.98	-2.56	-1.45	3.12	4.44	3.97	11.32	11.19	16.40	6.44	0.73	0.69	0.07	0.60

Correlations	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
MEAN	1.00																						
UP	0.66	1.00																					
LOW	0.65	0.03	1.00																				
UP-UNC	0.31	0.92	**-0.30**	1.00																			
DOWN-UNC	**-0.03**	0.50	**-0.78**	0.64	1.00																		
DEVST	0.17	0.75	**-0.51**	0.86	0.82	1.00																	
UF	0.10	0.08	0.06	0.05	0.00	**0.00**	1.00																
UM	0.01	0.01	0.00	0.01	0.01	0.00	0.45	1.00															
UM-MD	0.32	0.68	0.17	0.67	0.05	0.25	0.09	0.02	1.00														
LIV skew	0.08	0.08	0.04	0.05	0.01	0.04	**-0.01**	0.22	0.07	1.00													
RGDPX skew	0.12	0.16	**-0.01**	0.13	0.11	0.16	0.04	0.01	0.08	0.03	1.00												
Bull-Bear	0.07	**-0.01**	0.10	**-0.05**	**-0.07**	**-0.03**	**-0.16**	**-0.20**	**-0.01**	**-0.05**	**-0.01**	1.00											
BTX	0.02	0.14	**-0.09**	0.19	0.14	0.10	0.23	0.21	0.10	0.05	0.01	**0.00**	1.00										
Macro	**-0.10**	**-0.02**	**-0.14**	0.05	0.10	0.08	0.00	0.05	**-0.06**	0.01	0.02	0.01	**-0.19**	1.00									
VIX	0.06	0.03	0.11	**0.00**	**-0.10**	**-0.11**	0.46	0.28	0.14	0.05	**-0.01**	**-0.07**	0.33	**-0.19**	1.00								
ANX	**-0.09**	**-0.07**	**-0.08**	**-0.02**	0.03	0.00	0.16	0.34	**-0.07**	0.17	**-0.10**	**-0.27**	0.13	0.27	0.15	1.00							
Crash CI	**-0.13**	**-0.07**	**-0.06**	0.00	**-0.03**	0.00	**-0.10**	**-0.15**	0.04	**-0.12**	0.07	0.05	**-0.08**	**-0.08**	**-0.08**	**-0.22**	1.00						
VRP	**-0.10**	**-0.04**	**-0.09**	0.02	0.04	0.05	**-0.06**	**-0.12**	**-0.02**	0.03	**-0.02**	0.04	**-0.15**	**-0.04**	0.18	0.03	**-0.08**	1.00					
KJ	**-0.02**	0.03	**-0.03**	0.05	0.03	0.06	**-0.27**	**-0.23**	0.03	**-0.04**	0.08	**-0.08**	**-0.19**	0.04	**-0.28**	**-0.01**	0.09	0.16	1.00				
Catfin	0.00	0.01	**0.00**	0.02	0.00	0.01	0.25	0.09	0.03	**0.00**	0.00	**-0.02**	0.06	**-0.06**	0.52	0.01	0.04	0.19	0.02	1.00			
TAIL	0.01	**-0.05**	0.03	**-0.06**	**-0.03**	**-0.06**	0.18	0.03	**-0.07**	0.06	**-0.02**	0.03	**-0.04**	**-0.08**	0.06	**-0.03**	0.05	0.25	0.03	0.06	1.00		
FFHS	0.03	**-0.04**	0.08	**-0.08**	**-0.09**	**-0.05**	0.06	0.03	0.02	0.02	0.01	0.01	0.03	**-0.06**	0.20	**-0.01**	0.18	**-0.02**	**-0.03**	0.11	0.05	1.00	
FVaR	0.06	**-0.09**	0.12	**-0.17**	**-0.12**	**-0.18**	**-0.10**	**-0.13**	**-0.03**	**-0.05**	**-0.03**	0.06	0.07	**-0.14**	0.07	0.01	**-0.03**	0.10	0.04	**-0.05**	0.07	0.00	1.00

Summary Statistics	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
MEAN	15.14	21.25	10.02	6.12	5.12	4.38	0.94	0.79	0.84	-0.09	-0.01	0.08	0.43	0.00	19.70	16.74	33.29	16.56	0.00	0.28	0.00	271.97	-1.76
MEDIAN	14.59	20.61	9.79	5.87	4.95	4.29	0.91	0.78	0.79	-0.08	-0.02	0.08	0.31	-0.79	18.01	12.65	32.80	13.45	0.24	0.26	0.00	226.67	0.00
STDEV	2.08	2.81	1.88	1.11	0.75	0.83	0.14	0.08	0.50	0.17	0.10	0.10	0.44	2.14	7.48	13.27	7.83	20.69	1.00	0.11	0.00	258.09	16.74
SKEW	1.13	1.24	0.64	1.15	0.83	0.38	0.85	1.96	0.55	1.83	-0.66	0.06	2.85	2.23	1.72	2.40	0.73	-3.73	-0.91	1.25	2.67	8.38	-1.24
KURT	3.61	3.98	2.82	4.15	2.96	1.91	3.44	8.20	3.39	12.54	4.75	2.86	13.32	8.24	7.55	9.17	3.44	55.39	3.32	5.23	14.04	89.53	5.85
MAX	21.19	29.65	14.94	10.50	7.31	6.47	1.43	1.17	2.42	1.00	0.28	0.34	2.84	8.53	59.89	74.78	57.95	115.85	1.89	0.74	0.00	3097.55	30.00
MIN	11.32	16.40	6.44	4.44	3.97	3.12	0.73	0.69	-0.30	-0.55	-0.45	-0.15	0.02	-2.01	10.42	4.04	18.02	-218.56	-3.03	0.10	0.00	76.83	-80.00

Table 2.3: Out-of-sample predictability. The table shows the R^2_{OS} and the Δ Utility metrics using sentiment, uncertainty and fear proxies to forecast the monthly returns of the weighted S&P500 index at month t+1. Our analysis employs all data available for each time series. The first 40% of the existing data are used to estimate the model in-sample, 10% are used as hold out period while the remaining 50% is for the reported out-of-sample analysis. For both indicators we consider the overall predictability (Tot), and the capability to forecast positive (Bull) or negative (Bear) returns only. Results in bold are significant at the 5% level using the Clark and West (2007) approach.

Δ Utility	Tot	Bull	Bear
PC6	0.37	0.38	0.34
PC4	0.36	-0.37	1.42
PLS6	3.33	1.94	5.36
PLS4	1.76	-0.02	4.39
cefd	-0.27	1.04	-2.18
turn	0.55	2.20	-1.83
nipo	-1.05	-3.48	2.56
ripo	-0.02	0.48	-0.80
pdnd	-0.04	2.20	-3.28
s	2.19	14.80	-15.22
DEVST	0.54	-7.18	10.23
MEAN	0.84	6.67	-5.92
MEDIAN	0.61	5.57	-5.13
UP	0.62	6.76	-6.54
LOW	0.50	8.00	-8.18
UF	4.49	-8.65	21.28
UM	3.59	-3.06	11.76
SPV	0.48	-3.53	5.35
LIV	1.57	-1.45	5.25
UP-UNC	-0.46	2.04	-3.48
DOWN-UNC	-1.02	-3.33	1.78

R^2_{OS}	Tot	pval	Bull	pval	Bear	pval
PC6	**0.34**	0.01	**0.80**	0.00	-0.03	0.51
PC4	0.16	0.13	-0.33	0.91	**0.55**	0.00
PLS6	**2.11**	0.00	0.42	0.19	**3.47**	0.00
PLS4	**1.14**	0.00	0.08	0.35	**2.00**	0.00
cefd	-0.12	0.80	**0.99**	0.00	-1.02	1.00
turn	0.31	0.06	**2.31**	0.00	-1.30	1.00
nipo	-0.62	0.95	-2.84	1.00	**1.17**	0.00
ripo	0.88	0.07	-0.51	0.35	2.01	0.06
pdnd	-0.17	0.69	**1.69**	0.00	-1.68	1.00
s	**1.26**	0.01	**13.66**	0.00	-8.76	1.00
DEVST	-1.07	0.56	-9.05	1.00	**4.20**	0.00
MEAN	0.09	0.21	**11.71**	0.00	-7.59	1.00
MEDIAN	-0.03	0.24	**10.49**	0.00	-6.98	1.00
UP	0.21	0.18	**10.63**	0.00	-6.67	1.00
LOW	0.15	0.20	**12.04**	0.00	-7.71	1.00
UF	1.84	0.08	-17.11	1.00	**14.36**	0.00
UM	1.84	0.11	-9.20	0.91	**9.13**	0.01
SPV	-1.21	0.62	-7.78	0.97	**3.13**	0.05
LIV	-0.31	0.37	-3.63	0.76	1.89	0.15
UP-UNC	0.03	0.35	0.70	0.18	-0.42	0.59
DOWN-UNC	-0.93	0.51	-5.12	0.95	1.84	0.08

Δ Utility	Tot	Bull	Bear
UM-MD	-0.98	10.33	-13.57
LIV skew	-0.08	0.71	-0.98
RGDPX skew	1.05	7.53	-6.32
Bull-Bear	-1.39	0.55	-3.77
BTX	-0.24	-5.93	8.36
MACRO	1.23	-6.90	13.51
VIX	-4.32	-1.46	-8.06
ANX	-0.44	-2.11	1.58
CRASH	-0.44	4.06	-5.91
VRP	4.39	-0.94	11.04
KJ	-0.52	-2.75	2.56
CATFIN	-0.32	-3.59	4.22
TAIL	7.86	2.72	15.04
FFHS	-0.40	0.42	-1.58
FVaR	10.75	16.10	0.64
FCVaR	17.84	27.89	-0.55

R^2_{OS}	Tot	pval	Bull	pval	Bear	pval
UM-MD	-0.46	0.23	**10.15**	0.00	-6.74	0.97
LIV skew	-0.04	0.47	0.77	0.16	-0.52	0.79
RGDPX skew	**1.00**	0.02	**8.70**	0.00	-3.56	0.68
Bull-Bear	-0.67	0.59	-0.10	0.30	-1.01	0.72
BTX	-4.60	0.89	-6.70	1.00	-3.04	0.64
MACRO	-14.04	0.38	-60.89	0.96	**20.67**	0.04
VIX	-3.00	0.93	-2.13	0.68	-3.51	0.93
ANX	-1.33	0.57	-7.01	0.88	2.03	0.19
CRASH	-1.17	0.51	**3.69**	0.00	-4.05	1.00
VRP	**6.06**	0.02	**7.10**	0.04	5.45	0.08
KJ	-0.05	0.22	-1.65	0.56	1.25	0.10
CATFIN	-0.80	0.60	-6.60	1.00	**3.92**	0.01
TAIL	**4.60**	0.01	-22.55	0.71	**26.67**	0.00
FFHS	0.08	0.34	**0.82**	0.03	-0.50	0.97
FVaR	**9.54**	0.00	**14.44**	0.00	-1.83	0.33
FCVaR	**18.79**	0.00	**28.24**	0.00	-3.07	0.25

Table 2.4: In-sample predictability. The table presents the result for in sample univariate linear regressions. At each time time t the level of the chosen variable is regressed on the SP500 excess returns and on the SP500 standard deviation at time t+1. Standard deviations are computed trough a 40 months based rolling window. All t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980). For each time series all available monthly data are employed. Results significant at the 5% are reported in bold with the related R^2 statistic.

Excess Returns	**b**	**tstat**	R^2	**Volatility**	**b**	**tstat**	R^2
PC6	**-0.004**	**-2.01**	**0.01**	PC6	-0.001	-1.87	0.01
PC4	**-0.006**	**-2.27**	**0.01**	PC4	-0.001	-1.59	0.01
PNL6	**-0.026**	**-2.78**	**0.03**	PNL6	**0.006**	**2.99**	**0.01**
PNL4	**-0.023**	**-3.12**	**0.03**	PNL4	-0.002	-0.78	0.00
MEAN	-0.002	-1.69	0.01	MEAN	0.000	-0.78	0.00
MEDIAN	-0.002	-1.63	0.01	MEDIAN	0.000	-1.01	0.00
DEVST	-0.002	-0.68	0.00	DEVST	**0.004**	**5.31**	**0.07**
UP	-0.001	-1.72	0.01	UP	**0.001**	**4.61**	**0.02**
LOW	-0.002	-1.61	0.01	LOW	**-0.001**	**-4.37**	**0.05**
UF	**-0.048**	**-2.15**	**0.02**	UF	**0.046**	**12.52**	**0.29**
UM	-0.071	-1.92	0.02	UM	**0.039**	**5.55**	**0.06**
SPV	-0.005	-0.07	0.00	SPV	**0.091**	**6.52**	**0.07**
LIV	-0.017	-1.37	0.01	LIV	**0.016**	**8.15**	**0.07**
UP-UNC	-0.002	-1.24	0.00	UP-UNC	**0.006**	**14.09**	**0.26**
DOWN-UNC	-0.003	-0.92	0.00	DOWN-UNC	**0.008**	**13.87**	**0.23**

Excess Returns	**b**	**tstat**	R^2	**Volatility**	**b**	**tstat**	R^2
UM-MD	**-0.009**	**-2.06**	**0.01**	UM-MD	**0.367**	**5.06**	**6.32**
LIV skew	-0.013	-1.02	0.00	LIV skew	**4.275**	**11.12**	**24.56**
RGDPX skew	**-0.050**	**-2.30**	**0.02**	RGDPX skew	**3.493**	**4.29**	**4.62**
Bull-Bear	-0.020	-0.83	0.00	Bull-Bear	**0.735**	**5.54**	**8.31**
BTX	0.001	0.08	0.00	BTX	-1.046	-1.47	0.63
Macro	-0.001	-0.54	0.00	Macro	-0.300	-0.80	0.19
VIX	0.000	0.13	0.00	VIX	0.431	0.67	0.13
ANX	0.000	-1.00	0.00	ANX	**0.856**	**4.52**	**8.91**
CRASH	0.000	0.14	0.00	CRASH	**0.321**	**9.68**	**28.35**
VRP	**0.000**	**4.23**	**0.05**	VRP	**0.073**	**9.00**	**20.13**
KJ	0.004	1.10	0.00	KJ	**0.021**	**4.09**	**4.71**
Catfin	-0.022	-1.10	0.00	Catfin	**-0.053**	**-6.51**	**11.56**
TAIL	**-40.537**	**-7.02**	**0.11**	TAIL	**0.015**	**4.66**	**6.33**
FFHS	0.000	-0.56	0.00	FFHS	**-0.214**	**-1.99**	**1.27**
FVaR	**0.001**	**2.82**	**0.06**	FVaR	**576**	**3.36**	**3.16**

Table 2.5: The table shows the average percentile of the considered index, on the previous 10 years index values, the month before one of the worst/best 30 returns of the S&P500 for the period 01/1993-12/2016.

Percentiles	**30 Worst**	**30 Best**
Sent PC 6	55.75	49.11
Sent PLS 6	56.17	41.75
Sent PC 4	64.83	50.94
Sent PLS 4	61.50	44.42
DEVST	82.14	83.81
UP-UNC	64.75	66.00
DOWN-UNC	71.33	75.92
MEAN	53.39	59.67
MEDIAN	52.19	59.47
UP	57.44	61.25
LOW	48.44	55.17
UF	77.81	77.39
UM	69.83	57.25
SPF	60.47	48.69
LIV	71.47	68.72

Table 2.6: Granger causality and Lasso for sentiment and uncertainty proxies. We employ monthly data for the period from 12/1981 to 12/2016.
Panel A reports the results of the following Granger causality analysis. At first 4 legs are chosen as default initial size and the AIC criteria is employed to identify the best number of lags. After that, the F-statistic and the critical value from the F-distribution at the 5 percent significance level are computed. Finally, the table shows the difference between the value of the F-statistic and the critical value just computed. If F > critical value, we reject the null hypothesis that y does not Granger Cause x.
Panel B reports the results coming from the Lasso model selection approach with 10-fold cross-validation. The algorithm provides a series of one hundred lambda values (from the least to the most restrictive) and the related model parameters. Panel B reports the parameters estimated making use of the 60th and 90th lambda.

Panel A

PC 6 (1)	**caused by**	**causes**	**PC 4 (2)**	**caused by**	**causes**	**PLS 6 (3)**	**caused by**	**causes**	**DEVST (5)**	**caused by**	**causes**	**UP (10)**	**caused by**	**causes**	**LOW (11)**	**caused by**	**causes**
PC 6 (1)	0.00	0.00	PC 6 (1)	5.80	4.39	PC 6 (1)	2.37	5.70	PC 6 (1)	-3.21	-3.20	PC 6 (1)	-0.71	-2.37	PC 6 (1)	**1.51**	**-1.00**
PC 4 (2)	4.39	5.80	PC 4 (2)	0.00	0.00	PC 4 (2)	**2.67**	**-1.40**	PC 4 (2)	-2.62	-2.54	PC 4 (2)	**-1.12**	**5.20**	PC 4 (2)	2.76	3.90
PLS 6 (3)	5.70	2.37	PLS 6 (3)	**-1.40**	**2.67**	PLS 6 (3)	0.00	0.00	PLS 6 (3)	**-0.52**	**1.97**	PLS 6 (3)	**-0.01**	**6.32**	PLS 6 (3)	4.97	1.61
PLS 4 (4)	3.00	5.06	PLS 4 (4)	**10.29**	**-2.93**	PLS 4 (4)	3.14	10.70	PLS 4 (4)	-2.71	-3.30	PLS 4 (4)	**-0.96**	**4.55**	PLS 4 (4)	4.72	1.20
DEVST (5)	-3.20	-3.21	DEVST (5)	-2.54	-2.62	DEVST (5)	**1.97**	**-0.52**	DEVST (5)	0.00	0.00	DEVST (5)	**6.23**	**-2.97**	DEVST (5)	**3.95**	**-0.22**
UP-UNC (6)	-2.97	-1.09	UP-UNC (6)	1.60	1.29	UP-UNC (6)	1.76	4.77	UP-UNC (6)	**0.17**	**-3.84**	UP-UNC (6)	24.50	3.45	UP-UNC (6)	**-3.29**	**2.05**
DOWN-UNC (7)	-2.67	-2.15	DOWN-UNC (7)	-2.41	-0.89	DOWN-UNC (7)	**-0.94**	**1.49**	DOWN-UNC (7)	-2.39	-3.36	DOWN-UNC (7)	9.25	2.18	DOWN-UNC (7)	8.48	5.20
MEAN (8)	**2.72**	**-2.73**	MEAN (8)	4.03	2.70	MEAN (8)	8.06	6.83	MEAN (8)	**-1.17**	**1.42**	MEAN (8)	24.50	5.52	MEAN (8)	8.48	1.68
MEDIAN (9)	**5.21**	**-3.04**	MEDIAN (9)	4.97	3.40	MEDIAN (9)	8.54	6.88	MEDIAN (9)	-0.67	-0.61	MEDIAN (9)	**23.42**	**-0.27**	MEDIAN (9)	**9.49**	**-0.11**
UP (10)	-2.37	-0.71	UP (10)	**5.20**	**-1.12**	UP (10)	**6.32**	**-0.01**	UP (10)	**-2.97**	**6.23**	UP (10)	0.00	0.00	UP (10)	1.99	21.44
LOW (11)	**-1.00**	**1.51**	LOW (11)	3.90	2.76	LOW (11)	1.61	4.97	LOW (11)	-0.22	3.95	LOW (11)	21.44	1.99	LOW (11)	0.00	0.00
UF (12)	-1.04	-0.93	UF (12)	-2.74	-2.85	UF (12)	-3.78	-2.80	UF (12)	**4.96**	**-3.84**	UF (12)	-1.16	-0.62	UF (12)	8.91	1.22
UM (13)	-2.98	-1.14	UM (13)	**0.93**	**-0.58**	UM (13)	**1.27**	**-0.19**	UM (13)	**5.94**	**-1.73**	UM (13)	-0.41	-0.01	UM (13)	18.14	2.37
SPF (14)	-1.13	-3.73	SPF (14)	**0.20**	**-3.15**	SPF (14)	-3.45	-2.99	SPF (14)	**1.45**	**-3.75**	SPF (14)	-0.15	-3.74	SPF (14)	5.89	5.02
LIV (15)	**4.09**	**-1.46**	LIV (15)	**6.14**	**2.85**	LIV (15)	**-3.79**	**0.10**	LIV (15)	**1.56**	**-3.46**	LIV (15)	**-1.13**	**0.16**	LIV (15)	3.69	0.69

Panel B

PC6 (1)	**60%**	**90%**	**PC4 (2)**	**60%**	**90%**	**PLS6 (3)**	**60%**	**90%**	**DEVST (5)**	**60%**	**90%**	**UP (10)**	**60%**	**90%**	**LOW (11)**	**60%**	**90%**
DEVST (5)	**-0.34**	**-0.07**	DEVST (5)	**0.01**	0.00	DEVST (5)	**0.25**	0.00	DEVST (5)	0.00	0.00	DEVST (5)	0.00	0.00	DEVST (5)	**-0.04**	0.00
UP-UNC (6)	**0.54**	**0.11**	UP-UNC (6)	**0.28**	0.00	UP-UNC (6)	**0.29**	**0.09**	UP-UNC (6)	**-0.04**	0.00	UP-UNC (6)	**0.34**	**0.11**	UP-UNC (6)	0.00	0.00
DOWN-UNC (7)	**-0.23**	0.00	DOWN-UNC (7)	-0.07	0.00	DOWN-UNC (7)	**-0.04**	0.00	DOWN-UNC (7)	**0.85**	**0.50**	DOWN-UNC (7)	0.00	0.00	DOWN-UNC (7)	**-0.31**	0.00
MEAN (8)	0.00	0.00	MEAN (8)	0.00	0.00	MEAN (8)	0.00	0.00	MEAN (8)	0.00	0.00	MEAN (8)	**0.75**	**0.52**	MEAN (8)	**0.95**	**0.56**
MEDIAN (9)	0.00	0.00	MEDIAN (9)	0.00	0.00	MEDIAN (9)	0.00	0.00	MEDIAN (9)	**0.02**	0.00	MEDIAN (9)	0.00	0.00	MEDIAN (9)	**0.10**	0.00
UP (10)	0.00	0.00	UP (10)	0.00	**0.27**	UP (10)	0.00	**0.25**	UP (10)	0.00	0.00	UP (10)	0.00	0.00	UP (10)	0.00	0.00
LOW (11)	**0.34**	**0.25**	LOW (11)	**0.35**	**0.05**	LOW (11)	**0.34**	0.00	LOW (11)	0.00	0.00	LOW (11)	0.00	0.00	LOW (11)	0.00	0.00
UF (12)	0.08	0.00	UF (12)	**-0.12**	0.00	UF (12)	-0.20	0.00	UF (12)	**-0.01**	0.00	UF (12)	0.00	0.00	UF (12)	**-0.02**	0.00
UM (13)	**0.25**	**0.03**	UM (13)	**0.36**	0.00	UM (13)	**0.45**	**0.20**	UM (13)	**-0.05**	0.00	UM (13)	0.00	0.00	UM (13)	0.00	0.00
SPF (14)	**-0.02**	0.00	SPF (14)	**-0.18**	0.00	SPF (14)	**0.02**	0.00	SPF (14)	**0.26**	0.00	SPF (14)	0.00	0.00	SPF (14)	0.00	0.00
LIV (15)	**-0.13**	0.00	LIV (15)	**-0.02**	0.00	LIV (15)	0.00	0.00	LIV (15)	**-0.10**	0.00	LIV (15)	0.00	0.00	LIV (15)	0.00	0.00

Table 2.7: Granger causality and Lasso for fear and uncertainty proxies. Monthly data are employed. Panel A reports the results of the following Granger causality analysis. At first 4 legs are chosen as default initial size and the AIC criteria is employed to identify the best number of lags. After that, the F-statistic and the critical value from the F-distribution at the 5 percent significance level are computed. Finally, the table shows the difference between the value of the F-statistic and the critical value just computed. If F > critical value, we reject the null hypothesis that y does not Granger Cause x.
Panel B reports the results coming from the Lasso model selection approach with 10-fold cross-validation. The algorithm provides a series of one hundred lambda values (from the least to the most restrictive) and the related model parameters. Panel B reports the parameters estimated making use of the 60th and 90th lambda.
Panel A makes use of the maximum available data length for each pair of time series while Panel B is based on the period 01/2005-08/2015.

Panel A

VIX (15)	**caused by**	**causes**	**FVaR (23)**	**caused by**	**causes**	**Crash CI (17)**	**caused by**	**causes**	**LOW (3)**	**caused by**	**causes**	**UP (2)**	**caused by**	**causes**	**FFHS (22)**	**caused by**	**causes**
MEAN (1)	3.13	7.26	MEAN (1)	**1.67**	**-3.55**	MEAN (1)	-3.30	-1.57	MEAN (1)	8.48	1.68	MEAN (1)	24.50	5.52	MEAN (1)	-2.61	-2.86
UP (2)	**3.42**	**-2.16**	UP (2)	**0.61**	**-1.47**	UP (2)	-3.41	-3.54	UP (2)	1.99	21.44	UP (2)	0.00	0.00	UP (2)	**-3.69**	**2.75**
LOW (3)	0.45	21.54	LOW (3)	-0.50	-2.61	LOW (3)	**-3.24**	**0.06**	LOW (3)	0.00	0.00	LOW (3)	21.44	1.99	LOW (3)	-1.62	-2.48
UP-UNC (4)	0.28	5.28	UP-UNC (4)	-3.52	-1.49	UP-UNC (4)	-3.65	-1.35	UP-UNC (4)	**-3.29**	**2.05**	UP-UNC (4)	24.50	3.45	UP-UNC (4)	-3.56	-0.56
DOWN-UNC (5)	0.31	17.42	DOWN-UNC (5)	-3.55	-1.90	DOWN-UNC (5)	-3.68	-0.51	DOWN-UNC (5)	8.48	5.20	DOWN-UNC (5)	9.25	2.18	DOWN-UNC (5)	-3.13	-2.68
DEVST (6)	**-1.50**	**6.33**	DEVST (6)	**-2.17**	**0.06**	DEVST (6)	-3.68	-2.30	DEVST (6)	**3.95**	**-0.22**	DEVST (6)	**6.23**	**-2.97**	DEVST (6)	-3.65	-3.11
UF (7)	68.10	38.63	UF (7)	**0.95**	**-2.40**	UF (7)	**6.22**	**-2.70**	UF (7)	8.91	1.22	UF (7)	-1.16	-0.62	UF (7)	-0.33	-3.06
UM (8)	12.07	1.76	UM (8)	**-3.65**	**3.44**	UM (8)	**-3.53**	**4.65**	UM (8)	18.14	2.37	UM (8)	-0.41	-0.01	UM (8)	-3.48	-2.32
UM-MD (9)	-2.44	-2.03	UM-MD (9)	**0.22**	**-2.89**	UM-MD (9)	-3.53	-3.76	UM-MD (9)	**-3.23**	**2.93**	UM-MD (9)	5.96	4.26	UM-MD (9)	-3.88	-1.45
LIV skew (10)	-3.39	-3.33	LIV skew (10)	-2.44	-3.32	LIV skew (10)	-3.41	-3.46	LIV skew (10)	-2.10	-3.69	LIV skew (10)	**0.09**	**-3.54**	LIV skew (10)	**0.37**	**-3.74**
RGDPX skew (11)	-3.33	-3.15	RGDPX skew (11)	**1.11**	**-3.13**	RGDPX skew (11)	-2.66	-2.69	RGDPX skew (11)	**-3.49**	**2.20**	RGDPX skew (11)	**-1.40**	**0.77**	RGDPX skew (11)	-3.29	-3.60
Bull-Bear (12)	-3.50	-1.33	Bull-Bear (12)	-2.73	-1.63	Bull-Bear (12)	-3.60	-1.87	Bull-Bear (12)	**3.42**	**-1.94**	Bull-Bear (12)	**4.47**	**-2.17**	Bull-Bear (12)	-2.65	-0.84
BTX (13)	**-3.10**	**16.86**	BTX (13)	0.21	1.37	BTX (13)	**6.68**	**-3.32**	BTX (13)	**2.32**	**-3.85**	BTX (13)	-1.48	-3.85	BTX (13)	-3.80	-2.63
Macro (14)	**-0.43**	**14.50**	Macro (14)	**-1.31**	**2.56**	Macro (14)	-3.29	-0.49	Macro (14)	9.84	1.28	Macro (14)	-1.93	-2.79	Macro (14)	-3.60	-2.89
VIX (15)	0.00	0.00	VIX (15)	1.14	1.83	VIX (15)	**7.92**	**-2.96**	VIX (15)	21.54	0.45	VIX (15)	**-2.16**	**3.42**	VIX (15)	-3.85	-3.86
ANX (16)	**-1.80**	**3.84**	ANX (16)	**0.16**	**-1.91**	ANX (16)	**0.81**	**-3.28**	ANX (16)	**14.96**	**-3.59**	ANX (16)	-0.60	-3.56	ANX (16)	-3.52	-2.50
Crash CI (17)	**-2.96**	**7.92**	Crash CI (17)	**-2.15**	**1.63**	Crash CI (17)	0.00	0.00	Crash CI (17)	**0.06**	**-3.24**	Crash CI (17)	-3.54	-3.41	Crash CI (17)	-3.60	-1.24
VRP (18)	2.80	7.50	VRP (18)	-2.71	-2.86	VRP (18)	**-0.77**	**12.28**	VRP (18)	-1.70	-1.72	VRP (18)	4.30	1.01	VRP (18)	-3.10	-3.02
KJ (19)	-3.44	-2.36	KJ (19)	**1.91**	**-2.70**	KJ (19)	-3.62	-3.41	KJ (19)	2.55	0.24	KJ (19)	5.63	0.12	KJ (19)	-3.86	-2.46
Catfin (20)	-2.42	-3.03	Catfin (20)	-2.93	-3.65	Catfin (20)	**17.13**	**-3.10**	Catfin (20)	**0.72**	**-3.82**	Catfin (20)	-1.25	-3.58	Catfin (20)	-3.81	-3.76
TAIL (21)	29.60	3.80	TAIL (21)	**-3.45**	**2.29**	TAIL (21)	**0.09**	**-2.67**	TAIL (21)	**0.49**	**-3.85**	TAIL (21)	-0.36	-3.25	TAIL (21)	**2.35**	**-2.63**
FFHS (22)	-3.86	-3.85	FFHS (22)	**-3.58**	**0.74**	FFHS (22)	-1.24	-3.60	FFHS (22)	-2.48	-1.62	FFHS (22)	**2.75**	**-3.69**	FFHS (22)	0.00	0.00
FVaR (23)	1.83	1.14	FVaR (23)	0.00	0.00	FVaR (23)	**1.63**	**-2.15**	FVaR (23)	-2.61	-0.50	FVaR (23)	**-1.47**	**0.61**	FVaR (23)	**0.74**	**-3.58**

Panel B

VIX (15)	**60%**	**90%**	**FVaR (23)**	**60%**	**90%**	**Crash CI (17)**	**60%**	**90%**	**LOW (3)**	**60%**	**90%**	**UP (2)**	**60%**	**90%**	**FFHS (22)**	**60%**	**90%**
MEAN (1)	0.00	0.00	MEAN (1)	0.00	**-0.15**	MEAN (1)	0.00	0.00	MEAN (1)	**0.64**	**0.38**	MEAN (1)	**0.78**	**0.42**	MEAN (1)	**0.17**	**0.02**
UP (2)	0.00	0.00	UP (2)	**-0.28**	**-0.03**	UP (2)	**0.11**	0.00	UP (2)	0.00	0.00	UP (2)	0.00	0.00	UP (2)	0.00	0.00
LOW (3)	0.00	0.00	LOW (3)	0.00	0.00	LOW (3)	0.00	0.00	LOW (3)	0.00	0.00	LOW (3)	0.00	0.00	LOW (3)	0.00	**0.08**
UP-UNC (4)	0.00	0.00	UP-UNC (4)	0.00	0.00	UP-UNC (4)	0.00	0.00	UP-UNC (4)	0.00	0.00	UP-UNC (4)	**0.49**	**0.20**	UP-UNC (4)	**-0.10**	0.00
DOWN-UNC (5)	**-0.01**	0.00	DOWN-UNC (5)	0.00	0.00	DOWN-UNC (5)	0.00	0.00	DOWN-UNC (5)	**-0.42**	**-0.12**	DOWN-UNC (5)	0.00	0.00	DOWN-UNC (5)	0.00	0.00
DEVST (6)	0.00	0.00	DEVST (6)	**0.14**	0.00	DEVST (6)	**-0.33**	**-0.28**	DEVST (6)	0.00	**-0.16**	DEVST (6)	0.00	0.00	DEVST (6)	**0.14**	0.00
UF (7)	**0.86**	**0.52**	UF (7)	**0.45**	0.00	UF (7)	**-0.26**	**-0.03**	UF (7)	0.00	0.00	UF (7)	0.00	0.00	UF (7)	**-0.03**	0.00
UM (8)	0.00	0.00	UM (8)	**-0.18**	0.00	UM (8)	**0.38**	0.00	UM (8)	0.00	0.00	UM (8)	0.00	0.00	UM (8)	**-0.06**	0.00
UM-MD (9)	0.00	0.00	UM-MD (9)	**0.11**	0.00	UM-MD (9)	**0.07**	0.00	UM-MD (9)	0.00	0.00	UM-MD (9)	**0.02**	**0.09**	UM-MD (9)	**-0.05**	0.00
LIV skew (10)	**0.05**	0.00	LIV skew (10)	**-0.15**	**-0.05**	LIV skew (10)	**-0.16**	0.00	LIV skew (10)	0.00	0.00	LIV skew (10)	**-0.04**	0.00	LIV skew (10)	**0.12**	**0.04**
RGDPX skew (11)	0.00	0.00	RGDPX skew (11)	**-0.09**	**-0.02**	RGDPX skew (11)	**-0.03**	0.00	RGDPX skew (11)	0.00	0.00	RGDPX skew (11)	0.00	0.00	RGDPX skew (11)	0.00	0.00
Bull-Bear (12)	0.00	0.00	Bull-Bear (12)	**0.15**	0.00	Bull-Bear (12)	**0.06**	0.00	Bull-Bear (12)	0.00	0.00	Bull-Bear (12)	0.00	0.00	Bull-Bear (12)	**-0.16**	0.00
VIX (15)	0.00	0.00	VIX (15)	**-0.33**	0.00	VIX (15)	**-0.36**	**-0.25**	VIX (15)	**-0.04**	0.00	VIX (15)	0.00	0.00	VIX (15)	**0.04**	0.00
ANX (16)	0.00	0.00	ANX (16)	**0.32**	0.00	ANX (16)	**-0.26**	**-0.07**	ANX (16)	0.00	0.00	ANX (16)	0.00	0.00	ANX (16)	0.00	0.00
Crash CI (17)	0.00	0.00	Crash CI (17)	**0.19**	0.00	Crash CI (17)	0.00	0.00	Crash CI (17)	**0.09**	0.00	Crash CI (17)	0.00	0.00	Crash CI (17)	**0.21**	0.00
VRP (18)	**-0.08**	0.00	VRP (18)	0.00	0.00	VRP (18)	0.00	0.00	VRP (18)	0.00	0.00	VRP (18)	**0.03**	0.00	VRP (18)	**-0.01**	0.00
FFHS (22)	**0.03**	0.00	FFHS (22)	**-0.07**	0.00	FFHS (22)	**0.13**	0.00	FFHS (22)	0.00	0.00	FFHS (22)	0.00	0.00	FFHS (22)	0.00	0.00
FVaR (23)	**-0.18**	0.00	FVaR (23)	0.00	0.00	FVaR (23)	**0.05**	0.00	FVaR L15-L15 (23)	0.00	0.00	FVaR (23)	0.00	**-0.02**	FVaR (23)	**-0.04**	0.00

Table 2.8: Summary Statistics. The table reports properties of returns across all months for the 11 anomalies and the 7 factors listed in section 2. The length of the time series depends on the availability of data. For anomalies, 1, 2, 3, 4, 10, 11, 12, 13, 14, 15, 16, 17, 18 returns are available from 01/1965 to 11/2016, for anomalies 5, 6, 7, 8, 9 the returns available cover the periods from 08/1965, 01/1970, 02/1965, 05/1976, 01/1977 to 11/2016. The correlations are for the benchmark adjusted average returns, computed as fitted values $\varepsilon_{i,t}$ in the regression $R_{i,t} = a_i + bMKT_t + cSMB_t + dHML_t + \varepsilon_{i,t}$ where $R_{i,t}$ is a strategy's excess return in month t and MKT, SMB and HML come from the French data library. The Excess return is reported in percent terms. The remaining of the table shows Standard Deviation, Skewness, Kurtosis, Sharpe Ratio and Cornish-Fisher Ratio of the considered anomalies.

Anomaly	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Correlations: Spreads																		
(1) Asset Growth	1.00																	
(2) Gross Profitability	-0.35	1.00																
(3) Investment to Assets	0.83	-0.22	1.00															
(4) Net Stock Issues	0.38	0.15	0.41	1.00														
(5) Net Operating Assets	0.40	-0.03	0.49	-0.14	1.00													
(6) Total Accruals	0.41	-0.19	0.33	0.13	0.16	1.00												
(7) Ohlson's O	0.35	-0.14	0.33	0.27	-0.16	0.17	1.00											
(8) Return on Assets	-0.35	0.39	-0.26	0.09	-0.14	-0.10	-0.21	1.00										
(9) Failure Probability	-0.10	0.07	-0.10	-0.04	-0.12	0.00	-0.08	-0.31	1.00									
(10) Momentum	0.05	-0.02	0.05	0.04	0.07	0.01	-0.05	0.01	0.01	1.00								
(11) Composite Equity Issues	0.02	0.08	0.02	0.10	-0.04	0.08	0.09	0.03	0.04	-0.04	1.00							
(12) Size	0.11	0.02	0.11	0.08	0.07	0.13	0.12	0.03	-0.15	-0.17	0.08	1.00						
(13) Book to Market	0.01	0.04	0.07	0.08	0.09	0.02	0.00	-0.04	0.05	0.20	0.37	0.12	1.00					
(14) Operating Profitability	-0.10	0.08	-0.08	0.04	-0.05	-0.10	-0.04	0.03	0.11	0.21	0.39	-0.61	0.12	1.00				
(15) Investments	0.15	-0.07	0.08	0.01	0.04	0.14	0.01	-0.01	-0.03	0.05	0.07	0.40	0.36	-0.48	1.00			
(16) Earning to Price	0.01	0.09	0.07	0.04	0.14	-0.02	-0.01	0.02	0.07	0.20	0.21	-0.10	0.58	0.25	0.08	1.00		
(17) Cash Flows to Price	-0.02	0.04	0.05	0.05	0.05	0.01	0.03	0.05	0.09	0.18	0.13	-0.02	0.53	0.12	0.16	0.80	1.00	
(18) Dividend Yield	0.09	-0.03	0.09	0.01	0.12	0.05	0.02	-0.07	0.03	-0.14	-0.14	0.05	0.22	-0.26	0.24	0.35	0.22	1.00
Excess Returns																		
Long Leg	0.33	0.23	0.36	0.20	0.23	0.26	0.06	-0.16	0.51	0.20	0.35	0.88	1.20	0.86	1.17	1.11	1.15	0.85
Short Leg	-0.27	-0.12	-0.32	-0.19	-0.31	-0.48	-0.16	-0.58	-1.21	-0.32	-0.42	0.56	0.45	0.82	0.48	0.65	0.61	0.81
Spread	0.99	0.75	1.07	0.78	0.93	1.13	0.62	0.80	2.10	0.92	1.17	0.71	1.15	0.44	1.08	0.85	0.94	0.43
Standard Deciation																		
Long Leg	0.06	0.06	0.06	0.05	0.06	0.06	0.06	0.06	0.06	0.06	0.05	0.06	0.06	0.06	0.06	0.05	0.06	0.04
Short Leg	0.06	0.05	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.05	0.07	0.07	0.07	0.06	0.06	0.05
Spread	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.04	0.04	0.02	0.04	0.03	0.03	0.02	0.02	0.02	0.03
Skewness																		
Long Leg	-0.83	-0.87	-0.82	-0.98	-0.78	-0.86	-0.98	-1.19	-0.73	-1.25	-1.18	0.05	0.14	-0.38	0.13	-0.05	-0.10	0.05
Short Leg	-0.90	-0.90	-0.91	-0.85	-0.96	-0.99	-0.70	-1.05	-1.43	-0.38	-0.96	-0.35	-0.20	0.15	-0.19	-0.34	-0.36	-0.56
Spread	0.54	-0.16	0.44	0.18	0.26	0.33	0.75	-0.29	0.74	-0.86	1.28	0.92	0.17	-1.59	0.76	0.05	0.06	0.33
Kurtosis																		
Long Leg	6.34	6.40	6.26	7.29	5.65	6.69	7.14	7.66	6.35	7.54	8.04	5.56	6.95	6.04	5.74	7.17	7.08	7.60
Short Leg	6.07	6.15	6.46	5.81	6.82	7.05	5.63	6.97	9.56	5.56	5.77	4.88	5.29	5.84	5.56	5.21	5.35	5.83
Spread	4.18	3.73	4.76	6.54	7.71	5.35	8.76	3.56	9.44	7.64	13.88	6.50	5.76	14.18	6.03	4.50	4.29	4.30
Sharpe Ratio																		
Long Leg	0.06	0.04	0.06	0.04	0.04	0.05	0.01	-0.03	0.08	0.03	0.07	0.14	0.21	0.15	0.18	0.21	0.21	0.20
Short Leg	-0.04	-0.02	-0.05	-0.03	-0.05	-0.08	-0.03	-0.10	-0.21	-0.05	-0.07	0.12	0.07	0.12	0.07	0.11	0.10	0.15
Spread	0.49	0.31	0.57	0.38	0.52	0.45	0.26	0.32	0.54	0.24	0.48	0.18	0.38	0.16	0.53	0.36	0.43	0.17
CF Ratio																		
Long Leg	0.03	0.02	0.04	0.02	0.02	0.03	0.01	-0.01	0.05	0.02	0.04	0.09	0.15	0.09	0.13	0.14	0.14	0.14
Short Leg	-0.02	-0.01	-0.03	-0.02	-0.03	-0.04	-0.02	-0.05	-0.09	-0.03	-0.04	0.07	0.04	0.08	0.05	0.07	0.06	0.09
Spread	0.49	0.22	0.59	0.32	0.50	0.41	0.22	0.23	0.60	0.15	0.60	0.15	0.31	0.08	0.60	0.29	0.36	0.12

Table 2.9: Anomalies during periods of high and low level of sentiment. The table reports returns in months following high and low levels of sentiment, as identified on the base of the median level of the sentiment PLS 6 proxy. Also reported is the performance on a strategy that equally combines the strategies available within a given month (Combination). For each anomaly we make use of all data available. Details of the length of the time series can be found in the section 2 dedicated on Data. We report conditional Excess Returns (in percentage), and Sharpe Ratio for the long and short leg and for the Spread of the anomalies. We even report their difference.

PLS 6		Long Leg			Short Leg			Long-Short		
Excess Returns		High Sent	Low Sent	High-Low	High Sent	Low Sent	High-Low	High Sent	Low Sent	High-Low
	(1) Asset Growth	-0.18	0.84	-1.01	-0.96	0.41	-1.37	1.28	0.72	0.57
	(2) Gross Profitability	-0.26	0.73	-0.99	-0.66	0.43	-1.08	0.90	0.59	0.30
	(3) Investment to Assets	-0.13	0.85	-0.98	-0.97	0.32	-1.30	1.35	0.82	0.53
	(4) Net Stock Issues	-0.24	0.64	-0.88	-0.85	0.47	-1.32	1.11	0.46	0.65
	(5) Net Operating Assets	-0.34	0.76	-1.10	-0.93	0.29	-1.22	1.10	0.76	0.33
	(6) Total Accruals	-0.12	0.62	-0.74	-1.08	0.13	-1.21	1.47	0.78	0.68
	(7) Ohlson's O	-0.44	0.57	-1.02	-0.59	0.26	-0.86	0.65	0.61	0.05
	(8) Return on Assets	-0.80	0.48	-1.28	-1.12	-0.02	-1.11	0.83	0.75	0.07
	(9) Failure Probability	0.16	0.88	-0.72	-2.01	-0.39	-1.62	2.68	1.53	1.15
	(10) Momentum	-0.33	0.72	-1.05	-0.88	0.24	-1.12	1.05	0.78	0.28
	(11) Composite Equity Issues	-0.03	0.72	-0.74	-1.08	0.21	-1.29	1.55	0.80	0.75
	(12) Size	0.33	1.42	-1.08	0.23	0.90	-0.67	0.60	0.81	-0.21
	(13) Book to Market	0.84	1.56	-0.73	-0.17	1.07	-1.24	1.51	0.79	0.72
	(14) Operating Profitability	0.46	1.26	-0.80	0.20	1.43	-1.23	0.76	0.13	0.63
	(15) Investments	0.68	1.65	-0.97	-0.13	1.08	-1.21	1.31	0.86	0.46
	(16) Earning to Price	0.88	1.34	-0.46	0.09	1.21	-1.13	1.29	0.42	0.87
	(17) Cash Flows to Price	0.88	1.41	-0.53	0.05	1.17	-1.13	1.34	0.54	0.80
	(18) Dividend Yield	0.77	0.93	-0.16	0.44	1.18	-0.73	0.82	0.04	0.78
	Combination	**0.12**	**0.96**	**-0.85**	**-0.58**	**0.58**	**-1.16**	**1.20**	**0.68**	**0.52**
Sharpe Ratio										
	(1) Asset Growth	-2.75	18.17	-20.93	-12.89	8.16	-21.05	54.87	44.22	10.64
	(2) Gross Profitability	-3.85	15.34	-19.19	-11.18	9.94	-21.12	33.25	27.66	5.60
	(3) Investment to Assets	-1.98	18.03	-20.01	-13.08	6.47	-19.56	60.19	56.60	3.59
	(4) Net Stock Issues	-4.11	15.48	-19.58	-12.43	9.62	-22.05	46.41	29.40	17.01
	(5) Net Operating Assets	-5.01	15.85	-20.86	-13.35	6.08	-19.43	56.01	48.52	7.49
	(6) Total Accruals	-1.81	13.12	-14.93	-15.32	2.62	-17.95	58.14	32.49	25.65
	(7) Ohlson's O	-6.59	12.26	-18.84	-9.12	5.47	-14.59	23.86	29.10	-5.24
	(8) Return on Assets	-11.85	10.96	-22.81	-17.31	-0.35	-16.96	30.97	33.10	-2.13
	(9) Failure Probability	2.26	18.51	-16.25	-29.38	-9.16	-20.22	57.17	53.68	3.49
	(10) Momentum	-4.75	15.33	-20.08	-12.40	4.79	-17.19	24.08	25.43	-1.35
	(11) Composite Equity Issues	-0.47	18.97	-19.44	-15.47	4.55	-20.02	51.99	48.90	3.10
	(12) Size	4.49	26.30	-21.81	4.13	21.98	-17.84	13.61	22.36	-8.75
	(13) Book to Market	12.96	31.28	-18.32	-2.19	20.44	-22.63	41.59	34.89	6.70
	(14) Operating Profitability	6.89	26.81	-19.92	2.56	25.30	-22.75	23.36	5.43	17.92
	(15) Investments	9.35	30.10	-20.75	-1.71	20.53	-22.24	61.23	45.70	15.53
	(16) Earning to Price	14.66	28.89	-14.23	1.22	25.28	-24.05	45.56	24.49	21.07
	(17) Cash Flows to Price	14.20	29.89	-15.69	0.66	24.78	-24.11	52.98	30.90	22.08
	(18) Dividend Yield	16.21	25.62	-9.41	7.09	26.33	-19.23	27.86	2.15	25.71
	Combination	**2.10**	**20.61**	**-18.50**	**-8.34**	**11.82**	**-20.17**	**42.40**	**33.06**	**9.34**

Table 2.10: Anomalies during periods of high and low level of uncertainty. The table reports returns in months following high and low levels of macroeconomic uncertainty, as identified on the base of the median level of the macroeconomic uncertainty measure of Jurado et al. (2015). Also reported is the performance of a strategy that equally combines the strategies available within a given month (Combination). For each anomaly we make use of all data available. Details of the length of the time series can be found in the section 2 dedicated on Data. We report conditional Excess Returns (in percentage), Standard Deviation, and Sharpe Ratio for the long and short leg and for the Spread of the anomalies. We even report their difference.

UM		Long leg			Short Leg			Long-Short		
Excess Returns		High Unc	Low Unc	High-Low	High Unc	Low Unc	High-Low	High Unc	Low Unc	High-Low
	(1) Asset Growth	0.31	0.56	-0.24	-0.28	-0.10	-0.18	0.97	0.92	0.05
	(2) Gross Profitability	0.44	0.31	0.13	-0.20	0.19	-0.39	1.03	0.39	0.64
	(3) Investment to Assets	0.32	0.49	-0.16	-0.16	-0.28	0.11	0.87	1.03	-0.16
	(4) Net Stock Issues	0.29	0.40	-0.12	-0.14	-0.03	-0.11	0.81	0.70	0.11
	(5) Net Operating Assets	0.24	0.36	-0.12	-0.18	-0.22	0.04	0.80	0.85	-0.05
	(6) Total Accruals	0.34	0.30	0.04	-0.20	-0.38	0.18	0.93	0.95	-0.02
	(7) Ohlson's O	0.26	0.10	0.16	-0.17	0.05	-0.21	0.81	0.32	0.49
	(8) Return on Assets	-0.11	-0.10	-0.01	-0.77	-0.25	-0.52	1.04	0.42	0.62
	(9) Failure Probability	0.51	0.50	0.01	-1.32	-0.99	-0.33	2.22	1.76	0.46
	(10) Momentum	-0.13	0.54	-0.67	-0.28	-0.10	-0.18	0.54	0.91	-0.37
	(11) Composite Equity Issues	0.27	0.71	-0.44	-0.63	-0.11	-0.53	1.29	1.09	0.20
	(12) Size	0.70	0.95	-0.25	0.51	1.00	-0.49	0.57	0.22	0.36
	(13) Book to Market	1.04	1.40	-0.36	0.34	0.56	-0.22	1.08	1.11	-0.03
	(14) Operating Profitability	0.81	1.01	-0.20	0.58	0.90	-0.32	0.61	0.37	0.24
	(15) Investments	1.05	1.32	-0.27	0.30	0.57	-0.28	1.14	1.02	0.12
	(16) Earning to Price	1.04	1.20	-0.15	0.51	0.85	-0.34	0.92	0.61	0.31
	(17) Cash Flows to Price	1.13	1.16	-0.04	0.47	0.86	-0.39	1.05	0.58	0.47
	(18) Dividend Yield	0.86	1.01	-0.15	0.73	1.02	-0.30	0.51	0.26	0.26
	Combination	**0.52**	**0.68**	**-0.16**	**-0.05**	**0.20**	**-0.25**	**0.95**	**0.75**	**0.20**
Sharpe Ratio										
	(1) Asset Growth	5.62	11.31	-5.69	-4.41	-1.76	-2.65	44.02	56.60	-12.58
	(2) Gross Profitability	7.53	6.00	1.53	-3.72	3.91	-7.63	43.87	18.42	25.44
	(3) Investment to Assets	5.76	10.08	-4.33	-2.52	-5.12	2.60	39.18	65.37	-26.19
	(4) Net Stock Issues	6.04	9.77	-3.73	-2.24	-0.53	-1.70	32.49	34.67	-2.18
	(5) Net Operating Assets	3.93	7.03	-3.10	-3.05	-4.26	1.21	38.83	48.77	-9.94
	(6) Total Accruals	6.02	5.93	0.09	-3.49	-7.03	3.54	34.18	41.83	-7.65
	(7) Ohlson's O	4.51	1.99	2.53	-2.68	0.89	-3.57	28.71	16.19	12.52
	(8) Return on Assets	-1.85	-1.81	-0.04	-12.59	-4.80	-7.80	39.18	18.56	20.62
	(9) Failure Probability	7.62	9.30	-1.68	-23.31	-18.46	-4.84	46.24	63.21	-16.97
	(10) Momentum	-1.89	12.44	-14.34	-4.23	-2.19	-2.04	12.04	34.18	-22.14
	(11) Composite Equity Issues	5.23	22.05	-16.83	-9.56	-2.31	-7.26	39.48	49.77	-10.29
	(12) Size	10.11	19.56	-9.45	8.88	26.53	-17.65	13.84	6.42	7.42
	(13) Book to Market	17.12	32.78	-15.66	4.43	10.86	-6.44	29.76	48.37	-18.61
	(14) Operating Profitability	13.12	24.83	-11.71	7.69	17.10	-9.41	16.23	14.77	1.46
	(15) Investments	14.54	25.64	-11.10	4.04	11.74	-7.69	49.96	54.93	-4.98
	(16) Earning to Price	18.43	31.70	-13.27	7.77	19.36	-11.59	33.29	35.76	-2.47
	(17) Cash Flows to Price	18.94	29.40	-10.46	7.24	19.95	-12.71	42.72	34.04	8.69
	(18) Dividend Yield	18.09	35.12	-17.03	12.73	27.33	-14.60	19.30	14.70	4.60
	Combination	**8.83**	**16.29**	**-7.46**	**-1.06**	**5.07**	**-6.12**	**33.52**	**36.48**	**-2.96**

Table 2.11: Anomalies during periods of high and low level of volatility. The table reports returns in months following high and low levels of volatility, as identified on the base of the VIX index. Also reported is the performance on a strategy that equally combines the strategies available within a given month (Combination). For each anomaly we make use of all data available. Details of the length of the time series can be found in the section 2 dedicated on Data. We report conditional Excess Returns (in percentage), and Sharpe Ratio for the long and short leg and for the Spread of the anomalies. We even report their difference.

VIX		Long leg			Short Leg			Long-Short		
Excess Returns		High VIX	Low VIX	High-Low	High VIX	Low VIX	High-Low	High VIX	Low VIX	High-Low
	(1) Asset Growth	0.77	0.20	0.57	0.03	-0.29	0.32	0.98	0.71	0.27
	(2) Gross Profitability	0.67	0.06	0.61	0.06	-0.05	0.11	0.85	0.33	0.52
	(3) Investment to Assets	0.68	0.16	0.52	0.17	-0.46	0.63	0.76	0.84	-0.09
	(4) Net Stock Issues	0.46	0.27	0.19	0.18	-0.23	0.41	0.52	0.72	-0.20
	(5) Net Operating Assets	0.51	0.09	0.43	0.11	-0.33	0.44	0.64	0.64	0.00
	(6) Total Accruals	0.62	0.03	0.59	-0.07	-0.38	0.31	0.93	0.63	0.30
	(7) Ohlson's O	0.56	-0.11	0.66	0.12	-0.12	0.24	0.69	0.24	0.45
	(8) Return on Assets	0.20	-0.18	0.38	-0.13	-0.64	0.51	0.57	0.68	-0.11
	(9) Failure Probability	1.09	0.14	0.95	-0.84	-0.93	0.09	2.18	1.29	0.88
	(10) Momentum	0.08	0.29	-0.21	-0.04	-0.26	0.22	0.36	0.77	-0.41
	(11) Composite Equity Issues	0.56	0.46	0.11	-0.44	-0.30	-0.13	1.24	0.98	0.26
	(12) Size	1.18	0.74	0.44	0.91	0.54	0.37	0.51	0.42	0.09
	(13) Book to Market	1.36	1.13	0.23	0.97	0.21	0.76	0.64	1.15	-0.51
	(14) Operating Profitability	1.19	0.74	0.44	1.20	0.60	0.60	0.23	0.37	-0.14
	(15) Investments	1.73	0.89	0.83	0.66	0.38	0.28	1.31	0.73	0.58
	(16) Earning to Price	1.24	0.96	0.28	1.03	0.60	0.43	0.45	0.58	-0.13
	(17) Cash Flows to Price	1.26	0.99	0.27	1.02	0.56	0.47	0.48	0.66	-0.18
	(18) Dividend Yield	1.00	0.81	0.19	1.03	0.75	0.28	0.22	0.28	-0.06
	Combination	**0.84**	**0.43**	**0.42**	**0.33**	**-0.02**	**0.35**	**0.75**	**0.67**	**0.08**
Sharpe Ratio										
	(1) Asset Growth	12.70	5.05	7.65	0.49	-6.54	7.04	41.62	45.39	-3.77
	(2) Gross Profitability	10.54	1.36	9.19	0.97	-1.30	2.27	34.77	15.28	19.50
	(3) Investment to Assets	11.29	4.08	7.21	2.41	-10.74	13.15	32.33	57.32	-24.99
	(4) Net Stock Issues	9.23	8.34	0.89	2.57	-5.30	7.87	16.95	44.13	-27.18
	(5) Net Operating Assets	7.62	2.09	5.53	1.75	-7.96	9.72	25.52	45.19	-19.67
	(6) Total Accruals	9.95	0.85	9.10	-1.08	-8.85	7.77	30.88	27.93	2.94
	(7) Ohlson's O	9.19	-2.64	11.82	1.71	-3.03	4.74	22.20	12.78	9.42
	(8) Return on Assets	3.18	-4.18	7.37	-1.91	-15.13	13.23	20.07	30.95	-10.88
	(9) Failure Probability	14.69	3.33	11.35	-13.76	-21.30	7.53	40.76	55.02	-14.26
	(10) Momentum	1.18	7.46	-6.28	-0.49	-7.01	6.52	7.11	32.63	-25.52
	(11) Composite Equity Issues	11.15	15.85	-4.70	-6.01	-7.89	1.88	31.87	50.94	-19.07
	(12) Size	15.13	19.16	-4.03	14.67	19.08	-4.42	10.13	17.41	-7.28
	(13) Book to Market	19.86	32.60	-12.75	11.41	5.14	6.28	16.29	52.86	-36.57
	(14) Operating Profitability	18.67	22.27	-3.60	13.94	14.51	-0.57	5.16	19.48	-14.31
	(15) Investments	20.76	22.51	-1.75	8.23	9.82	-1.59	48.25	49.54	-1.30
	(16) Earning to Price	20.14	29.83	-9.69	15.03	17.22	-2.19	16.38	37.66	-21.28
	(17) Cash Flows to Price	19.23	30.31	-11.08	15.34	16.05	-0.71	19.51	43.13	-23.62
	(18) Dividend Yield	20.21	29.68	-9.48	17.57	24.01	-6.44	8.06	18.90	-10.85
	Combination	**13.04**	**12.66**	**0.38**	**4.60**	**0.60**	**4.00**	**23.77**	**36.47**	**-12.70**

Table 2.12: Anomalies during periods of high and low level of Variance Risk Premium. The table reports returns in months following high and low levels of VRP as identified on the base of the approach proposed by Zhou (2017). Also reported is the performance on a strategy that equally combines the strategies available within a given month (Combination). For each anomaly we make use of all data available. Details of the length of the time series can be found in the section 2 dedicated on Data. We report conditional Excess Returns (in percentage), and Sharpe Ratio for the long and short leg and for the Spread of the anomalies. We even report their difference.

VRP			Long Leg			Short Leg			Long-Short	
Excess Returns		High VRP	Low VRP	High-Low	High VRP	Low VRP	High-Low	High VRP	Low VRP	High-Low
	(1) Asset Growth	0.84	0.13	0.72	0.11	-0.36	0.47	0.99	0.70	0.28
	(2) Gross Profitability	0.77	-0.05	0.82	0.02	-0.01	0.03	1.00	0.18	0.83
	(3) Investment to Assets	0.79	0.06	0.73	0.21	-0.50	0.71	0.83	0.77	0.06
	(4) Net Stock Issues	0.62	0.10	0.52	0.24	-0.29	0.53	0.64	0.61	0.03
	(5) Net Operating Assets	0.59	0.01	0.58	0.09	-0.31	0.40	0.75	0.53	0.23
	(6) Total Accruals	0.53	0.12	0.41	-0.06	-0.38	0.32	0.85	0.72	0.13
	(7) Ohlson's O	0.56	-0.10	0.66	0.35	-0.35	0.70	0.46	0.46	0.00
	(8) Return on Assets	0.28	-0.25	0.53	-0.07	-0.70	0.63	0.60	0.66	-0.06
	(9) Failure Probability	1.10	0.13	0.97	-0.82	-0.95	0.14	2.17	1.30	0.87
	(10) Momentum	0.82	-0.45	1.27	0.56	-0.86	1.41	0.51	0.62	-0.11
	(11) Composite Equity Issues	1.08	-0.06	1.15	0.30	-1.04	1.34	1.04	1.19	-0.15
	(12) Size	1.85	0.06	1.79	1.37	0.09	1.28	0.74	0.19	0.55
	(13) Book to Market	2.09	0.40	1.70	1.52	-0.34	1.86	0.83	0.95	-0.12
	(14) Operating Profitability	1.68	0.25	1.43	1.88	-0.08	1.97	0.05	0.55	-0.50
	(15) Investments	2.37	0.25	2.11	1.33	-0.28	1.61	1.29	0.75	0.54
	(16) Earning to Price	1.85	0.34	1.50	1.55	0.08	1.47	0.55	0.48	0.07
	(17) Cash Flows to Price	1.85	0.41	1.44	1.56	0.02	1.54	0.54	0.60	-0.05
	(18) Dividend Yield	1.54	0.26	1.28	1.51	0.26	1.25	0.28	0.22	0.06
	Combination	**1.18**	**0.09**	**1.09**	**0.65**	**-0.33**	**0.98**	**0.78**	**0.64**	**0.15**
Sharpe Ratio										
	(1) Asset Growth	14.87	2.81	12.05	1.65	-7.57	9.22	42.06	44.67	-2.61
	(2) Gross Profitability	12.70	-1.09	13.79	0.34	-0.28	0.62	41.71	8.25	33.46
	(3) Investment to Assets	14.10	1.24	12.86	3.14	-10.44	13.58	35.98	50.70	-14.72
	(4) Net Stock Issues	13.59	2.73	10.85	3.66	-5.95	9.62	21.45	32.84	-11.39
	(5) Net Operating Assets	9.33	0.16	9.17	1.47	-6.68	8.15	32.43	30.94	1.49
	(6) Total Accruals	9.27	2.57	6.70	-1.07	-8.14	7.07	30.43	28.09	2.34
	(7) Ohlson's O	9.72	-2.33	12.05	5.33	-7.73	13.06	15.96	21.24	-5.29
	(8) Return on Assets	4.56	-5.61	10.16	-1.05	-14.79	13.74	22.39	27.07	-4.68
	(9) Failure Probability	15.89	2.67	13.22	-13.92	-20.41	6.49	44.63	40.27	4.36
	(10) Momentum	14.06	-8.85	22.91	8.36	-16.63	24.99	11.65	17.79	-6.13
	(11) Composite Equity Issues	24.77	-1.74	26.51	4.81	-19.52	24.33	34.72	37.50	-2.78
	(12) Size	26.68	1.23	25.45	25.04	2.19	22.85	15.23	7.01	8.23
	(13) Book to Market	33.97	9.02	24.94	20.41	-6.02	26.43	24.43	32.66	-8.23
	(14) Operating Profitability	29.20	5.98	23.23	24.85	-1.49	26.33	1.32	19.56	-18.25
	(15) Investments	32.19	4.71	27.48	18.68	-5.35	24.02	50.69	42.82	7.88
	(16) Earning to Price	33.36	8.57	24.79	25.39	1.81	23.58	23.01	23.41	-0.39
	(17) Cash Flows to Price	31.46	9.51	21.95	26.14	0.52	25.62	25.12	30.86	-5.74
	(18) Dividend Yield	34.89	7.73	27.16	28.71	6.65	22.06	11.33	11.94	-0.62
	Combination	**20.26**	**2.19**	**18.07**	**10.11**	**-6.66**	**16.76**	**26.92**	**28.20**	**-1.28**

Table 2.13: Anomalies during periods of high and low level of fear. The table reports returns in months following high and low levels of fear as identified on the base of the FVaR proxy. Also reported is the performance on a strategy that equally combines the strategies available within a given month (Combination). For each anomaly we make use of all data available. Details of the length of the time series can be found in the section 2 dedicated on Data. We report conditional Excess Returns (in percentage), and Sharpe Ratio for the long and short leg and for the Spread of the anomalies. We even report their difference.

FVaR		Long Leg			Short Leg			Long-Short		
Excess Returns		High Fear	Low Fear	High-Low	High Fear	Low Fear	High-Low	High Fear	Low Fear	High-Low
	(1) Asset Growth	0.28	0.08	0.20	-0.02	-0.20	0.18	0.36	0.44	-0.07
	(2) Gross Profitability	0.31	0.04	0.27	0.09	0.09	0.00	0.29	0.11	0.18
	(3) Investment to Assets	0.17	0.03	0.14	-0.02	-0.17	0.15	0.25	0.35	-0.10
	(4) Net Stock Issues	0.22	-0.02	0.25	0.09	-0.14	0.24	0.20	0.28	-0.08
	(5) Net Operating Assets	0.30	0.12	0.18	0.10	-0.11	0.22	0.26	0.39	-0.13
	(6) Total Accruals	-0.24	0.52	-0.76	-0.01	0.12	-0.13	-0.16	0.55	-0.72
	(7) Ohlson's O	0.20	0.06	0.15	-0.12	-0.03	-0.09	0.39	0.24	0.15
	(8) Return on Assets	0.31	0.16	0.14	-0.19	-0.61	0.42	0.56	0.93	-0.37
	(9) Failure Probability	0.40	0.68	-0.28	-0.10	-0.79	0.69	0.57	1.63	-1.06
	(10) Momentum	0.64	-0.95	1.60	0.75	-1.04	1.79	-0.04	0.24	-0.28
	(11) Composite Equity Issues	0.98	-0.80	1.78	0.50	-1.09	1.59	0.55	0.45	0.10
	(12) Size	1.39	-0.28	1.67	1.59	-0.28	1.88	-0.14	0.16	-0.30
	(13) Book to Market	1.62	-0.37	1.99	1.40	-0.26	1.66	0.29	0.05	0.24
	(14) Operating Profitability	1.67	-0.18	1.85	1.40	-0.29	1.69	0.34	0.27	0.07
	(15) Investments	1.80	-0.27	2.07	1.21	-0.32	1.54	0.65	0.21	0.44
	(16) Earning to Price	1.68	-0.37	2.05	1.48	-0.11	1.59	0.27	-0.10	0.37
	(17) Cash Flows to Price	1.84	-0.21	2.05	1.40	-0.18	1.59	0.50	0.12	0.38
	(18) Dividend Yield	1.61	-0.51	2.12	1.49	-0.24	1.74	0.18	-0.11	0.29
	Combination	**0.84**	**-0.13**	**0.97**	**0.61**	**-0.31**	**0.93**	**0.30**	**0.34**	**-0.05**
Sharpe Ratio										
	(1) Asset Growth	4.91	1.47	3.44	-0.34	-3.59	3.25	22.95	32.27	-9.32
	(2) Gross Profitability	5.98	0.77	5.21	1.57	1.68	-0.11	15.01	5.78	9.22
	(3) Investment to Assets	2.85	0.49	2.36	-0.26	-2.77	2.51	13.57	24.76	-11.19
	(4) Net Stock Issues	4.63	-0.50	5.12	1.57	-2.45	4.02	12.07	18.11	-6.04
	(5) Net Operating Assets	5.16	2.21	2.95	1.71	-1.95	3.66	18.04	26.73	-8.69
	(6) Total Accruals	-3.81	9.16	-12.97	-0.15	2.29	-2.45	-5.81	19.00	-24.81
	(7) Ohlson's O	3.37	1.05	2.32	-2.10	-0.57	-1.53	24.68	12.06	12.62
	(8) Return on Assets	5.55	3.19	2.36	-3.34	-10.15	6.81	21.40	38.63	-17.23
	(9) Failure Probability	6.69	10.02	-3.33	-2.04	-15.33	13.30	17.73	36.25	-18.52
	(10) Momentum	14.03	-14.99	29.02	12.99	-15.79	28.78	-0.93	6.62	-7.55
	(11) Composite Equity Issues	24.09	-14.45	38.54	10.85	-17.62	28.47	32.14	30.46	1.69
	(12) Size	25.72	-4.45	30.17	35.27	-5.16	40.43	-5.16	8.07	-13.22
	(13) Book to Market	29.82	-6.08	35.91	27.35	-4.17	31.52	12.40	2.18	10.22
	(14) Operating Profitability	32.40	-2.97	35.37	25.26	-4.48	29.74	16.48	15.59	0.89
	(15) Investments	29.80	-4.23	34.03	23.39	-4.96	28.35	32.78	14.71	18.07
	(16) Earning to Price	33.88	-5.93	39.81	31.17	-1.88	33.06	19.26	-6.29	25.55
	(17) Cash Flows to Price	34.64	-3.23	37.87	29.90	-3.16	33.06	29.60	6.99	22.61
	(18) Dividend Yield	35.88	-9.37	45.24	31.72	-4.08	35.80	7.87	-4.46	12.33
	Combination	**16.42**	**-2.10**	**18.52**	**12.47**	**-5.23**	**17.70**	**15.78**	**15.97**	**-0.19**

Table 2.14: Anomalies during periods of high and low level of fear. The table reports returns in months following high and low levels of fear as identified on the base of the FCVaR proxy. Also reported is the performance on a strategy that equally combines the strategies available within a given month (Combination). For each anomaly we make use of all data available. Details of the length of the time series can be found in section 2 dedicated on Data. We report conditional Excess Returns (in percentage), and Sharpe Ratio for the long and short leg and for the Spread of the anomalies. We even report their difference.

FCVaR		Long Leg			Short Leg			Long-Short		
Excess Returns		High Fear	Low Fear	High-Low	High Fear	Low Fear	High-Low	High Fear	Low Fear	High-Low
	(1) Asset Growth	0.05	0.26	-0.21	-0.28	0.07	-0.36	0.52	0.23	0.29
	(2) Gross Profitability	0.10	0.40	-0.31	-0.13	0.20	-0.33	0.41	0.24	0.17
	(3) Investment to Assets	-0.06	0.27	-0.33	-0.18	0.04	-0.22	0.30	0.27	0.03
	(4) Net Stock Issues	-0.03	0.28	-0.31	-0.27	0.19	-0.46	0.42	0.13	0.29
	(5) Net Operating Assets	-0.05	0.48	-0.53	-0.13	0.15	-0.29	0.26	0.36	-0.10
	(6) Total Accruals	-0.10	0.25	-0.35	-0.05	0.02	-0.08	0.13	0.26	-0.13
	(7) Ohlson's O	-0.08	0.26	-0.33	-0.39	0.34	-0.73	0.50	-0.04	0.54
	(8) Return on Assets	0.12	0.53	-0.41	-0.54	-0.44	-0.11	0.84	1.00	-0.16
	(9) Failure Probability	0.14	0.80	-0.65	-0.46	-0.33	-0.13	0.79	1.17	-0.38
	(10) Momentum	1.54	-1.83	3.37	1.38	-1.56	2.94	0.34	-0.24	0.58
	(11) Composite Equity Issues	1.43	-1.13	2.56	1.24	-1.78	3.03	0.37	0.70	-0.32
	(12) Size	1.99	-0.87	2.86	1.98	-0.59	2.56	0.20	-0.24	0.44
	(13) Book to Market	2.21	-0.91	3.12	1.81	-0.65	2.46	0.59	-0.22	0.81
	(14) Operating Profitability	2.23	-0.66	2.88	1.97	-0.91	2.88	0.44	0.29	0.15
	(15) Investments	2.40	-0.82	3.22	1.76	-0.90	2.66	0.82	0.12	0.70
	(16) Earning to Price	2.09	-0.68	2.77	1.97	-0.57	2.54	0.30	-0.08	0.38
	(17) Cash Flows to Price	2.36	-0.68	3.04	1.85	-0.57	2.41	0.70	-0.07	0.77
	(18) Dividend Yield	1.75	-0.52	2.27	1.99	-0.66	2.65	-0.06	0.18	-0.23
	Combination	**1.00**	**-0.25**	**1.26**	**0.75**	**-0.44**	**1.19**	**0.44**	**0.23**	**0.21**
Sharpe Ratio										
	(1) Asset Growth	1.07	4.13	-3.06	-6.51	1.09	-7.60	36.90	14.65	22.25
	(2) Gross Profitability	2.36	6.47	-4.10	-2.98	3.32	-6.30	22.24	12.27	9.97
	(3) Investment to Assets	-1.27	3.99	-5.25	-3.76	0.53	-4.30	21.49	14.80	6.69
	(4) Net Stock Issues	-0.74	5.04	-5.78	-5.77	2.77	-8.54	28.89	8.08	20.81
	(5) Net Operating Assets	-1.12	7.36	-8.48	-3.01	2.22	-5.23	25.81	19.24	6.57
	(6) Total Accruals	-2.21	3.70	-5.91	-1.22	0.38	-1.61	5.37	8.40	-3.04
	(7) Ohlson's O	-1.70	3.85	-5.55	-8.78	5.50	-14.28	27.13	-2.07	29.20
	(8) Return on Assets	2.66	8.68	-6.01	-12.17	-6.52	-5.65	35.00	40.72	-5.71
	(9) Failure Probability	3.30	10.51	-7.21	-10.02	-6.03	-3.98	28.41	25.91	2.51
	(10) Momentum	39.48	-28.91	68.39	38.88	-20.05	58.93	15.29	-4.61	19.90
	(11) Composite Equity Issues	48.62	-19.15	67.77	34.73	-27.26	61.99	26.59	38.29	-11.70
	(12) Size	49.01	-12.34	61.35	70.44	-9.41	79.85	9.28	-9.40	18.67
	(13) Book to Market	56.15	-13.27	69.42	47.44	-9.28	56.72	30.59	-8.97	39.56
	(14) Operating Profitability	64.16	-9.52	73.68	46.84	-12.61	59.45	26.53	14.22	12.31
	(15) Investments	51.84	-11.09	62.94	48.14	-12.47	60.61	43.83	7.28	36.56
	(16) Earning to Price	59.82	-9.95	69.77	59.68	-8.68	68.36	24.57	-4.19	28.76
	(17) Cash Flows to Price	65.13	-9.31	74.44	56.34	-8.78	65.12	52.49	-3.75	56.24
	(18) Dividend Yield	56.58	-8.71	65.29	60.73	-10.08	70.81	-3.27	6.10	-9.37
	Combination	**27.40**	**-3.81**	**31.21**	**22.72**	**-6.41**	**29.13**	**25.40**	**9.83**	**15.57**

Table 2.15: Risk Return relationship. The following table considers the PLS 6 sentiment measure, the UM uncertainty proxy, the VIX index, and the FVaR fear proxy at time t, and regress them on the excess returns and standard deviation at time t+1. $Y_{i,t} = a + bX_{t-1} + u_t$ where $Y_{i,t}$ is the excess return or standard deviation in month t on either the long leg, short leg, or their difference, X is one of the following predictors: PLS6, UM, VIX, VRP, FVaR.

Excess Returns	Long Leg		Short Leg		Spread	
PLS 6	b	t stat	b	t stat	b	t stat
(1) Asset Growth	-0.81	-3.57	-1.06	-4.09	0.38	4.65
(2) Gross Profitability	-0.78	-3.24	-0.80	-3.80	0.15	1.54
(3) Investment to Assets	-0.79	-3.44	-1.02	-3.96	0.36	4.70
(4) Net Stock Issues	-0.76	-3.63	-0.96	-3.94	0.33	4.00
(5) Net Operating Assets	-0.82	-3.42	-0.96	-3.93	0.28	3.83
(6) Total Accruals	-0.61	-2.34	-0.96	-3.40	0.51	4.42
(7) Ohlson's O	-0.87	-3.67	-0.78	-3.34	0.04	0.43
(8) Return on Assets	-0.88	-3.14	-0.75	-2.72	0.04	0.33
(9) Failure Probability	-0.57	-1.91	-0.93	-3.29	0.53	2.76
(10) Momentum	-0.90	-3.75	-0.98	-3.93	0.21	1.35
(11) Composite Equity Issues	-0.71	-3.63	-1.05	-4.34	0.47	4.75
(12) Size	-0.97	-3.69	-0.65	-3.29	-0.18	-1.11
(13) Book to Market	-0.75	-3.17	-1.00	-3.67	0.39	3.12
(14) Operating Profitability	-0.81	-3.44	-1.00	-3.65	0.33	2.80
(15) Investments	-0.89	-3.37	-1.01	-3.78	0.26	3.10
(16) Earning to Price	-0.60	-2.75	-0.94	-3.78	0.47	4.91
(17) Cash Flows to Price	-0.66	-2.91	-0.93	-3.81	0.41	4.57
(18) Dividend Yield	-0.42	-2.45	-0.75	-3.38	0.46	4.46
Comination	-0.49	-2.52	-0.70	-3.42	0.39	9.57
UM	b	t stat	b	t stat	b	t stat
(1) Asset Growth	-2.11	-0.67	-2.52	-0.71	0.70	0.60
(2) Gross Profitability	0.47	0.14	-3.62	-1.18	4.38	3.29
(3) Investment to Assets	-1.92	-0.61	-1.04	-0.29	-0.59	-0.51
(4) Net Stock Issues	-2.31	-0.87	-2.82	-0.81	0.79	0.59
(5) Net Operating Assets	-1.43	-0.43	-1.74	-0.52	0.59	0.52
(6) Total Accruals	0.59	0.18	-0.45	-0.14	1.34	0.89
(7) Ohlson's O	-0.84	-0.26	-0.89	-0.26	0.35	0.24
(8) Return on Assets	-0.97	-0.29	-2.43	-0.72	1.74	1.17
(9) Failure Probability	1.00	0.27	-2.25	-0.68	3.54	1.51
(10) Momentum	-7.78	-2.34	-1.36	-0.39	-6.13	-2.79
(11) Composite Equity Issues	-5.49	-2.14	-5.29	-1.54	0.09	0.05
(12) Size	-1.30	-0.36	-5.03	-1.73	4.02	1.79
(13) Book to Market	-2.99	-0.95	-1.02	-0.26	-1.68	-0.93
(14) Operating Profitability	-2.08	-0.67	-1.21	-0.31	-0.59	-0.31
(15) Investments	-1.03	-0.27	-1.80	-0.48	1.06	0.85
(16) Earning to Price	-2.27	-0.79	-2.65	-0.80	0.68	0.49
(17) Cash Flows to Price	-1.58	-0.52	-2.72	-0.83	1.42	1.13
(18) Dividend Yield	-3.08	-1.32	-3.60	-1.25	0.81	0.60
Comination	-1.95	-0.84	-2.36	-0.94	0.70	1.27

Standard Deviation	Long Leg		Short Leg		Spread	
PLS 6	b	t stat	b	t stat	b	t stat
(1) Asset Growth	0.33	6.22	0.50	8.39	0.22	10.76
(2) Gross Profitability	0.33	6.14	0.28	5.75	0.06	3.09
(3) Investment to Assets	0.28	5.05	0.46	7.55	0.24	12.91
(4) Net Stock Issues	0.33	5.33	0.42	7.84	0.19	5.14
(5) Net Operating Assets	0.36	6.58	0.42	6.85	0.17	5.69
(6) Total Accruals	0.22	3.69	0.31	4.58	-0.01	-0.50
(7) Ohlson's O	0.34	5.66	0.36	6.79	0.22	7.14
(8) Return on Assets	0.31	4.85	0.37	5.00	0.14	6.65
(9) Failure Probability	0.50	6.47	0.21	2.89	0.48	5.98
(10) Momentum	0.16	2.85	0.62	8.98	0.39	7.10
(11) Composite Equity Issues	0.23	3.87	0.45	8.28	0.23	4.23
(12) Size	0.49	7.62	0.37	7.20	0.30	5.40
(13) Book to Market	0.15	2.13	0.74	10.91	0.46	10.88
(14) Operating Profitability	0.34	5.63	0.54	7.63	0.28	4.84
(15) Investments	0.34	5.07	0.61	9.16	0.11	4.76
(16) Earning to Price	0.07	1.04	0.65	11.43	0.49	17.88
(17) Cash Flows to Price	0.11	1.65	0.66	11.58	0.40	17.93
(18) Dividend Yield	0.08	1.36	0.36	6.09	0.23	8.81
Comination	0.19	3.56	0.34	6.09	0.17	10.18
UM	b	t stat	b	t stat	b	t stat
(1) Asset Growth	8.60	11.97	6.11	7.19	0.30	0.88
(2) Gross Profitability	5.83	7.51	5.95	7.87	-0.51	-2.31
(3) Investment to Assets	9.58	13.86	8.03	9.23	1.76	5.26
(4) Net Stock Issues	7.85	10.94	6.67	8.11	-0.87	-1.34
(5) Net Operating Assets	7.56	9.36	7.80	9.60	0.28	0.55
(6) Total Accruals	8.48	12.55	4.81	6.14	2.20	6.47
(7) Ohlson's O	8.61	11.36	5.88	6.86	-0.41	-0.76
(8) Return on Assets	5.30	6.93	8.01	9.00	1.85	6.94
(9) Failure Probability	9.61	10.60	3.50	4.21	4.41	4.26
(10) Momentum	4.46	5.15	10.33	11.22	6.15	6.80
(11) Composite Equity Issues	8.03	10.83	5.53	6.26	-2.41	-2.57
(12) Size	8.43	9.36	8.44	10.83	-1.47	-1.65
(13) Book to Market	9.59	11.78	7.29	6.25	2.32	3.10
(14) Operating Profitability	9.75	13.83	7.97	7.05	-0.71	-0.71
(15) Investments	9.78	9.89	7.73	7.50	1.62	4.34
(16) Earning to Price	9.65	12.58	8.19	10.73	2.38	4.52
(17) Cash Flows to Price	10.63	13.09	8.41	11.69	2.74	7.07
(18) Dividend Yield	9.75	13.24	9.37	14.79	3.91	13.68
Comination	7.18	12.14	6.48	10.07	0.47	2.06

Table 2.16: Continues from above

Excess Returns	Long Leg		Short Leg		Spread	
VIX	b	t stat	b	t stat	b	t stat
(1) Asset Growth	0.02	1.45	0.02	1.20	0.00	0.53
(2) Gross Profitability	0.02	1.59	0.02	1.08	0.01	1.47
(3) Investment to Assets	0.02	1.20	0.02	1.49	-0.01	-0.99
(4) Net Stock Issues	0.01	1.26	0.02	1.33	-0.01	-0.77
(5) Net Operating Assets	0.02	1.44	0.02	1.03	0.01	1.46
(6) Total Accruals	0.02	1.22	0.01	0.83	0.01	0.94
(7) Ohlson's O	0.01	1.00	0.02	1.48	-0.01	-1.02
(8) Return on Assets	0.02	1.49	0.03	1.91	-0.01	-0.88
(9) Failure Probability	0.03	1.59	0.01	0.88	0.01	1.33
(10) Momentum	0.05	3.44	0.05	3.30	0.00	-0.08
(11) Composite Equity Issues	0.04	3.74	0.05	3.20	-0.01	-0.89
(12) Size	0.05	3.31	0.05	4.18	0.00	0.22
(13) Book to Market	0.05	3.57	0.06	3.47	-0.01	-0.99
(14) Operating Profitability	0.05	3.72	0.06	3.34	-0.01	-0.89
(15) Investments	0.06	3.43	0.06	3.46	0.00	0.49
(16) Earning to Price	0.05	3.87	0.05	3.80	0.00	-0.56
(17) Cash Flows to Price	0.05	3.81	0.05	3.87	0.00	-0.14
(18) Dividend Yield	0.05	4.54	0.04	3.60	0.00	0.72
Comination	0.03	3.47	0.04	3.33	0.00	-0.03
FVaR	b	t stat	b	t stat	b	t stat
(1) Asset Growth	0.02	0.65	0.02	0.64	0.00	-0.41
(2) Gross Profitability	0.03	1.10	0.01	0.39	0.02	1.60
(3) Investment to Assets	0.02	0.74	0.01	0.45	0.01	0.61
(4) Net Stock Issues	0.02	0.79	0.02	0.64	0.00	-0.34
(5) Net Operating Assets	0.02	0.69	0.01	0.41	0.01	0.62
(6) Total Accruals	0.00	0.03	0.02	0.68	-0.02	-1.44
(7) Ohlson's O	0.02	0.52	0.01	0.42	0.00	0.06
(8) Return on Assets	0.02	0.71	0.02	0.82	-0.01	-0.60
(9) Failure Probability	0.00	-0.02	0.03	1.30	-0.04	-1.96
(10) Momentum	0.05	1.61	0.06	1.95	-0.02	-0.94
(11) Composite Equity Issues	0.06	2.33	0.06	1.95	0.00	-0.05
(12) Size	0.06	2.02	0.06	2.37	0.00	-0.18
(13) Book to Market	0.07	2.26	0.06	2.03	0.00	0.30
(14) Operating Profitability	0.06	2.03	0.07	2.09	-0.01	-0.98
(15) Investments	0.07	2.20	0.06	1.91	0.01	1.22
(16) Earning to Price	0.06	2.18	0.05	1.93	0.01	0.84
(17) Cash Flows to Price	0.07	2.10	0.06	2.00	0.01	0.77
(18) Dividend Yield	0.06	2.47	0.06	1.97	0.00	0.36
Comination	0.04	1.82	0.04	1.78	0.00	-0.81

Standard Deviation	Long Leg		Short Leg		Spread	
VIX	b	t stat	b	t stat	b	t stat
(1) Asset Growth	0.10	11.03	0.08	8.06	0.02	4.29
(2) Gross Profitability	0.08	8.72	0.09	9.73	0.01	2.64
(3) Investment to Assets	0.10	10.11	0.09	7.60	0.03	5.65
(4) Net Stock Issues	0.07	7.50	0.10	9.57	0.05	5.86
(5) Net Operating Assets	0.11	11.30	0.08	7.68	0.04	6.93
(6) Total Accruals	0.09	10.23	0.07	8.46	0.03	8.12
(7) Ohlson's O	0.09	8.89	0.10	9.02	0.03	4.19
(8) Return on Assets	0.06	7.08	0.12	10.21	0.02	4.15
(9) Failure Probability	0.12	9.56	0.07	7.82	0.09	6.21
(10) Momentum	0.09	8.63	0.12	9.41	0.09	7.56
(11) Composite Equity Issues	0.07	6.77	0.11	9.70	0.06	4.52
(12) Size	0.13	11.02	0.11	10.27	0.06	4.83
(13) Book to Market	0.12	10.66	0.14	9.17	0.07	6.74
(14) Operating Profitability	0.09	8.51	0.15	10.41	0.08	6.39
(15) Investments	0.15	11.87	0.13	9.37	0.04	9.44
(16) Earning to Price	0.10	8.32	0.10	10.00	0.04	5.82
(17) Cash Flows to Price	0.11	8.58	0.10	10.53	0.03	6.43
(18) Dividend Yield	0.08	6.55	0.09	9.46	0.03	7.25
Comination	0.07	8.63	0.08	9.07	0.02	6.18
FVaR	b	t stat	b	t stat	b	t stat
(1) Asset Growth	-0.03	-2.74	-0.03	-3.54	-0.01	-2.77
(2) Gross Profitability	-0.03	-3.45	-0.02	-3.19	0.00	-2.89
(3) Investment to Assets	-0.03	-2.81	-0.04	-3.62	-0.01	-3.19
(4) Net Stock Issues	-0.03	-3.33	-0.03	-3.21	0.00	-2.33
(5) Net Operating Assets	-0.03	-2.87	-0.03	-3.50	0.00	-2.87
(6) Total Accruals	-0.03	-2.90	-0.03	-3.79	-0.01	-3.40
(7) Ohlson's O	-0.03	-3.31	-0.03	-3.09	0.00	-2.73
(8) Return on Assets	-0.03	-3.30	-0.03	-3.16	-0.01	-3.38
(9) Failure Probability	-0.04	-3.31	-0.02	-2.94	-0.03	-4.03
(10) Momentum	-0.02	-2.40	-0.04	-3.34	-0.03	-3.59
(11) Composite Equity Issues	-0.03	-3.58	-0.02	-2.73	0.00	0.30
(12) Size	-0.03	-3.00	-0.03	-3.24	-0.01	-2.45
(13) Book to Market	-0.04	-3.07	-0.03	-3.08	-0.01	-2.16
(14) Operating Profitability	-0.03	-3.19	-0.03	-3.00	-0.01	-2.40
(15) Investments	-0.04	-2.86	-0.03	-3.21	-0.01	-2.02
(16) Earning to Price	-0.04	-3.22	-0.03	-3.07	-0.01	-3.30
(17) Cash Flows to Price	-0.04	-3.26	-0.03	-3.01	-0.01	-3.21
(18) Dividend Yield	-0.04	-3.46	-0.03	-2.75	-0.01	-3.06
Comination	-0.03	-3.41	-0.03	-3.42	0.00	-1.79

Table 2.17: Anomalies out-of-sample predictability. This table shows the performance of employing the forecasts coming from the considered indexes in determining the weight of a portfolio optimization problem which has the predicted portfolio and the risk free rate as only possible assets and a weight of the risky asset bounded between -1 and +1.5. We report the out-of-sample performance generated by such strategies in terms of average return, standard deviation and Sharpe Ratio. Mean returns and standard deviation are reported in percentage. All forecasts are for month t+1 using the chosen index value at month t. All time series are divided accordingly to the following criteria: 25 % of the data are used for the in sample estimation, 15% are use as hold out period and the remaining is employed for the out of sample performance evaluation of the predictive power of the relevant variables. In this table we report the performance generated for the combination strategy: the long leg is an equally weighted combination of the long legs of the 18 anomalies-factors considered and the short leg is an equally weighted combination of the short legs of the 18 anomalies-factors considered.

Long Leg				**Short Leg**			
Combination	Mean	Vol	SR	Combination	Mean	Vol	SR
Sentiment				**Sentiment**			
PC 6	-0.13	0.02	**-6.07**	PC 6	0.28	0.03	**10.77**
PLS 6	0.11	0.02	**5.16**	PLS 6	0.53	0.03	**17.81**
Uncertainty				**Uncertainty**			
DEVST	-0.04	0.02	**-2.19**	DEVST	0.15	0.03	**4.64**
UF	0.32	0.03	**9.56**	UF	0.39	0.04	**10.64**
UM	0.18	0.03	**5.87**	UM	0.25	0.03	**7.33**
Investors views				**Investors views**			
MEAN	0.12	0.02	**5.91**	MEAN	0.38	0.03	**13.53**
UP	0.02	0.02	**0.88**	UP	0.27	0.03	**9.60**
LOW	0.27	0.02	**11.73**	LOW	0.52	0.03	**18.67**
Fear				**Fear**			
Bull-Bear	1.17	0.04	**32.70**	Bull-Bear	0.88	0.03	**26.31**
BTX	0.03	0.03	**0.96**	BTX	-0.11	0.03	**-3.44**
MACRO	0.13	0.03	**4.51**	MACRO	0.05	0.03	**1.50**
VIX	0.71	0.04	**19.91**	VIX	0.64	0.04	**17.22**
ANX	-0.21	0.03	**-6.30**	ANX	-0.25	0.02	**-10.37**
VRP	0.04	0.04	**1.00**	VRP	-0.25	0.04	**-6.84**
KJ	-0.08	0.01	**-6.42**	KJ	0.30	0.04	**8.41**
CATFIN	1.15	0.04	**28.42**	CATFIN	1.19	0.04	**28.69**
TAIL	1.46	0.04	**37.43**	TAIL	1.30	0.04	**33.97**
FVaR	0.63	0.03	**21.84**	FVaR	0.39	0.03	**13.11**

2.8 Online Appendix

The online appendix is divided into two parts: the first one provide further details on the indexes employed during the paper while the second part provides a number of additional tests and empirical analysis that for seek of brevity have been removed from the main text.

2.8.1 Fear Indexes

Fear is defined as the complement of sentiment. Consequently, we have employed a large set of indexes which are good candidates to capture this phenomenon. We divide the indexes into three main groups: one based on surveys, the second based on macroeconomic and equity measures and the third one based on option-based measures. In the list of surveys based indexes we list:

- Crash Confidence Index[56]: the percent of the population who attach little probability to a stock market crash in the next six months. We consider both the institutional and the Individual Survey. Data comes from the Yale School of Management website. The time series considered ranges from 01-1990 to 12-2016.

- The Anxious Index[57]: the survey asks to estimate the probability that real GDP will contract in the quarter in which the survey is taken and the following four quarters. The anxious index is the average probability of a decline in real GDP in the quarter after a survey is taken. Data come from the Federal Reserve Bank of Philadelphia. In this study, we consider the forecast for the second quarter after the quarter in which the survey takes place. Data spans the period from 01-1990 to 12-2016.

- Bull-Bear, Bull-Neutral and Bear-Neutral spreads[58]. These indicators come from the American Association of Individual Investors. The survey on weekly base reports the percentage of bullish, bearish and neutral investors. For each series, we compute the 47 weeks average, and then we compute the three spreads. The time series available starts the 07-1988 and ends in the 12-2016.

- The difference: (Upper view-Mean view) - (Mean view-Lower view). The indicator captures the relationship between the mean view and extreme views.

[56] https://som.yale.edu/faculty-research/our-centers-initiatives/international-center-finance/data/stock-market-confidence-indices

[57] https://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/anxious-index

[58] http://www.aaii.com/sentimentsurvey

The mean view (or the representative investor one) is the number of forecast weighted average view of the EPS long-term growth. Data come from the IBES database and spans the period 07/1988-12/2016.

- Livingston six months ahead Skewness[59]. This index is built computing the average skewness of the six months ahead forecasts about a list of economic variables coming from the Livingston survey. The list includes the following economic variables RGDPX (Real Gross Domestic Product), gdpx (Nominal Gross Domestic Product), IP (Industrial Production Index), CPI (Consumer Price Index), WMFG (Average Weekly Earnings in Manufacturing), RTTR (Nominal Retail Sales and Food Services). Missing data are estimated through interpolation. The time series used involves the period 07/1988-12/2016.

- Livingston RGDPX[60] six month ahead Skewness. These two indexes are built using the skewness of the 6 and 12 months ahead forecasts about RGDPX coming from the Livingston survey. Missing data are estimated through interpolation. The time series used involves the period 07/1988-12/2016.

In the list of macroeconomic and equity-based indexes we list:

- The tail risk measure of Kelly and Jiang [2014][61]. This risk measure is directly estimable from the cross-section of returns. The authors exploit firm-level price crashes every month to capture common fluctuations in tail risk. Data comes row from the authors and spans the period 01-1973/12-2010.

- The economic uncertainty measure of Bali et al. [2014][62]. The authors use the PCA to extract a common component from the eight macroeconomic risk factors that capture different dimensions of the business cycle: uncertainty about default risk, about short-term and long-term interest rate changes, about aggregate dividend yield, about the equity market, about inflation, about output growth, and about unemployment. Data comes row from the authors and includes the period 01-1993/08-2013.

- The CATFIN measure of aggregate systemic risk proposed by Allen et al. [2012][63]. CATFIN comes from the first principal component extracted from the 1% VaR measures for a cross-section of financial firms. Data comes row from the authors and includes the period 01-1973/12-2010

[59] https://www.philadelphiafed.org/research-and-data/real-time-center/livingston-survey
[60] https://www.philadelphiafed.org/research-and-data/real-time-center/livingston-survey
[61] We thank the authors for sharing the data
[62] We thank the authors for sharing the data
[63] We thank the authors for sharing the data

- The tail-risk measure based on the risk-neutral excess expected shortfall of a cross-section of stock returns proposed by Almeida et al. [2017][64]. Remarkably, the authors rely on an innovative way to risk neutralize the returns without relying on option price information. The available time series include the period 01-1973/12-2010. We warmly thank the authors for sharing their code.

In the list of option-based fear indexes we list:

- The VIX index. While Fear and volatility are often considered synonyms, this is improper. Indeed trading opportunities are largely linked to the mismatch between Fear and Volatility (Schneider and Trojani [2015]). The time series employed come from the Federal Reserve of Philadelphia and spans the period from 01-1990/12-2016.

- The Variance Risk Premium (VRP)[65]. In this study we make use of the version of the VRP proposed by Zhou Hao and the data come from the website of the author. In the paper, it is shown (Zhou [2017]) the predictive power of the index and how it interacts with other predictors. The available data spans the period from 01-1990 to 12-2016.

- The tail risk proxy extrapolated from options proposed by Bollerslev et al. [2015][66]. This measure captures the compensation demanded by investors for bearing jump tail risk. The authors show how it has a strong predictive power at intermediate horizons and that it summarizes much of the predictability coming from the variance risk premium. Available data spans the period 01-1996/08-2013. We thank the author for the support in replicating the model.

2.8.2 Uncertainty Indexes

To model uncertainty, we will rely on three separate approaches. The first one relies on modeling the aggregate volatility of analyst forecasts about firms' earnings. The second is based on the volatility and skewness of the economists' forecast about economic variables. Finally, the third approach is based on the uncertainty indexes proposed by Jurado et al. [2015].
The first approach was originally introduced by Diether et al. [2002]. The authors employed one (fiscal) year $I-B-E-S$ earnings estimates for stocks which are covered by two or more analysts, and which have a price greater than five

[64] We warmly thank the authors for sharing their codes and data

[65] https://sites.google.com/site/haozhouspersonalhomepage/

[66] We thank Professor Todorov for the support in replicating the model

dollars. Unfortunately, one-year earning forecasts are strongly influenced by the management of the firm under scrutiny. Consequently, Yu [2011] employs the long earning per share long-term $I - B - E - S$ growth rate for stocks which are covered by two or more analysts. This measure of uncertainty is shown to be less affected by the managers and accordingly it is more reliable. In conclusion, we will employ this more robust methodology using the number of views each firm receive to weight the standard deviation of the views. We employ Analysts forecasts from December 1981 to December 2016.
The second measure of uncertainty comes from the work of Jurado et al. [2015]. Monthly data, which spans the period from 7/1960 to 12/2016, come from the website of Professor Sydney. The authors distinguish between two uncertainty measures: a financial one and a macroeconomic one: this allows us to perform further analysis on different dimensions of uncertainty. After that, we employ as proxies for uncertainty the dispersion of the forecasts coming from surveys. A similar approach has been successfully employed by Buraschi and Jiltsov [2006] and Colacito et al. [2016]. The surveys which we employ are:

- The Survey of Professional Forecasters: it surveys economic variable forecasts (including output, inflation, and interest rates) prepared by private sector economists. We focus on GDP, the GDP implicit price deflator, corporate profits after tax, civilian unemployment, industrial production, and the start of new housing units. These are the variables most related to our definition of economic fundamentals. For each series and each time t we estimate the coefficient of variation. Finally, we employ the first principal component as the proxy for uncertainty; missing data are fulfilled through linear interpolation.

- The Livingston Survey: was started in 1946 and it is the oldest continuous survey of economists' expectations. It summarizes the forecasts of economists from industry, government, banking, and academia. Every June and December, the Livingston Survey asks participants to forecast a set of key macroeconomic variables, including real and nominal GDP. Survey participants are asked to provide forecasts for these variables for the end of the current month, six months ahead, and 12 months ahead. For each date, we have a cross-section of up to 50 forecasts. We focus on six months ahead forecasts for the following time series: Real Gross Domestic Product, Nominal Corporate Profits after taxes real gross domestic product, Nominal Gross Domestic Product, Industrial Production, Civilian Unemployment Rate, Average Weekly Earnings. As a measure of dispersion, we employ the difference between the Log 75th Percentile and the Log 25th Percentile of the Forecasts for Levels. The difference is multiplied by 100. After that, each data is divided by the average of the last ten observation plus the observation itself.

The uncertainty proxy at time t arises computing the simple average on the seven times series found with the methodology just detailed. Finally, missing data are found through linear interpolation.

2.8.3 Anomalies

In this part, we analyze documented differences in cross-sectional average returns that resist adjustment for exposures to the three factors model of Fama and French [1993]. We employ the list of eleven anomalies proposed by Stambaugh et al. [2015] plus the four factors of Fama and French [2015], plus three additional ratios of economic variables on prices (dividend yield, price-earnings, cash flow price). All data are monthly and span the period from 01-1965 to 12-2016 except the Net Operating Assets, the Accruals, the Return on Assets and the Distress anomaly for which data are available respectively only from 8-1965, 1-1970, 5-1976, and 1-1977.

Anomalies 1 and 2: Financial distress. Campbell et al. [2008] show that firms with high failure probability have lower, not higher, subsequent returns (anomaly 1). In their model, the failure probability is estimated by a dynamic logit model which employs both accounting and equity market variables. Another measure of distress is the O-score (Ohlson [1980], anomaly 2) . The Ohlson O-score is computed as the probability of bankruptcy in a static model using accounting variables only.

Anomalies 3 and 4: Net stock issues and composite equity issues. The stock issuing market is by definition related to sentiment-driven mispricing: smart managers issue shares when sentiment-driven traders move prices to overvalued levels. Loughran and Ritter [1995] show that, in post-issue years, equity issuers underperform non-issuers with similar characteristics (anomaly 3). We compute net stock issues as the growth rate of the split-adjusted shares outstanding in the previous fiscal year. Daniel and Titman [2006] propose an alternative measure, composite equity issuance, defined as the amount of equity a firm issues (or retires) in exchange for cash or services. Consequently, seasoned issues and share-based acquisitions increase the issuance aggregate measure, while repurchases and dividends, reduce the issuance measure (anomaly 4).

Anomaly 5: Total accruals. Sloan [1996] demonstrates that firms with high accruals earn abnormal lower returns on average than firms with low accruals. In this paper, total accruals are estimated as changes in non-cash working capital minus depreciation expense scaled by average total assets for the previous two fiscal years.

Anomaly 6: Net operating assets. Hirshleifer et al. [2004] find that net operating assets, computed as the difference on the balance sheet between all operating assets and all operating liabilities divided by total assets is a negative predictor of long-run stock returns. They motivate this finding on the ground that investors with limited attention tend to focus on accounting profitability, ignoring information about cash profitability.

Anomaly 7: Momentum. The momentum effect, proposed by Jegadeesh and Titman [1993] is one of the most widespread anomalies in asset pricing literature. The intuition is that very negative and very positive returns performance is expected to persist on average for a few months. The portfolios employed in this paper are ranked on cumulative returns from month -7 to month -2, and the holding period for each portfolio is six months.

Anomaly 8: Gross profitability premium. Novy-Marx [2013] discovers that sorting on gross-profit-to-assets creates abnormal benchmark-adjusted returns, with more profitable firms, having higher returns than less profitable ones.

Anomaly 9: Asset growth. Cooper et al. [2008] show how companies that grow their total asset more earn lower subsequent returns. They explain that this phenomenon is the consequence of investors' initial overreaction to changes in future business prospects implied by asset expansions. Asset growth is computed as the growth rate of the total assets (item AT) in the previous fiscal year.

Anomaly 10: Return on assets. Chen et al. [2011] show that firms with higher past return on assets gain higher subsequent returns. Return on assets is measured as the ratio of the quarterly earnings (item IBQ) to last quarter's assets (item ATQ).

Anomaly 11: Investment-to-assets. Titman et al. [2003] show that higher past investment predicts abnormally lower future returns. Here, investment-to-assets is computed as the annual change in gross property, plant, and equipment plus the annual change in inventories scaled by the lagged book value of assets.

Anomaly 12, 13, 14, and 15: these are the four factors proposed by the extended model of Fama and French (2015) Fama and French [2015]. In this case and the next one data comes from the Kennet French library. Anomaly 16, 17 and 18: recently Gerakos and Linnainmaa [2018] have shown how the value premium is specific to variation in book-to-market that emanates from size changes, while no premium stems from the remaining variation. The new understanding of the value factor calls for a new reintroduction of old anomalies based on financial ratios which were previously considered to be summarized by the Fama and French model (Fama and French [1993]) . Among the possible ratios we focus on three of the most notorious ones: Dividend Yield, Earning Price and Cash-flow Price.

2.8.4 Predictive models

In the following pages we detail the predictive models employed in the tables of this appendix.

Basic linear models

The "Kitchen Sink" Regression is a simple OLS multivariate regression which includes all the predictors at once. The estimation is performed employing all observations up to time t (the last available information) to perform the parameter estimation and then to use the estimated parameters to make inference for time t+1 employing regressors values at time t. In formulas this can be summarize in a two step procedure:

$$R_{t+1} = \alpha + \beta X_t + \epsilon_t$$

where R is a t*1 vector and X is a t*N and N is the number of predictors considered in the analysis.

$$\hat{r}_{t+1} = \hat{\alpha}_t + \hat{\beta}_t x_t$$

where $\hat{r}_{t+1}$ is the univariate forecast produced by the model $\hat{\alpha}_t$ and $\hat{\beta}_t$ are the coefficient estimated in the previous step employing data up to time t and x_t is the value of predictors at time t.

Schwartz Information Criterion

A possible way to mitigate the possibility of in sample over-fitting is to select a criterion that accounts for both the benefits and costs of adding variables to the regression. Accordingly, we employ the SIC (Schwartz Information Criterion), constraining the choice to up to 3 predictors for each regression. The actual implementation is extremely intuitive. For each date t, we use all data available up to that moment, we consider all individual regressors and all possible combinations among two or three regressors, and we compute the related SIC values

$$log(SIC) = log(\frac{SSR}{T}) + k * \frac{log(T)}{T}$$

where T is the number of observations and k is the number of predictors. After that, for each date t, we pick the model with the lowest SIC, and we employ it to make inference using the values of predictors at time t to forecast the value of r at time t+1

$$\hat{r}_{t+1} = \hat{\alpha}_t + \hat{\beta}_t x_t$$

Combination Forecasts

Combination forecasts are the most common machine learning approach employed in the literature (Rapach et al. [2010], Aiolfi and Timmermann [2006], Strauss and Detzel [2017]). This approach is based on a two-stage estimation.

1. At first for each date t, we run a separate univariate regression for each regressor on the equity premium at time t+1 using all data available up to that date
$$R_{t+1} = \alpha + \beta x_{i,t} + \epsilon_t$$
2. After that each univariate OLS model previously estimated is employed to make inference at time t+1
$$\hat{r}_{t+1} = \hat{\alpha}_t + \hat{\beta}_t x_t$$
3. Finally, we combine the forecasts generated by univariate regressions via combination forecasts methods.
$$\hat{r}_{t+1,Comb} = \sum_{i=1}^{N} w_{i,t} \hat{r}_{t+1}$$

Finally, a the POOLED-DMSPE approach computes the weights in the third step in the following way:
$$w_{i,t} = \frac{\phi_{i,t}^{-1}}{\sum_{k=1}^{K} \phi_{j,t}^{-1}}$$
where
$$\phi_{i,t} = \sum_{s=m}^{t-1} \theta^{t-1-s} (r_{s+1} - \hat{r}_{i,s+1})$$
θ is a discount factor equal to 0.5 in this study, m+1 is the start of the holdout period and K is the number of past periods considered to compute the weights (K=13 in this paper). The DMSPE method thus assigns greater weight to individual forecasts that had better forecasting performance in terms of lower mean-squared prediction errors.

Diffusion Indices

The diffusion index approach assumes a latent factor model structure for the potential predictors:
$$x_{i,t} = \lambda_i' f_t + e_{i,t}$$
with (i=1, ..., K) where f_t is a q-vector of latent factors, λ_i is a q-vector of factor loadings, and $e_{i,t}$ is a zero-mean disturbance term. Co-movements in the predictors are primarily governed by movements in the small number of factors (the number of factors is much smaller than the number of predictors). For either the strict or approximate factor model, the latent factors can be consistently estimated by principal components. To implement this approach we started standardizing all

the predictors (standard deviation of 1 and zero mean). After that for each date t, we compute the first principal component employing all data available up to t-1. The first principal component is then employed as a regressor to estimate the following univariate regression model:

$$r_t = \alpha_{DI} + \beta'_{DI} f_{t-1} + \epsilon_t$$

where f_t is the t*1 vector of the values of the first principal component and ϵ_{t+1} is the disturbance term. Finally, the model previously estimated with data up to t-1 and the value f_t of the first principal component at time t, is used to make inference for time t+1

$$r_{t+1} = \alpha_{DI} + \beta'_{DI} f_t$$

2.8.5 Additional Tables and Figures

Table 2.18: Long term predictive power of sentiment indexes. This table shows the Δ Utility and the R^2_{OS} metrics for forecasts of the S&P500 returns at months t+2, t+3, t+6 and t+12 using sentiment predictors at month t.

Δ Utility t+2	Tot	Bull	Bear
PC6	0.49	0.81	0.03
PC4	0.44	-0.19	1.35
PLS6	2.46	10.60	-8.82
PLS4	1.58	0.47	3.18
cefd	-0.39	0.75	-2.03
turn	0.58	2.32	-1.90
nipo	-0.18	-1.41	1.60
ripo	-0.66	1.55	-3.83
pdnd	-0.05	1.75	-2.63
s	1.52	13.66	-14.98
SIC	2.81	16.39	-15.49
Pool Mean	1.13	2.58	-0.94
DMSFE	1.13	2.66	-1.06
Diff Index	1.05	0.68	1.60

R^2_{OS} t+2	Tot	pval	Bull	pval	Bear	pval
PC6	**0.43**	0.00	**1.17**	0.00	-0.21	0.81
PC4	0.16	0.15	-0.27	0.84	**0.54**	0.01
PLS6	**2.96**	0.00	**7.51**	0.00	-1.03	0.48
PLS4	**1.37**	0.00	-0.26	0.58	**2.80**	0.00
cefd	-0.19	0.93	**0.80**	0.00	-1.05	1.00
turn	0.36	0.07	**2.35**	0.00	-1.38	0.99
nipo	-0.37	0.95	-2.21	1.00	**1.24**	0.00
ripo	1.08	0.08	-2.48	0.73	**4.20**	0.02
pdnd	-0.27	0.77	**1.11**	0.00	-1.48	1.00
s	**1.24**	0.02	**11.94**	0.00	-8.15	1.00
SIC	**2.19**	0.00	**10.51**	0.00	-5.12	0.89
Pool Mean	**1.01**	0.00	**2.33**	0.00	-0.15	0.57
DMSFE	**0.98**	0.00	**2.26**	0.00	-0.14	0.54
Diff Index	**0.92**	0.00	**1.06**	0.01	0.80	0.03

Δ Utility t+3	Tot	Bull	Bear
PC6	0.39	0.72	-0.09
PC4	0.33	-0.22	1.12
PLS6	2.32	9.73	-7.96
PLS4	1.40	0.10	3.28
cefd	-0.47	0.58	-1.99
turn	0.40	1.61	-1.35
nipo	0.00	-1.49	2.16
ripo	-0.63	1.07	-3.08
pdnd	-0.04	1.61	-2.40
s	1.43	11.92	-12.94
SIC	2.84	15.64	-14.48
Pool Mean	1.01	2.13	-0.59
DMSFE	1.01	2.19	-0.68
Diff Index	0.93	0.44	1.63

R^2_{OS} t+3	Tot	pval	Bull	pval	Bear	pval
PC6	**0.30**	0.01	**0.93**	0.00	-0.26	0.94
PC4	0.06	0.31	-0.25	0.88	0.33	0.06
PLS6	**2.88**	0.00	**6.92**	0.00	-0.67	0.42
PLS4	**1.16**	0.00	-0.41	0.72	**2.53**	0.00
cefd	-0.24	0.96	**0.67**	0.00	-1.03	1.00
turn	0.19	0.15	**1.35**	0.00	-0.83	0.96
nipo	-0.33	0.86	-2.66	1.00	**1.72**	0.00
ripo	1.02	0.08	-2.31	0.76	**3.95**	0.01
pdnd	-0.29	0.77	**0.96**	0.00	-1.39	1.00
s	**1.17**	0.02	**10.50**	0.00	-7.02	1.00
SIC	**2.51**	0.00	**10.27**	0.00	-4.30	0.84
Pool Mean	**0.87**	0.00	**1.89**	0.00	-0.01	0.47
DMSFE	**0.86**	0.00	**1.82**	0.00	0.01	0.44
Diff Index	**0.76**	0.00	**0.81**	0.01	**0.70**	0.03

Δ Utility t+6	Tot	Bull	Bear
PC6	0.30	0.93	-0.61
PC4	0.10	0.22	-0.08
PLS6	2.00	8.05	-6.46
PLS4	1.17	-0.21	3.18
cefd	-0.69	0.73	-2.75
turn	0.62	1.75	-0.98
nipo	0.37	-0.76	2.01
ripo	-0.53	0.80	-2.46
pdnd	-0.05	1.92	-2.87
s	1.18	10.70	-11.92
SIC	2.34	13.03	-12.25
Pool Mean	0.87	2.03	-0.80
DMSFE	0.88	2.08	-0.84
Diff Index	0.76	0.41	1.27

R^2_{OS} t+6	Tot	pval	Bull	pval	Bear	pval
PC6	0.17	0.06	**0.95**	0.00	-0.51	1.00
PC4	-0.15	0.77	0.21	0.10	-0.47	0.93
PLS6	**2.65**	0.00	**5.86**	0.00	-0.17	0.36
PLS4	**0.89**	0.00	-0.44	0.83	**2.06**	0.00
cefd	-0.33	0.97	**0.87**	0.00	-1.39	1.00
turn	0.34	0.08	**1.62**	0.00	-0.78	0.88
nipo	-0.21	0.67	-2.66	1.00	**1.95**	0.00
ripo	0.90	0.09	-1.66	0.73	**3.14**	0.02
pdnd	-0.35	0.75	**1.16**	0.00	-1.68	1.00
s	**0.94**	0.03	**9.56**	0.00	-6.63	1.00
SIC	**2.27**	0.01	8.80	0.00	-3.47	0.80
Pool Mean	**0.73**	0.00	1.82	0.00	-0.24	0.72
DMSFE	**0.72**	0.00	1.78	0.00	-0.22	0.68
Diff Index	**0.57**	0.00	0.73	0.00	**0.43**	0.05

Δ Utility t+12	Tot	Bull	Bear
PC6	-0.22	2.53	-4.13
PC4	-0.61	2.79	-5.43
PLS6	1.22	4.11	-2.88
PLS4	-0.25	1.04	-2.10
cefd	-1.49	3.24	-8.19
turn	0.13	2.10	-2.69
nipo	1.00	2.50	-1.15
ripo	-0.62	1.90	-4.20
pdnd	-0.06	2.94	-4.33
s	0.87	7.72	-8.67
SIC	1.26	7.32	-7.21
Pool Mean	0.14	2.94	-3.82
DMSFE	0.15	2.96	-3.84
Diff Index	-0.18	1.94	-3.21

R^2_{OS} t+12	Tot	pval	Bull	pval	Bear	pval
PC6	-0.34	0.82	**1.76**	0.00	-2.20	1.00
PC4	-0.74	0.88	2.54	0.00	-3.62	1.00
PLS6	**1.34**	0.00	**3.84**	0.00	-0.86	0.84
PLS4	-0.28	0.86	**1.11**	0.00	-1.49	1.00
cefd	-0.62	0.87	**3.33**	0.00	-4.09	1.00
turn	-0.05	0.39	**0.87**	0.03	-0.85	0.98
nipo	0.18	0.27	-1.25	0.90	**1.43**	0.02
ripo	-0.36	0.82	**1.76**	0.00	-2.23	1.00
pdnd	-0.27	0.66	**2.18**	0.00	-2.42	1.00
s	0.51	0.08	**6.96**	0.00	-5.16	1.00
SIC	0.51	0.09	**6.93**	0.00	-5.13	1.00
Pool Mean	0.03	0.37	**2.43**	0.00	-2.07	1.00
DMSFE	0.04	0.37	**2.44**	0.00	-2.07	1.00
Diff Index	-0.27	0.79	**1.63**	0.00	-1.93	1.00

Table 2.19: This table shows the conditional correlations among the monthly returns of the sentiment and uncertainty indexes under study for the period 01-1982/12-2016. Six cases are considered: correlation when the returns on the SP500 are positive, negative, when the returns pf the PC4 sentiment proxy are positive, negative and when the returns of the Macro uncertainty index are positive, negative.

Rising PC4	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
PC 6 (1)	1.00													
PC 4 (2)	0.76	1.00												
PLS 6 (3)	0.51	0.21	1.00											
PLS 4 (4)	0.76	0.72	0.52	1.00										
DEVST (5)	-0.16	-0.09	-0.04	-0.09	1.00									
MEAN (6)	0.07	0.09	0.01	0.04	0.07	1.00								
MEDIAN (7)	0.12	0.10	0.01	0.03	-0.08	0.93	1.00							
UP (8)	-0.10	-0.03	-0.04	-0.05	0.72	0.60	0.40	1.00						
LOW (9)	0.12	0.11	0.03	0.10	-0.61	0.66	0.65	-0.06	1.00					
UF (10)	0.06	0.00	0.16	0.15	0.00	0.09	0.04	0.09	0.09	1.00				
UM (11)	-0.03	-0.07	0.14	0.00	0.06	-0.05	-0.04	0.04	-0.09	0.38	1.00			
SPF (12)	0.02	-0.01	0.07	0.03	0.03	-0.08	-0.11	-0.05	-0.02	0.00	0.02	1.00		
LIV (13)	0.02	0.08	-0.09	0.01	0.01	-0.03	-0.05	0.04	-0.04	0.07	0.18	0.06	1.00	
SP500 (14)	-0.17	-0.23	-0.12	-0.24	0.07	0.01	0.05	0.02	-0.06	-0.33	-0.21	0.01	-0.14	1.00

Declining PC4	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
PC 6 (1)	1.00													
PC 4 (2)	0.77	1.00												
PLS 6 (3)	0.48	0.17	1.00											
PLS 4 (4)	0.81	0.72	0.60	1.00										
DEVST (5)	0.07	0.08	-0.07	0.03	1.00									
MEAN (6)	0.26	0.22	0.24	0.30	0.26	1.00								
MEDIAN (7)	0.27	0.23	0.24	0.30	0.15	0.94	1.00							
UP (8)	0.16	0.12	0.07	0.15	0.78	0.70	0.53	1.00						
LOW (9)	0.15	0.12	0.27	0.22	-0.44	0.64	0.57	0.09	1.00					
UF (10)	0.16	0.02	0.11	0.15	0.00	0.08	0.09	0.07	0.03	1.00				
UM (11)	0.18	0.24	0.19	0.29	-0.04	0.03	0.03	-0.01	0.05	0.47	1.00			
SPF (12)	-0.04	0.08	-0.04	0.01	-0.03	-0.01	-0.02	-0.02	0.04	0.04	0.19	1.00		
LIV (13)	0.09	0.20	0.01	0.12	0.08	0.01	0.02	0.02	-0.07	0.13	0.28	0.11	1.00	
SP500 (14)	0.02	0.10	-0.08	0.00	0.07	0.10	0.11	0.07	0.02	-0.25	-0.20	-0.11	-0.01	1.00

Rising UM	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
PC 6 (1)	1.00													
PC 4 (2)	0.87	1.00												
PLS 6 (3)	0.50	0.32	1.00											
PLS 4 (4)	0.83	0.82	0.57	1.00										
DEVST (5)	-0.04	0.02	-0.03	0.03	1.00									
MEAN (6)	0.27	0.29	0.21	0.30	0.13	1.00								
MEDIAN (7)	0.33	0.35	0.21	0.32	0.04	0.94	1.00							
UP (8)	0.10	0.14	0.11	0.18	0.71	0.69	0.53	1.00						
LOW (9)	0.15	0.13	0.21	0.17	-0.47	0.70	0.62	0.16	1.00					
UF (10)	0.02	-0.04	0.15	0.09	0.16	0.11	0.10	0.19	-0.05	1.00				
UM (11)	0.06	0.00	0.20	0.16	0.06	-0.03	-0.04	0.04	-0.06	0.49	1.00			
SPF (12)	-0.08	-0.07	-0.07	-0.03	0.05	0.07	0.04	0.08	0.04	-0.02	0.13	1.00		
LIV (13)	-0.05	0.00	-0.05	0.05	0.16	-0.02	-0.02	0.09	-0.14	0.20	0.27	0.11	1.00	
SP500 (14)	0.00	0.01	-0.13	-0.04	0.02	0.06	0.06	0.03	0.03	-0.39	-0.28	0.04	-0.16	1.00

Declining UM	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
PC 6 (1)	1.00													
PC 4 (2)	0.84	1.00												
PLS 6 (3)	0.51	0.24	1.00											
PLS 4 (4)	0.86	0.79	0.57	1.00										
DEVST (5)	-0.03	-0.03	-0.08	-0.06	1.00									
MEAN (6)	0.26	0.21	0.13	0.25	0.21	1.00								
MEDIAN (7)	0.29	0.24	0.15	0.26	0.07	0.94	1.00							
UP (8)	0.06	0.03	-0.03	0.03	0.77	0.65	0.45	1.00						
LOW (9)	0.18	0.16	0.14	0.22	-0.56	0.59	0.59	-0.07	1.00					
UF (10)	0.26	0.13	0.10	0.23	-0.13	0.12	0.12	-0.01	0.21	1.00				
UM (11)	0.17	0.24	0.11	0.23	-0.07	0.15	0.21	-0.03	0.14	0.22	1.00			
SPF (12)	0.01	0.08	0.04	0.03	-0.04	-0.11	-0.12	-0.10	0.00	0.02	0.05	1.00		
LIV (13)	0.11	0.17	-0.04	0.06	-0.02	0.02	0.02	-0.01	0.02	-0.05	0.12	0.06	1.00	
SP500 (14)	-0.17	-0.16	-0.07	-0.19	0.11	0.04	0.07	0.07	-0.08	-0.13	-0.09	-0.15	0.04	1.00

Positive Ret SP500	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
PC 6 (1)	1.00													
PC 4 (2)	0.82	1.00												
PLS 6 (3)	0.55	0.29	1.00											
PLS 4 (4)	0.85	0.76	0.65	1.00										
DEVST (5)	0.03	0.02	-0.01	0.01	1.00									
MEAN (6)	0.25	0.22	0.15	0.24	0.19	1.00								
MEDIAN (7)	0.28	0.25	0.16	0.26	0.06	0.94	1.00							
UP (8)	0.12	0.09	0.04	0.10	0.78	0.64	0.45	1.00						
LOW (9)	0.13	0.11	0.12	0.15	-0.58	0.60	0.59	-0.08	1.00					
UF (10)	0.22	0.14	0.13	0.24	-0.01	0.10	0.11	0.06	0.07	1.00				
UM (11)	0.14	0.21	0.06	0.16	0.01	0.06	0.08	0.04	0.04	0.39	1.00			
SPF (12)	-0.03	0.04	0.03	0.03	-0.04	-0.02	-0.04	-0.03	0.03	0.02	0.22	1.00		
LIV (13)	-0.05	0.03	-0.16	-0.05	0.04	0.04	0.04	0.06	-0.02	0.09	0.11	0.12	1.00	
SP500 (14)	-0.24	-0.10	-0.25	-0.22	0.16	-0.06	-0.07	0.10	-0.21	0.10	-0.07	-0.08	-0.05	1.00

Negative Ret SP500	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
PC 6 (1)	1.00													
PC 4 (2)	0.88	1.00												
PLS 6 (3)	0.45	0.25	1.00											
PLS 4 (4)	0.85	0.84	0.49	1.00										
DEVST (5)	-0.14	-0.04	-0.14	-0.07	1.00									
MEAN (6)	0.28	0.29	0.19	0.32	0.14	1.00								
MEDIAN (7)	0.35	0.33	0.20	0.34	0.04	0.94	1.00							
UP (8)	0.00	0.06	0.00	0.08	0.67	0.71	0.54	1.00						
LOW (9)	0.20	0.18	0.24	0.25	-0.43	0.72	0.62	0.21	1.00					
UF (10)	0.08	-0.02	0.16	0.10	0.04	0.14	0.13	0.14	0.06	1.00				
UM (11)	0.08	0.03	0.30	0.19	0.00	-0.03	-0.02	-0.03	-0.04	0.48	1.00			
SPF (12)	-0.01	0.02	-0.03	0.00	0.05	-0.05	-0.07	-0.04	-0.01	0.05	0.03	1.00		
LIV (13)	0.17	0.21	0.11	0.19	0.06	-0.06	-0.06	-0.02	-0.11	0.13	0.41	0.06	1.00	
SP500 (14)	0.09	0.01	-0.04	0.05	-0.09	0.06	0.08	-0.07	0.13	-0.42	-0.29	-0.21	-0.15	1.00

Table 2.20: Johansen Cointegration test. We provide the p value for rank 0 and 1 Cointegration test between Sentiment proxies and uncertainty ones. The data are monthly and spans the period 12/1981-12/2016

PC 6	r0	r1	PC 4	r0	r1	PLS 6	r0	r1	PLS 4	r0	r1	DEVST	r0	r1	MEAN	r0	r1
PC 6	0.00	0.00	PC 6	**0.00**	**0.30**	PC 6	0.00	0.00	PC 6	0.95	0.85	PC 6	0.73	0.57	PC 6	0.91	1.00
PC 4	**0.00**	**0.30**	PC 4	0.00	0.00	PC 4	0.00	0.00	PC 4	**0.04**	**0.12**	PC 4	0.87	0.64	PC 4	**0.02**	**0.52**
PLS 6	0.00	0.00	PLS 6	0.00	0.00	PLS 6	0.00	0.00	PLS 6	0.00	0.00	PLS 6	0.20	0.45	PLS 6	0.20	0.99
PLS 4	0.95	0.85	PLS 4	**0.04**	**0.12**	PLS 4	0.00	0.00	PLS 4	0.00	0.00	PLS 4	0.81	0.55	PLS 4	**0.02**	**0.48**
DEVST	0.73	0.57	DEVST	0.87	0.64	DEVST	0.20	0.45	DEVST	0.81	0.55	DEVST	0.00	0.00	DEVST	**0.07**	**0.89**
MEAN	0.91	1.00	MEAN	**0.02**	**0.52**	MEAN	0.20	0.99	MEAN	**0.02**	**0.48**	MEAN	**0.07**	**0.89**	MEAN	0.00	0.00
MEDIAN	0.93	1.00	MEDIAN	**0.00**	**0.44**	MEDIAN	0.26	0.99	MEDIAN	**0.01**	**0.38**	MEDIAN	**0.02**	**0.88**	MEDIAN	0.17	1.00
UP	0.88	0.79	UP	0.87	0.84	UP	0.13	0.78	UP	0.47	0.83	UP	0.64	0.95	UP	**0.00**	**0.92**
LOW	0.28	0.91	LOW	**0.01**	**0.17**	LOW	**0.08**	**0.88**	LOW	**0.02**	**0.41**	LOW	0.28	0.64	LOW	**0.00**	**0.84**
UF	**0.01**	**0.08**	UF	0.72	0.48	UF	**0.02**	**0.16**	UF	0.20	0.14	UF	**0.08**	**0.23**	UF	**0.01**	**0.59**
UM	**0.05**	**0.79**	UM	**0.09**	**0.54**	UM	**0.05**	**0.32**	UM	0.11	0.65	UM	**0.02**	**0.04**	UM	**0.00**	**0.07**
SPF	**0.02**	**0.75**	SPF	**0.09**	**0.53**	SPF	**0.03**	**0.30**	SPF	0.11	0.63	SPF	0.31	0.37	SPF	0.14	0.78
LIV	0.00	0.01	LIV	0.00	0.00	LIV	0.10	0.22	LIV	0.00	0.04	LIV	0.37	0.34	LIV	**0.01**	**0.58**

UP	r0	r1	LOW	r0	r1	UF	r0	r1	UM	r0	r1	SPF	r0	r1	LIV	r0	r1
PC 6	0.88	0.79	PC 6	0.28	0.91	PC 6	**0.01**	**0.08**	PC 6	**0.05**	**0.79**	PC 6	**0.02**	**0.75**	PC 6	0.00	0.01
PC 4	0.87	0.84	PC 4	**0.01**	**0.17**	PC 4	0.72	0.48	PC 4	**0.09**	**0.54**	PC 4	**0.09**	**0.53**	PC 4	0.00	0.00
PLS 6	0.13	0.78	PLS 6	**0.08**	**0.88**	PLS 6	**0.02**	**0.16**	PLS 6	**0.05**	**0.32**	PLS 6	**0.03**	**0.30**	PLS 6	0.10	0.22
PLS 4	0.47	0.83	PLS 4	**0.02**	**0.41**	PLS 4	0.20	0.14	PLS 4	0.11	0.65	PLS 4	0.11	0.63	PLS 4	**0.00**	**0.04**
DEVST	0.64	0.95	DEVST	0.28	0.64	DEVST	**0.08**	**0.23**	DEVST	**0.02**	**0.04**	DEVST	0.31	0.37	DEVST	0.37	0.34
MEAN	**0.00**	**0.92**	MEAN	**0.00**	**0.84**	MEAN	**0.01**	**0.59**	MEAN	**0.00**	**0.07**	MEAN	0.14	0.78	MEAN	**0.01**	**0.58**
MEDIAN	**0.00**	**0.94**	MEDIAN	**0.00**	**0.88**	MEDIAN	**0.00**	**0.59**	MEDIAN	**0.00**	**0.04**	MEDIAN	**0.03**	**0.72**	MEDIAN	0.00	0.49
UP	0.00	0.00	UP	**0.01**	**0.77**	UP	0.93	0.88	UP	0.22	0.79	UP	0.68	0.80	UP	0.96	0.87
LOW	**0.01**	**0.77**	LOW	0.00	0.00	LOW	0.00	0.01	LOW	0.00	0.00	LOW	0.32	0.34	LOW	**0.01**	**0.06**
UF	0.93	0.88	UF	0.00	0.01	UF	0.00	0.00	UF	**0.06**	**0.59**	UF	0.15	0.52	UF	0.29	0.71
UM	0.22	0.79	UM	0.00	0.00	UM	**0.06**	**0.59**	UM	0.00	0.00	UM	0.00	0.01	UM	0.00	0.00
SPF	0.68	0.80	SPF	0.32	0.34	SPF	0.15	0.52	SPF	0.00	0.01	SPF	0.00	0.00	SPF	0.21	0.45
LIV	0.96	0.87	LIV	**0.01**	**0.06**	LIV	0.29	0.71	LIV	0.00	0.00	LIV	0.21	0.45	LIV	0.00	0.00

Table 2.21: Granger causality analysis employing monthly data from 12/1981 to 12/2016. 12 legs are chosen as default initial size and the AIC criteria is employed to identify the best number of lags. The table report the difference between the value of the F-statistic and the critical value from the F-distribution. If F > critical value, we reject the null hypothesis that y does not Granger Cause x.

PC 6	caused by	causes	PC 4	caused by	causes	PLS 6	caused by	causes	PLS 4	caused by	causes	DEVST	caused by	causes	MEAN	caused by	causes
PC 6	0.00	0.00	PC 6	5.80	4.39	PC 6	**-3.55**	**3.06**	PC 6	5.25	3.00	PC 6	-3.21	-3.20	PC 6	**-2.73**	**2.72**
PC 4	4.39	5.80	PC 4	0.00	0.00	PC 4	3.21	7.59	PC 4	0.84	10.29	PC 4	-2.62	-2.54	PC 4	**2.70**	**4.03**
PLS 6	**3.06**	**-3.55**	PLS 6	7.59	3.21	PLS 6	0.00	0.00	PLS 6	**11.51**	**-0.26**	PLS 6	-1.74	-3.42	PLS 6	**-2.96**	**7.24**
PLS 4	3.00	5.25	PLS 4	10.29	0.84	PLS 4	**-0.26**	**11.51**	PLS 4	0.00	0.00	PLS 4	-2.71	-0.43	PLS 4	3.97	7.75
DEVST	-3.20	-3.21	DEVST	-2.54	-2.62	DEVST	-3.42	-1.74	DEVST	-0.43	-2.71	DEVST	0.00	0.00	DEVST	**1.42**	**-1.17**
MEAN	**2.72**	**-2.73**	MEAN	4.03	2.70	MEAN	**7.24**	**-2.96**	MEAN	7.75	3.97	MEAN	**-1.17**	**1.42**	MEAN	0.00	0.00
MEDIAN	**5.21**	**-3.04**	MEDIAN	4.97	3.40	MEDIAN	**8.41**	**-3.40**	MEDIAN	8.87	4.28	MEDIAN	-0.67	-0.61	MEDIAN	**4.56**	**-2.77**
UP	-2.37	-0.71	UP	**5.20**	**-1.12**	UP	**3.74**	**-0.13**	UP	**6.81**	**-0.96**	UP	**-2.97**	**6.23**	UP	5.52	24.50
LOW	-1.00	1.51	LOW	3.90	2.76	LOW	-0.03	-3.01	LOW	3.07	4.72	LOW	**-0.22**	**3.95**	LOW	1.68	8.48
UF	-1.04	-0.93	UF	-2.74	-2.85	UF	-3.82	0.61	UF	-0.25	-1.69	UF	**4.96**	**-3.84**	UF	1.07	0.92
UM	-2.98	-2.53	UM	**0.93**	**-1.78**	UM	-3.72	-2.52	UM	-1.06	-1.69	UM	**5.94**	**-3.08**	UM	6.14	0.42
SPF	-1.13	-3.67	SPF	**0.20**	**-3.68**	SPF	-3.61	-3.61	SPF	**0.20**	**-3.59**	SPF	**1.45**	**-3.33**	SPF	0.54	5.37
LIV	**4.09**	**-0.87**	LIV	6.14	3.03	LIV	**2.34**	**-0.11**	LIV	**5.96**	**-0.28**	LIV	**1.56**	**-3.74**	LIV	**-0.54**	**1.58**
UP	caused by	causes	LOW	caused by	causes	UF	caused by	causes	UM	caused by	causes	SPF	caused by	causes	LIV	caused by	causes
PC 6	-0.71	-2.37	PC 6	**1.51**	**-1.00**	PC 6	-0.93	-1.04	PC 6	-2.53	-2.98	PC 6	-3.67	-1.13	PC 6	**-0.87**	**4.09**
PC 4	**-1.12**	**5.20**	PC 4	2.76	3.90	PC 4	-2.85	-2.74	PC 4	**-1.78**	**0.93**	PC 4	**-3.68**	**0.20**	PC 4	3.03	6.14
PLS 6	**-0.13**	**3.74**	PLS 6	-3.01	-0.03	PLS 6	**0.61**	**-3.82**	PLS 6	-2.52	-3.72	PLS 6	-3.61	-3.61	PLS 6	**-0.11**	**2.34**
PLS 4	**-0.96**	**6.81**	PLS 4	4.72	3.07	PLS 4	-1.69	-0.25	PLS 4	-1.69	-1.06	PLS 4	**-3.59**	**0.20**	PLS 4	**-0.28**	**5.96**
DEVST	**6.23**	**-2.97**	DEVST	3.95	-0.22	DEVST	**-3.84**	**4.96**	DEVST	**-3.08**	**5.94**	DEVST	-3.33	1.45	DEVST	**-3.74**	**1.56**
MEAN	24.50	5.52	MEAN	8.48	1.68	MEAN	0.92	1.07	MEAN	0.42	6.14	MEAN	5.37	0.54	MEAN	**1.58**	**-0.54**
MEDIAN	**23.42**	**-0.27**	MEDIAN	**9.49**	**-0.11**	MEDIAN	0.98	0.66	MEDIAN	0.34	5.81	MEDIAN	**5.83**	**-0.09**	MEDIAN	**1.99**	**-0.62**
UP	0.00	0.00	UP	1.99	21.44	UP	-0.62	-1.16	UP	-1.39	-0.41	UP	-3.58	-0.15	UP	-0.43	-1.13
LOW	21.44	1.99	LOW	0.00	0.00	LOW	1.22	8.91	LOW	1.99	18.14	LOW	4.92	5.89	LOW	1.08	3.69
UF	-1.16	-0.62	UF	8.91	1.22	UF	0.00	0.00	UF	-2.85	-2.16	UF	**1.16**	**-3.67**	UF	6.28	0.66
UM	-0.41	-1.39	UM	18.14	1.99	UM	-2.16	-2.85	UM	0.00	0.00	UM	**7.14**	**-3.00**	UM	**9.21**	**-3.07**
SPF	-0.15	-3.58	SPF	5.89	4.92	SPF	**-3.67**	**1.16**	SPF	**-3.00**	**7.14**	SPF	0.00	0.00	SPF	-3.63	-1.32
LIV	-1.13	-0.43	LIV	3.69	1.08	LIV	0.66	6.28	LIV	**-3.07**	**9.21**	LIV	-1.32	-3.63	LIV	0.00	0.00

Table 2.22: Long term predictive power of uncertainty indexes. This table shows the Δ Utility and the R^2_{OS} metrics for forecasts of the S&P500 returns at months t+2, t+3, t+6 and t+12 using uncertainty predictors at month t.

Δ Utility t+2	Tot	Bull	Bear
DEVST	1.91	-6.31	11.61
MEAN	0.71	6.81	-5.93
MEDIAN	0.62	6.13	-5.38
UP	0.37	6.50	-6.35
LOW	0.31	9.29	-9.38
UF	4.09	0.75	8.03
UM	3.57	0.72	6.94
SPV	0.91	-0.19	2.21
LIV	2.22	2.21	2.36
SIC	2.57	0.59	4.96
Pool Mean	2.17	2.05	2.43
DMSFE	2.21	2.09	2.45
Diff Index	2.95	4.26	1.61

R^2_{OS} t+2	Tot	pval	Bull	pval	Bear	pval
DEVST	-1.47	0.58	-16.97	1.00	**7.92**	0.00
MEAN	0.19	0.22	**8.84**	0.00	-5.05	1.00
MEDIAN	0.13	0.25	**7.88**	0.00	-4.56	1.00
UP	0.15	0.23	**7.12**	0.00	-4.08	0.98
LOW	0.11	0.23	**11.63**	0.00	-6.87	1.00
UF	2.18	0.10	-10.18	0.97	**9.67**	0.00
UM	1.66	0.15	-9.62	0.92	**8.50**	0.02
SPV	-1.34	0.64	-8.03	0.95	2.71	0.08
LIV	-0.60	0.44	-4.12	0.77	1.53	0.20
SIC	-1.19	0.40	-10.81	0.94	**4.63**	0.04
Pool Mean	0.70	0.20	-0.56	0.49	1.47	0.15
DMSFE	0.74	0.20	-0.80	0.53	1.68	0.14
Diff Index	0.77	0.12	5.13	0.00	-1.88	0.73

Δ Utility t+3	Tot	Bull	Bear
DEVST	2.49	-7.23	14.02
MEAN	0.24	7.53	-7.69
MEDIAN	0.07	6.88	-7.35
UP	0.21	7.15	-7.40
LOW	-0.03	10.24	-11.07
UF	3.20	1.45	5.29
UM	2.49	1.50	3.70
SPV	-0.04	1.15	-1.38
LIV	2.13	2.58	1.77
SIC	2.66	0.62	5.12
Pool Mean	1.74	2.76	0.70
DMSFE	1.81	2.78	0.83
Diff Index	2.81	4.76	0.74

R^2_{OS} t+3	Tot	pval	Bull	pval	Bear	pval
DEVST	-1.07	0.45	-20.01	1.00	**10.40**	**0.00**
MEAN	-0.20	0.30	**10.14**	**0.00**	-6.47	1.00
MEDIAN	-0.32	0.36	**9.29**	**0.00**	-6.15	1.00
UP	0.07	0.23	**7.93**	**0.00**	-4.68	0.99
LOW	-0.08	0.26	**13.10**	**0.00**	-8.07	1.00
UF	1.57	0.13	-6.67	0.93	**6.56**	**0.01**
UM	0.95	0.22	-6.29	0.85	**5.34**	**0.05**
SPV	-1.41	0.72	-4.54	0.86	0.48	0.35
LIV	-0.42	0.42	-2.42	0.64	0.78	0.29
SIC	-2.38	0.58	-10.47	0.93	2.53	0.07
Pool Mean	0.44	0.24	0.91	0.22	0.15	0.38
DMSFE	0.46	0.24	0.72	0.26	0.31	0.35
Diff Index	0.54	0.15	5.97	0.00	-2.75	0.85

Δ Utility t+6	Tot	Bull	Bear
DEVST	3.90	-12.47	23.87
MEAN	-0.08	7.98	-8.85
MEDIAN	-0.39	7.34	-8.82
UP	1.42	7.35	-5.11
LOW	-1.78	9.42	-13.90
UF	3.47	1.80	5.47
UM	2.79	0.34	5.69
SPV	-1.42	2.82	-6.28
LIV	4.21	2.29	6.53
SIC	4.42	-1.12	10.98
Pool Mean	2.44	1.95	3.11
DMSFE	2.58	1.86	3.49
Diff Index	3.72	4.88	2.55

R^2_{OS} t+6	Tot	pval	Bull	pval	Bear	pval
DEVST	-0.48	0.13	-41.51	1.00	**24.38**	0.00
MEAN	-0.47	0.36	**10.95**	0.00	-7.39	1.00
MEDIAN	-0.80	0.46	**10.26**	0.00	-7.50	1.00
UP	**1.87**	0.03	**5.49**	0.00	-0.32	0.41
LOW	-2.25	0.74	**13.47**	0.00	-11.77	1.00
UF	1.92	0.08	-3.88	0.84	**5.43**	0.01
UM	1.64	0.17	-6.34	0.89	**6.47**	0.03
SPV	-1.98	0.92	1.40	0.16	-4.02	1.00
LIV	0.89	0.18	-5.81	0.83	**4.95**	0.03
SIC	-5.82	0.49	-36.32	1.00	**12.67**	0.00
Pool Mean	1.05	0.11	-0.34	0.46	1.90	0.07
DMSFE	1.14	0.11	-0.82	0.55	**2.33**	0.05
Diff Index	1.56	0.05	4.54	0.01	-0.25	0.39

Δ Utility t+12	Tot	Bull	Bear
DEVST	3.90	-11.20	22.22
MEAN	-0.07	5.91	-6.60
MEDIAN	-0.35	5.50	-6.76
UP	1.13	4.92	-3.05
LOW	-1.15	7.63	-10.70
UF	4.93	-1.57	12.57
UM	3.92	-2.53	11.52
SPV	-1.79	2.17	-6.31
LIV	5.56	-0.44	12.63
SIC	3.13	-1.77	8.88
Pool Mean	3.22	0.13	6.85
DMSFE	3.23	-0.02	7.06
Diff Index	3.51	3.13	4.07

R^2_{OS} t+12	Tot	pval	Bull	pval	Bear	pval
DEVST	0.43	0.12	-33.43	1.00	**20.95**	0.00
MEAN	-1.09	0.53	**8.61**	0.00	-6.98	1.00
MEDIAN	-1.44	0.61	**8.40**	0.00	-7.40	1.00
UP	1.38	0.07	2.16	0.08	0.90	0.21
LOW	-1.83	0.72	**11.19**	0.00	-9.71	1.00
UF	**3.13**	0.03	-9.42	0.99	**10.74**	0.00
UM	2.39	0.12	-11.43	0.99	**10.76**	0.00
SPV	-1.34	0.96	1.66	0.07	-3.16	1.00
LIV	1.45	0.10	-13.94	0.99	**10.79**	0.00
SIC	-1.36	0.30	-17.13	1.00	**8.19**	0.00
Pool Mean	1.31	0.09	-2.70	0.89	**3.74**	0.01
DMSFE	1.42	0.09	-3.26	0.92	**4.25**	0.00
Diff Index	1.27	0.08	1.71	0.12	0.99	0.20

Table 2.23: In this table we presents the result univariate linear regressions. Monthly data for the period 01/1982-12/2016 are employed. A list of predictors at time t is regressed on the SP500 returns at time t+1, t+3, t+6 and t+12. The estimated betas with the related t statistic and R^2 are reported. In the upper panel we regress the level of the variables on the SP500 returns, while in the lower panel we regress the deltas on the SP500 returns.

Level	t+1			t+3			t+6			t+12		
	b	t stat	R^2	b	t stat	R^2	b	t stat	R^2	b	t stat	R^2
Sentiment PC 4	**-0.006**	**-2.46**	0.014	**-0.006**	**-2.34**	0.013	**-0.006**	**-2.33**	0.013	**-0.005**	**-2.16**	0.011
Sentiment PLS 4	**-0.023**	**-3.33**	0.026	**-0.020**	**-2.83**	0.019	**-0.017**	**-2.36**	0.013	-0.013	-1.80	0.008
DEVST	-0.002	-0.66	0.001	-0.002	-0.92	0.002	-0.004	-1.64	0.006	-0.002	-0.80	0.002
MEAN	**-0.002**	**-1.96**	0.009	**-0.002**	**-1.97**	0.009	-0.002	-1.94	0.009	-0.002	-1.64	0.007
MEDIAN	-0.002	-1.90	0.009	-0.002	-1.87	0.008	-0.002	-1.80	0.008	-0.002	-1.58	0.006
UP	**-0.001**	**-1.96**	0.009	**-0.002**	**-2.05**	0.010	**-0.002**	**-2.44**	0.014	-0.001	-1.79	0.008
LOW	-0.002	-1.79	0.008	-0.002	-1.85	0.008	-0.002	-1.42	0.005	-0.002	-1.44	0.005
UF	**-0.048**	**-3.15**	0.023	-0.023	-1.51	0.005	-0.009	-0.60	0.001	-0.012	-0.77	0.001
UM	**-0.071**	**-2.75**	0.018	-0.037	-1.42	0.005	-0.012	-0.46	0.001	-0.015	-0.59	0.001
SPV	-0.005	-0.10	0.000	0.018	0.33	0.000	0.055	1.00	0.002	0.052	0.94	0.002
LIV	-0.017	-1.61	0.006	-0.011	-1.04	0.003	-0.013	-1.25	0.004	-0.013	-1.25	0.004

Delta	t+1			t+3			t+6			t+12		
	b	t stat	R^2	b	t stat	R^2	b	t stat	R^2	b	t stat	R^2
Sentiment PC 4	-0.024	-1.34	0.004	**-0.006**	**-2.34**	0.013	**-0.006**	**-2.33**	0.013	**-0.005**	**-2.16**	0.011
Sentiment PLS 4	-0.081	-1.47	0.005	**-0.020**	**-2.83**	0.019	**-0.017**	**-2.36**	0.013	-0.013	-1.80	0.008
DEVST	-0.008	-0.65	0.001	-0.002	-0.92	0.002	-0.004	-1.64	0.006	-0.002	-0.80	0.002
MEAN	0.003	0.23	0.000	**-0.002**	**-1.97**	0.009	-0.002	-1.94	0.009	-0.002	-1.64	0.007
MEDIAN	-0.001	-0.07	0.000	-0.002	-1.87	0.008	-0.002	-1.80	0.008	-0.002	-1.58	0.006
UP	-0.003	-0.49	0.001	**-0.002**	**-2.05**	0.010	**-0.002**	**-2.44**	0.014	-0.001	-1.79	0.008
LOW	0.008	0.96	0.002	-0.002	-1.85	0.008	-0.002	-1.42	0.005	-0.002	-1.44	0.005
UF	-0.084	-0.96	0.002	-0.023	-1.51	0.005	-0.009	-0.60	0.001	-0.012	-0.77	0.001
UM	-0.020	-0.11	0.000	-0.037	-1.42	0.005	-0.012	-0.46	0.001	-0.015	-0.59	0.001
SPV	-0.217	-0.72	0.001	0.018	0.33	0.000	0.055	1.00	0.002	0.052	0.94	0.002
LIV	-0.066	-1.03	0.003	-0.011	-1.04	0.003	-0.013	-1.25	0.004	-0.013	-1.25	0.004

Table 2.24: In this table we perform a series of univariate regression employing monthly data for the period 01/1982-12/2016. At first a time series of deltas is computed, after that for each deltas time series an ARMA model is estimated. At first 4-4 lags are employed and the best form of the model is identified through the BIC criterion. Finally, the residual coming from the chosen ARMA model are employed as the independent variable of the regression. The estimated betas of the univariate regressions are reported with the related t statistic and the R^2 of the regression.

t+1	Sen PC4	Sen PLS4	DEVST	MEAN	MEDIAN	UP	LOW	UF	UM	SPV	LIV
Beta	-0.017	-0.045	0.000	-0.005	-0.011	0.000	-0.002	**-0.433**	**-1.097**	-0.222	-0.081
t Beta	-0.620	-0.654	0.023	-0.444	-0.753	-0.008	-0.350	-4.416	-4.116	-0.726	-0.806
R^2	0.001	0.001	0.000	0.000	0.001	0.000	0.000	0.045	0.039	0.001	0.002
t+3	Sen PC4	Sen PLS4	DEVST	MEAN	MEDIAN	UP	LOW	UF	UM	SPV	LIV
Beta	-0.013	-0.073	0.003	0.022	**0.031**	0.005	0.006	**-0.201**	-0.078	0.270	-0.092
t Beta	-0.460	-1.066	0.302	1.878	2.124	1.228	1.008	-2.012	-0.286	0.882	-0.920
R^2	0.001	0.003	0.000	0.008	0.011	0.004	0.002	0.010	0.000	0.002	0.002
t+6	Sen PC4	Sen PLS4	DEVST	MEAN	MEDIAN	UP	LOW	UF	UM	SPV	LIV
Beta	-0.019	-0.073	0.014	-0.007	-0.002	0.001	-0.012	0.093	-0.347	-0.175	0.006
t Beta	-0.660	-1.068	1.336	-0.635	-0.146	0.333	-1.891	0.930	-1.276	-0.571	0.060
R^2	0.001	0.003	0.004	0.001	0.000	0.000	0.009	0.002	0.004	0.001	0.000
t+12	Sen PC4	Sen PLS4	DEVST	MEAN	MEDIAN	UP	LOW	UF	UM	SPV	LIV
Beta	0.013	0.000	0.003	0.004	0.001	0.000	-0.001	-0.038	-0.243	-0.530	0.089
t Beta	0.445	0.006	0.247	0.348	0.037	-0.052	-0.086	-0.376	-0.896	-1.743	0.892
R^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.007	0.002

Table 2.25: This table shows the conditional correlation using for fear and uncertainty proxies. Three cases are considered positive-negative returns of the SP500, rising-declining macroeconomic uncertainty (UM) and rising-declining Fear (FVaR)

Pos RET SP500	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)
MEAN (1)	1.00
UP (2)	0.64	1.00
LOW (3)	0.60	-0.07	1.00
DEVST (4)	0.20	0.78	-0.57	1.00
UF (5)	0.10	0.06	0.08	-0.01	1.00
UM (6)	0.06	0.04	0.04	0.01	0.39	1.00
UM-MD (7)	0.36	0.69	0.16	0.28	0.09	0.09	1.00
LIV skew (8)	0.09	0.05	0.10	-0.01	-0.07	0.23	0.08	1.00
RGDPX skew (9)	0.06	0.16	-0.08	0.19	0.03	0.04	0.10	0.08	1.00
Bull-Bear (10)	-0.05	-0.08	0.01	-0.05	-0.06	-0.18	-0.05	-0.09	-0.03	1.00
Bull-Neurtal (11)	-0.10	-0.12	0.01	-0.07	-0.09	-0.08	-0.03	-0.14	-0.07	0.72	1.00
Bear-Neutral (12)	-0.03	-0.02	0.00	-0.02	-0.01	0.16	0.03	-0.03	-0.05	-0.59	0.14	1.00
BTX (13)	0.02	0.11	-0.06	0.08	0.02	-0.05	0.07	-0.06	0.00	0.00	-0.02	-0.03	1.00
MACRO (14)	-0.06	-0.01	-0.09	0.06	0.00	0.01	-0.07	0.03	0.03	0.01	0.00	-0.01	-0.34	1.00
VIX (15)	0.16	-0.02	0.27	-0.19	0.15	0.09	0.12	-0.05	0.00	0.13	0.19	0.03	0.18	-0.40	1.00
ANX (16)	-0.06	-0.04	-0.01	-0.03	0.12	0.35	0.02	0.19	-0.06	-0.25	-0.07	0.27	0.00	0.33	-0.02	1.00
CRASH (17)	-0.18	-0.14	-0.09	-0.04	-0.06	-0.17	-0.05	-0.14	0.09	0.03	0.03	-0.02	-0.04	-0.07	0.02	-0.18	1.00
VRP (18)	-0.02	-0.08	0.06	-0.04	0.12	0.09	-0.01	-0.01	-0.04	0.19	0.13	-0.13	-0.05	-0.12	0.63	-0.01	-0.03	1.00
KJ (19)	0.07	0.14	-0.01	0.11	-0.05	-0.14	0.12	-0.03	0.08	-0.11	-0.12	0.02	-0.11	0.07	-0.15	0.05	0.00	-0.04	1.00
CATFIN (20)	0.08	0.02	0.06	0.04	0.04	0.02	0.02	-0.02	0.01	0.17	0.16	-0.06	-0.03	-0.08	0.39	-0.05	0.07	0.27	0.15	1.00
TAIL (21)	0.07	-0.05	0.07	-0.07	0.12	0.04	-0.07	0.05	-0.03	0.15	0.10	-0.10	0.03	-0.08	0.23	-0.05	0.08	0.18	-0.01	0.01	1.00
FFHS 2 (22)	0.07	-0.03	0.10	-0.06	-0.11	-0.02	0.00	0.02	0.01	0.03	0.05	0.01	0.02	-0.08	0.07	-0.06	0.11	0.01	-0.11	0.01	0.15	1.00
FFHS 3 (23)	0.00	-0.05	0.04	-0.05	-0.07	-0.04	0.00	0.01	0.00	0.00	0.05	0.05	-0.01	-0.03	0.04	-0.03	0.02	-0.02	0.04	-0.01	0.11	0.70	1.00
FVaR (24)	0.10	-0.04	0.08	-0.17	-0.07	-0.13	-0.12	0.07	0.00	0.08	0.12	0.00	0.12	0.10	0.07	-0.01	0.12	0.08	0.23	0.11	0.20	0.02	-0.01	1.00
FVaR 10 (25)	0.09	0.00	0.05	-0.12	-0.03	-0.09	-0.09	0.12	0.00	0.05	0.12	0.03	0.10	0.09	0.05	0.02	0.11	0.06	0.27	0.11	0.23	0.01	-0.02	0.95	1.00

Neg RET SP500	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)
MEAN (1)	1.00
UP (2)	0.70	1.00
LOW (3)	0.78	0.22	1.00
DEVST (4)	-0.21	0.43	-0.71	1.00
UF (5)	0.32	0.21	0.24	-0.12	1.00
UM (6)	-0.03	0.00	-0.14	0.04	0.61	1.00
UM-MD (7)	0.26	0.34	0.52	-0.27	0.02	-0.22	1.00
LIV skew (8)	-0.04	0.23	-0.29	0.32	0.01	0.28	-0.13	1.00
RGDPX skew (9)	0.21	0.06	0.17	-0.02	0.09	-0.02	-0.08	-0.17	1.00
Bull-Bear (10)	0.14	0.09	0.20	-0.06	-0.07	-0.18	0.22	0.07	-0.07	1.00
Bull-Neurtal (11)	0.15	0.16	0.13	0.03	0.02	-0.02	0.17	0.12	-0.26	0.80	1.00
Bear-Neutral (12)	-0.08	0.01	-0.20	0.12	0.12	0.27	-0.19	0.00	-0.14	-0.82	-0.33	1.00
BTX (13)	-0.09	-0.06	-0.08	-0.05	0.47	0.58	-0.02	0.37	-0.09	0.06	0.13	0.02	1.00
MACRO (14)	-0.29	-0.12	-0.31	0.17	0.12	0.19	-0.12	-0.01	-0.05	-0.11	-0.09	0.10	0.09	1.00
VIX (15)	0.22	0.12	0.22	-0.19	0.67	0.44	0.10	0.12	0.02	0.07	0.17	0.05	0.56	0.05	1.00
ANX (16)	-0.19	-0.10	-0.27	0.11	0.40	0.45	-0.26	0.12	-0.08	-0.25	-0.15	0.26	0.42	0.29	0.21	1.00
CRASH (17)	-0.05	0.07	-0.01	0.12	-0.15	-0.03	0.23	-0.08	-0.02	-0.11	-0.09	0.10	-0.25	-0.12	-0.22	-0.28	1.00
VRP (18)	-0.25	-0.20	-0.21	0.09	-0.39	-0.39	-0.13	0.02	0.02	0.08	0.02	-0.10	-0.39	0.03	-0.38	-0.03	-0.08	1.00
KJ (19)	-0.19	-0.18	-0.19	0.20	-0.50	-0.35	-0.18	-0.12	0.03	-0.22	-0.26	0.12	-0.28	-0.05	-0.51	-0.10	0.33	0.48	1.00
CATFIN (20)	-0.02	-0.02	0.04	-0.06	0.16	0.05	0.08	0.08	0.17	0.04	0.08	0.01	-0.01	-0.02	0.33	-0.17	0.02	0.02	0.18	1.00
TAIL (21)	-0.04	-0.22	0.02	-0.19	0.06	0.07	-0.19	0.01	-0.05	-0.01	0.00	0.02	-0.28	-0.07	0.00	0.03	-0.03	0.52	0.11	0.14	1.00
FFHS 2 (22)	0.00	-0.05	0.06	-0.02	0.09	0.00	0.03	-0.04	0.02	0.11	0.21	0.02	0.03	-0.03	0.15	-0.08	0.35	-0.06	0.08	0.07	-0.07	1.00
FFHS 3 (23)	0.03	-0.02	0.07	-0.01	0.13	0.01	0.02	-0.02	0.04	0.05	0.18	0.09	0.00	-0.03	0.20	-0.07	0.32	-0.06	0.08	0.12	-0.02	0.97	1.00
FVaR (24)	0.05	-0.15	0.21	-0.21	-0.26	-0.20	0.09	-0.28	-0.07	0.12	0.09	-0.10	0.02	-0.43	-0.12	-0.07	-0.18	0.09	-0.10	-0.27	-0.05	-0.08	-0.09	1.00
FVaR 10 (25)	-0.01	-0.16	0.10	-0.12	-0.35	-0.27	-0.02	-0.23	-0.06	0.08	0.05	-0.08	-0.21	-0.52	-0.26	-0.09	-0.16	0.33	0.03	-0.24	0.20	-0.10	-0.10	0.90	1.00

Rising Uncertainty	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)
MEAN (1)	1.00
UP (2)	0.69	1.00
LOW (3)	0.70	0.16	1.00
DEVST (4)	0.13	0.71	-0.47	1.00
UF (5)	0.11	0.19	-0.05	0.16	1.00
UM (6)	-0.03	0.04	-0.06	0.06	0.49	1.00
UM-MD (7)	0.28	0.70	0.09	0.41	0.10	0.00	1.00
LIV skew (8)	0.13	0.14	0.06	0.08	-0.03	0.03	0.09	1.00
RGDPX skew (9)	0.20	0.17	0.13	0.08	0.05	-0.11	0.10	-0.06	1.00
Bull-Bear (10)	0.20	0.12	0.18	0.00	-0.12	-0.08	0.07	-0.03	0.06	1.00
Bull-Neurtal (11)	0.19	0.17	0.14	0.09	-0.08	0.00	0.16	-0.09	0.02	0.76	1.00
Bear-Neutral (12)	-0.07	0.04	-0.10	0.12	0.09	0.13	0.10	-0.07	-0.08	-0.56	0.12	1.00
BTX (13)	-0.02	0.16	-0.15	0.11	0.28	0.34	0.23	0.08	-0.02	0.08	0.01	-0.12	1.00
MACRO (14)	-0.04	0.01	-0.11	0.07	0.10	0.13	-0.01	-0.01	0.04	0.01	-0.02	-0.03	-0.02	1.00
VIX (15)	0.11	0.20	0.00	0.08	0.51	0.37	0.16	0.04	-0.02	-0.10	0.00	0.16	0.52	0.00	1.00
ANX (16)	-0.14	-0.06	-0.16	0.02	0.12	0.22	-0.06	0.09	-0.18	-0.25	-0.10	0.25	0.30	0.11	0.22	1.00
CRASH (17)	-0.16	-0.12	-0.12	0.05	-0.09	-0.12	-0.04	-0.09	0.07	-0.05	0.01	0.08	-0.14	-0.02	-0.12	-0.22	1.00
VRP (18)	-0.09	0.06	-0.22	0.18	-0.19	-0.25	0.02	0.02	-0.01	0.04	-0.03	-0.09	-0.32	0.02	-0.04	0.01	-0.02	1.00
KJ (19)	-0.02	-0.01	0.00	0.00	-0.32	-0.27	0.09	-0.09	0.10	-0.05	-0.10	-0.04	-0.25	0.04	-0.32	0.02	0.16	0.24	1.00
CATFIN (20)	0.00	0.06	-0.04	0.07	0.33	0.15	0.05	-0.05	0.01	-0.09	-0.06	0.07	0.11	0.04	0.49	0.05	0.06	0.09	0.11	1.00
TAIL (21)	0.06	0.04	0.02	0.02	0.15	0.01	-0.07	-0.01	-0.05	0.01	0.00	-0.02	-0.18	-0.04	0.06	0.01	0.03	0.38	0.10	0.09	1.00
FFHS 2 (22)	0.13	0.06	0.15	-0.09	0.21	0.18	0.07	0.17	0.04	-0.03	-0.05	0.00	0.07	0.10	0.34	0.04	-0.13	-0.19	-0.15	0.28	0.09	1.00
FFHS 3 (23)	0.02	-0.02	0.05	-0.06	0.11	0.13	0.00	0.09	0.00	0.01	-0.08	-0.09	-0.02	0.04	0.13	-0.02	-0.14	-0.07	-0.03	0.10	0.12	0.87	1.00
FVaR (24)	0.16	0.04	0.16	-0.21	-0.07	-0.18	0.01	0.01	0.01	0.02	-0.06	-0.07	0.14	-0.29	0.04	0.02	0.05	0.09	0.10	-0.24	0.07	-0.02	0.00	1.00
FVaR 10 (25)	0.09	0.00	0.08	-0.13	-0.16	-0.24	-0.06	0.04	0.00	0.00	-0.03	-0.03	-0.08	-0.40	-0.11	0.00	0.00	0.33	0.20	-0.20	0.26	-0.07	-0.01	0.92	1.00

Declining Uncertainty	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)
MEAN (1)	1.00
UP (2)	0.65	1.00
LOW (3)	0.59	-0.07	1.00
DEVST (4)	0.21	0.77	-0.56	1.00
UF (5)	0.12	-0.01	0.21	-0.13	1.00
UM (6)	0.15	-0.03	0.14	-0.07	0.22	1.00
UM-MD (7)	0.37	0.66	0.24	0.16	0.06	-0.08	1.00
LIV skew (8)	0.05	0.02	0.05	0.00	-0.15	0.18	0.03	1.00
RGDPX skew (9)	0.04	0.14	-0.10	0.20	-0.01	0.04	0.06	0.09	1.00
Bull-Bear (10)	-0.07	-0.10	0.01	-0.04	-0.08	-0.07	-0.04	0.01	-0.04	1.00
Bull-Neurtal (11)	-0.09	-0.17	0.02	-0.10	-0.14	-0.02	-0.14	-0.01	-0.10	0.72	1.00
Bear-Neutral (12)	0.00	-0.06	0.00	-0.05	-0.04	0.08	-0.10	-0.02	-0.06	-0.62	0.10	1.00
BTX (13)	0.04	0.13	-0.07	0.10	0.14	-0.01	0.00	0.00	0.01	0.00	0.00	0.01	1.00
MACRO (14)	-0.16	-0.05	-0.16	0.09	-0.09	-0.01	-0.10	0.02	0.00	0.01	0.04	0.03	-0.31	1.00
VIX (15)	0.00	-0.15	0.21	-0.26	0.38	0.17	0.10	0.01	-0.02	0.00	0.01	0.00	0.16	-0.37	1.00
ANX (16)	-0.04	-0.09	-0.01	-0.03	0.08	0.31	-0.12	0.16	-0.08	-0.21	-0.05	0.25	-0.02	0.39	0.05	1.00
CRASH (17)	-0.09	-0.02	-0.02	-0.02	-0.07	-0.16	0.12	-0.13	0.09	0.11	0.07	-0.09	-0.02	-0.12	-0.02	-0.20	1.00
VRP (18)	-0.10	-0.21	0.06	-0.09	0.19	0.04	-0.08	0.04	-0.04	0.06	0.04	-0.03	0.04	-0.12	0.57	0.07	-0.17	1.00
KJ (19)	-0.01	0.07	-0.07	0.09	-0.16	-0.02	0.00	0.04	0.07	-0.18	-0.18	0.06	-0.11	0.06	-0.21	0.03	0.00	0.05	1.00
CATFIN (20)	0.00	-0.02	0.04	-0.03	0.18	0.10	0.02	0.05	-0.01	0.04	0.03	-0.01	0.00	-0.14	0.56	-0.03	0.02	0.35	-0.03	1.00
TAIL (21)	-0.04	-0.11	0.04	-0.10	0.19	-0.04	-0.08	0.10	0.01	0.05	0.07	0.00	0.09	-0.14	0.05	-0.08	0.07	0.07	-0.01	0.05	1.00
FFHS 2 (22)	0.00	-0.08	0.07	-0.05	0.03	0.04	0.01	0.00	0.00	0.01	0.07	0.07	0.03	-0.10	0.19	-0.01	0.30	0.08	-0.02	0.08	0.05	1.00
FFHS 3 (23)	-0.03	-0.08	0.04	-0.04	0.01	0.04	0.01	0.02	0.01	-0.07	0.09	0.22	0.03	-0.06	0.15	0.06	0.25	0.04	0.05	0.05	0.02	0.75	1.00
FVaR (24)	-0.07	-0.23	0.09	-0.19	-0.10	0.01	-0.06	-0.06	-0.06	0.09	0.20	0.05	0.04	0.04	0.15	0.04	-0.15	0.11	-0.03	0.22	0.08	0.01	-0.04	1.00
FVaR 10 (25)	-0.08	-0.17	0.04	-0.13	-0.06	0.03	-0.05	0.00	-0.04	0.05	0.15	0.06	0.00	0.05	0.17	0.08	-0.09	0.09	0.05	0.19	0.12	0.00	-0.05	0.94	1.00

Rising Fear	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)
MEAN (1)	1.00
UP (2)	0.24	1.00
LOW (3)	0.81	-0.32	1.00
DEVST (4)	-0.49	0.67	-0.88	1.00
UF (5)	0.38	0.11	0.37	-0.23	1.00
UM (6)	0.17	0.20	0.09	-0.03	0.67	1.00
UM-MD (7)	0.50	0.19	0.59	-0.36	0.40	0.23	1.00
LIV skew (8)	0.13	0.11	-0.01	0.04	0.16	0.47	-0.16	1.00
RGDPX skew (9)	0.13	0.21	0.00	0.11	0.07	0.02	0.06	0.03	1.00
Bull-Bear (10)	-0.04	-0.15	-0.01	-0.06	-0.07	-0.01	-0.19	0.09	0.07	1.00
Bull-Neurtal (11)	-0.02	-0.02	-0.06	0.03	-0.02	0.06	-0.20	0.17	-0.18	0.74	1.00
Bear-Neutral (12)	0.05	0.20	-0.04	0.11	0.08	0.06	0.10	0.01	-0.26	-0.83	-0.24	1.00
BTX (13)	-0.15	0.00	-0.14	0.05	0.22	0.27	-0.04	-0.11	-0.13	-0.04	0.11	0.14	1.00
MACRO (14)	-0.22	-0.05	-0.19	0.14	0.05	0.09	-0.14	0.10	0.04	0.16	0.07	-0.17	-0.31	1.00
VIX (15)	0.16	-0.08	0.24	-0.25	0.58	0.32	0.25	0.03	0.08	-0.21	-0.18	0.16	0.45	-0.26	1.00
ANX (16)	0.02	0.02	0.02	0.01	0.45	0.44	0.05	0.25	-0.01	-0.30	-0.19	0.27	0.04	0.39	0.25	1.00
CRASH (17)	-0.12	-0.14	-0.02	-0.06	-0.35	-0.21	-0.01	-0.11	-0.18	0.00	0.16	0.15	-0.10	-0.12	-0.30	-0.27	1.00
VRP (18)	0.25	0.15	0.13	0.00	-0.12	-0.31	0.06	-0.05	0.16	-0.06	-0.10	0.00	-0.45	-0.16	-0.17	-0.19	0.02	1.00
KJ (19)	0.03	0.07	0.01	0.10	-0.20	-0.17	0.05	0.00	0.05	-0.12	-0.07	0.12	-0.33	0.07	-0.34	0.07	0.22	0.64	1.00
CATFIN (20)	0.13	0.14	0.08	0.05	0.16	0.06	0.11	-0.04	0.28	-0.02	-0.13	-0.07	-0.11	-0.04	0.38	-0.07	-0.06	0.15	0.29	1.00
TAIL (21)	0.29	0.06	0.23	-0.19	0.14	-0.16	0.12	-0.07	0.02	-0.08	0.08	0.17	-0.21	-0.26	0.00	-0.16	0.11	0.49	0.19	0.03	1.00
FFHS 2 (22)	0.10	-0.12	0.18	-0.21	0.24	0.14	0.12	-0.11	-0.11	-0.12	-0.03	0.14	0.26	-0.28	0.41	-0.07	0.00	-0.13	-0.34	0.35	0.26	1.00
FFHS 3 (23)	0.09	0.01	0.10	-0.08	0.15	0.09	0.11	0.01	-0.12	-0.21	-0.09	0.22	0.12	-0.24	0.39	-0.03	-0.05	-0.02	-0.24	0.40	0.30	0.90	1.00
FVaR (24)	-0.02	-0.12	0.04	-0.10	0.03	0.03	-0.06	0.05	-0.08	-0.12	0.01	0.17	0.12	-0.26	0.16	0.09	0.15	0.07	0.00	0.12	0.00	0.15	0.11	1.00
FVaR 10 (25)	0.08	0.07	0.00	0.02	-0.06	-0.09	-0.06	0.02	-0.06	-0.12	0.05	0.22	-0.26	-0.30	-0.08	0.00	0.17	0.37	0.16	0.01	0.31	0.01	0.05	0.78	1.00

Declining Fear	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)
MEAN (1)	1.00
UP (2)	0.75	1.00
LOW (3)	0.62	0.03	1.00
DEVST (4)	0.02	0.61	-0.67	1.00
UF (5)	-0.03	0.08	-0.21	0.17	1.00
UM (6)	-0.05	-0.05	-0.12	0.11	0.56	1.00
UM-MD (7)	0.37	0.32	0.58	-0.14	-0.19	-0.26	1.00
LIV skew (8)	0.35	0.24	0.32	-0.01	0.07	0.28	0.32	1.00
RGDPX skew (9)	0.10	0.18	0.00	0.18	0.00	-0.05	0.15	0.07	1.00
Bull-Bear (10)	0.04	0.07	0.13	-0.01	-0.41	-0.25	0.34	0.16	-0.08	1.00
Bull-Neurtal (11)	-0.04	-0.01	0.06	0.02	-0.30	-0.08	0.23	0.29	-0.28	0.68	1.00
Bear-Neutral (12)	-0.09	-0.10	-0.12	0.03	0.30	0.28	-0.27	0.04	-0.14	-0.77	-0.05	1.00
BTX (13)	0.28	0.28	0.21	0.10	0.27	0.23	0.27	0.62	0.21	0.10	-0.02	-0.15	1.00
MACRO (14)	-0.18	-0.05	-0.23	0.07	0.26	0.08	-0.08	-0.03	-0.10	-0.18	-0.14	0.13	-0.08	1.00
VIX (15)	0.08	-0.04	0.12	-0.09	0.56	0.41	-0.04	0.34	-0.05	-0.04	0.04	0.09	0.42	0.05	1.00
ANX (16)	-0.04	-0.05	-0.03	0.00	0.51	0.52	-0.07	0.29	0.11	-0.27	-0.24	0.16	0.48	0.18	0.26	1.00
CRASH (17)	-0.26	-0.20	-0.16	-0.02	-0.03	-0.17	-0.10	-0.27	-0.08	0.30	0.15	-0.28	-0.18	0.00	0.06	-0.28	1.00
VRP (18)	-0.17	-0.20	-0.01	-0.06	-0.24	-0.24	-0.02	0.09	-0.11	0.29	0.08	-0.32	0.06	0.18	0.16	-0.32	0.11	1.00
KJ (19)	-0.17	0.08	-0.30	0.04	-0.24	-0.37	0.09	-0.10	0.00	-0.02	-0.08	-0.05	-0.02	0.03	-0.24	-0.12	0.20	-0.02	1.00
CATFIN (20)	-0.14	-0.14	0.02	-0.05	0.47	0.39	0.07	0.28	-0.20	-0.08	0.12	0.22	0.18	0.10	0.80	0.15	0.10	0.15	-0.03	1.00
TAIL (21)	0.05	0.03	-0.05	-0.01	0.25	0.36	-0.12	0.24	-0.06	0.12	0.01	-0.15	0.13	-0.03	0.35	0.09	0.10	0.28	0.16	0.21	1.00
FFHS 2 (22)	0.09	0.02	0.09	0.01	-0.01	0.04	0.00	0.10	0.07	0.00	0.05	0.05	-0.02	0.09	0.20	0.06	0.23	0.05	-0.20	0.12	0.09	1.00
FFHS 3 (23)	0.06	-0.01	0.08	-0.03	-0.02	-0.02	0.00	0.02	0.12	-0.09	0.15	0.25	0.00	0.09	0.13	0.11	0.22	-0.01	0.02	0.04	0.07	0.68	1.00
FVaR (24)	0.22	0.06	0.24	-0.12	-0.49	-0.32	0.07	0.04	0.04	0.27	0.14	-0.24	-0.17	-0.35	-0.24	-0.45	0.09	0.36	0.26	-0.22	0.08	-0.13	0.01	1.00
FVaR 10 (25)	0.18	0.06	0.20	-0.09	-0.40	-0.27	0.09	0.05	0.05	0.20	0.08	-0.21	-0.10	-0.52	-0.21	-0.42	0.11	0.24	0.28	-0.15	0.14	-0.12	-0.01	0.93	1.00

Table 2.26: This table shows the results of the Johansen test for the cointegration for fear and uncertainty proxies.

MEAN (1)	r0	r1	UP (2)	r0	r1	LOW (3)	r0	r1	DEVST (4)	r0	r1	UF (5)	r0	r1	UM (6)	r0	r1	UM-MD (7)	r0	r1	LIV skew (8)	r0	r1
MEAN (1)	0.00	0.00	MEAN (1)	**0.00**	**0.92**	MEAN (1)	**0.00**	**0.84**	MEAN (1)	0.07	0.89	MEAN (1)	**0.01**	**0.59**	MEAN (1)	0.00	0.07	MEAN (1)	0.05	0.99	MEAN (1)	0.38	1.00
UP (2)	**0.00**	**0.92**	UP (2)	0.00	0.00	UP (2)	**0.01**	**0.77**	UP (2)	0.64	0.95	UP (2)	0.93	0.88	UP (2)	0.22	0.79	UP (2)	0.09	0.94	UP (2)	0.50	0.95
LOW (3)	**0.00**	**0.84**	LOW (3)	**0.01**	**0.77**	LOW (3)	0.00	0.00	LOW (3)	0.28	0.64	LOW (3)	0.00	0.01	LOW (3)	0.00	0.00	LOW (3)	0.14	0.94	LOW (3)	0.48	0.92
DEVST (4)	**0.07**	**0.89**	DEVST (4)	0.64	0.95	DEVST (4)	0.28	0.64	DEVST (4)	0.00	0.00	DEVST (4)	0.08	0.23	DEVST (4)	0.02	0.04	DEVST (4)	0.48	0.62	DEVST (4)	0.46	0.59
UF (5)	**0.01**	**0.59**	UF (5)	0.93	0.88	UF (5)	0.00	0.01	UF (5)	0.08	0.23	UF (5)	0.00	0.00	UF (5)	0.06	0.59	UF (5)	0.57	0.82	UF (5)	0.57	0.80
UM (6)	**0.00**	**0.07**	UM (6)	0.22	0.79	UM (6)	0.00	0.00	UM (6)	0.02	0.04	UM (6)	0.06	0.59	UM (6)	0.00	0.00	UM (6)	0.19	0.68	UM (6)	**0.02**	**0.47**
UM-MD (7)	**0.05**	**0.99**	UM-MD (7)	0.09	0.94	UM-MD (7)	0.14	0.94	UM-MD (7)	0.48	0.62	UM-MD (7)	0.57	0.82	UM-MD (7)	0.19	0.68	UM-MD (7)	0.00	0.00	UM-MD (7)	0.07	0.05
LIV skew (8)	0.38	1.00	LIV skew (8)	0.50	0.95	LIV skew (8)	0.48	0.92	LIV skew (8)	0.46	0.59	LIV skew (8)	0.57	0.80	LIV skew (8)	**0.02**	**0.47**	LIV skew (8)	0.07	0.05	LIV skew (8)	0.00	0.00
RGDPX skew (9)	0.93	1.00	RGDPX skew (9)	0.84	0.95	RGDPX skew (9)	0.94	0.97	RGDPX skew (9)	0.52	0.56	RGDPX skew (9)	0.91	0.79	RGDPX skew (9)	**0.02**	**0.14**	RGDPX skew (9)	0.08	0.47	RGDPX skew (9)	0.36	0.41
Bull-Bear (10)	**0.01**	**0.87**	Bull-Bear (10)	0.31	0.82	Bull-Bear (10)	0.44	0.81	Bull-Bear (10)	0.92	0.65	Bull-Bear (10)	0.71	0.56	Bull-Bear (10)	0.64	0.48	Bull-Bear (10)	0.23	0.69	Bull-Bear (10)	0.51	0.70
Bull-Neurtal (11)	1.00	1.00	Bull-Neurtal (11)	1.00	0.99	Bull-Neurtal (11)	1.00	0.98	Bull-Neurtal (11)	0.70	0.78	Bull-Neurtal (11)	0.99	0.88	Bull-Neurtal (11)	0.99	0.85	Bull-Neurtal (11)	0.39	0.90	Bull-Neurtal (11)	0.45	0.80
Bear-Neutral (12)	**0.09**	**0.48**	Bear-Neutral (12)	0.44	0.40	Bear-Neutral (12)	0.57	0.35	Bear-Neutral (12)	0.89	0.81	Bear-Neutral (12)	0.82	0.74	Bear-Neutral (12)	**0.01**	**0.41**	Bear-Neutral (12)	**0.04**	**0.69**	Bear-Neutral (12)	0.19	0.67
BTX (13)	**0.00**	**0.97**	BTX (13)	0.00	1.00	BTX (13)	**0.00**	**0.93**	BTX (13)	**0.00**	**0.38**	BTX (13)	**0.00**	**0.73**	BTX (13)	**0.00**	**0.92**	BTX (13)	**0.00**	**0.68**	BTX (13)	**0.00**	**0.16**
MACRO (14)	**0.00**	**0.51**	MACRO (14)	0.57	0.79	MACRO (14)	**0.00**	**0.14**	MACRO (14)	0.73	0.73	MACRO (14)	**0.00**	**0.09**	MACRO (14)	**0.00**	**0.00**	MACRO (14)	0.84	0.61	MACRO (14)	**0.04**	**0.18**
VIX (15)	**0.00**	**0.96**	VIX (15)	**0.00**	**0.98**	VIX (15)	**0.00**	**0.70**	VIX (15)	**0.00**	**0.58**	VIX (15)	**0.00**	**0.84**	VIX (15)	**0.00**	**0.82**	VIX (15)	**0.00**	**0.40**	VIX (15)	0.00	0.06
ANX (16)	**0.00**	**0.49**	ANX (16)	0.51	0.79	ANX (16)	**0.00**	**0.06**	ANX (16)	0.69	0.47	ANX (16)	0.10	0.52	ANX (16)	**0.00**	**0.18**	ANX (16)	0.37	0.42	ANX (16)	0.01	0.06
CRASH (17)	0.60	1.00	CRASH (17)	0.82	0.99	CRASH (17)	0.33	0.91	CRASH (17)	0.43	0.51	CRASH (17)	0.09	0.70	CRASH (17)	0.61	0.80	CRASH (17)	0.48	0.40	CRASH (17)	0.07	0.06
VRP (18)	**0.00**	**1.00**	VRP (18)	**0.00**	**0.99**	VRP (18)	**0.00**	**0.97**	VRP (18)	**0.00**	**0.56**	VRP (18)	**0.00**	**0.83**	VRP (18)	**0.00**	**0.79**	VRP (18)	**0.00**	**0.38**	VRP (18)	0.00	0.06
KJ (19)	**0.00**	**1.00**	KJ (19)	**0.00**	**0.81**	KJ (19)	**0.00**	**0.91**	KJ (19)	**0.00**	**0.71**	KJ (19)	**0.00**	**0.59**	KJ (19)	0.00	0.05	KJ (19)	**0.00**	**0.10**	KJ (19)	**0.00**	**0.14**
CATFIN (20)	**0.00**	**1.00**	CATFIN (20)	**0.00**	**0.85**	CATFIN (20)	**0.00**	**0.87**	CATFIN (20)	**0.00**	**0.68**	CATFIN (20)	**0.00**	**0.69**	CATFIN (20)	0.00	0.06	CATFIN (20)	0.00	0.06	CATFIN (20)	**0.00**	**0.12**
TAIL (21)	**0.00**	**1.00**	TAIL (21)	**0.00**	**0.81**	TAIL (21)	**0.00**	**0.72**	TAIL (21)	**0.00**	**0.55**	TAIL (21)	**0.00**	**0.64**	TAIL (21)	0.00	0.05	TAIL (21)	0.00	0.07	TAIL (21)	**0.00**	**0.09**
FFHS 2 (22)	0.00	0.00	FFHS 2 (22)	0.00	0.00	FFHS 2 (22)	**0.00**	**0.22**	FFHS 2 (22)	**0.00**	**0.34**	FFHS 2 (22)	**0.00**	**0.87**	FFHS 2 (22)	**0.00**	**0.94**	FFHS 2 (22)	**0.00**	**0.11**	FFHS 2 (22)	**0.00**	**0.50**
FFHS 3 (23)	0.00	0.00	FFHS 3 (23)	0.00	0.00	FFHS 3 (23)	**0.00**	**0.22**	FFHS 3 (23)	**0.00**	**0.34**	FFHS 3 (23)	**0.00**	**0.87**	FFHS 3 (23)	**0.00**	**0.95**	FFHS 3 (23)	**0.00**	**0.11**	FFHS 3 (23)	**0.00**	**0.50**
FVaR (24)	**0.00**	**0.84**	FVaR (24)	**0.00**	**0.83**	FVaR (24)	**0.00**	**0.75**	FVaR L15-L15 (24)	**0.00**	**0.47**	FVaR (24)	**0.00**	**0.94**	FVaR L15-L15 (24)	**0.00**	**0.99**	FVaR L15-L15 (24)	**0.00**	**0.15**	FVaR L15-L15 (24)	**0.00**	**0.55**
FVaR L10-L10 (25)	**0.00**	**0.84**	FVaR L10-L10 (25)	**0.00**	**0.83**	FVaR 10 (25)	**0.00**	**0.74**	FVaR 10 (25)	**0.00**	**0.46**	FVaR L10-L10 (25)	**0.00**	**0.95**	FVaR (25)	**0.00**	**0.99**	FVaR 10 (25)	**0.00**	**0.15**	FVaR 10 (25)	**0.00**	**0.55**

RGDPX skew (9)	r0	r1	Bull-Bear (10)	r0	r1	Bull-Neurtal (11)	r0	r1	Bear-Neutral (12)	r0	r1	BTX (13)	r0	r1	MACRO (14)	r0	r1	VIX (15)	r0	r1	ANX (16)	r0	r1
MEAN (1)	0.93	1.00	MEAN (1)	**0.01**	**0.87**	MEAN (1)	1.00	1.00	MEAN (1)	0.09	0.48	MEAN (1)	**0.00**	**0.97**	MEAN (1)	**0.00**	**0.51**	MEAN (1)	**0.00**	**0.96**	MEAN (1)	**0.00**	**0.49**
UP (2)	0.84	0.95	UP (2)	0.31	0.82	UP (2)	1.00	0.99	UP (2)	0.44	0.40	UP (2)	**0.00**	**1.00**	UP (2)	0.57	0.79	UP (2)	**0.00**	**0.98**	UP (2)	0.51	0.79
LOW (3)	0.94	0.97	LOW (3)	0.44	0.81	LOW (3)	1.00	0.98	LOW (3)	0.57	0.35	LOW (3)	**0.00**	**0.93**	LOW (3)	**0.00**	**0.14**	LOW (3)	**0.00**	**0.70**	LOW (3)	**0.00**	**0.06**
DEVST (4)	0.52	0.56	DEVST (4)	0.92	0.65	DEVST (4)	0.70	0.78	DEVST (4)	0.89	0.81	DEVST (4)	**0.00**	**0.38**	DEVST (4)	0.73	0.73	DEVST (4)	**0.00**	**0.58**	DEVST (4)	0.69	0.47
UF (5)	0.91	0.79	UF (5)	0.71	0.56	UF (5)	0.99	0.88	UF (5)	0.82	0.74	UF (5)	**0.00**	**0.73**	UF (5)	0.00	0.09	UF (5)	**0.00**	**0.84**	UF (5)	0.10	0.52
UM (6)	**0.02**	**0.14**	UM (6)	0.64	0.48	UM (6)	0.99	0.85	UM (6)	**0.01**	**0.41**	UM (6)	**0.00**	**0.92**	UM (6)	0.00	0.00	UM (6)	**0.00**	**0.82**	UM (6)	0.00	0.18
UM-MD (7)	**0.08**	**0.47**	UM-MD (7)	0.23	0.69	UM-MD (7)	0.39	0.90	UM-MD (7)	**0.04**	**0.69**	UM-MD (7)	**0.00**	**0.68**	UM-MD (7)	0.84	0.61	UM-MD (7)	**0.00**	**0.40**	UM-MD (7)	0.37	0.42
LIV skew (8)	0.36	0.41	LIV skew (8)	0.51	0.70	LIV skew (8)	0.45	0.80	LIV skew (8)	0.19	0.67	LIV skew (8)	**0.00**	**0.16**	LIV skew (8)	**0.04**	**0.18**	LIV skew (8)	**0.00**	**0.06**	LIV skew (8)	**0.01**	**0.06**
RGDPX skew (9)	0.00	0.00	RGDPX skew (9)	0.34	0.41	RGDPX skew (9)	0.82	0.75	RGDPX skew (9)	**0.00**	**0.14**	RGDPX skew (9)	**0.00**	**0.93**	RGDPX skew (9)	0.90	0.61	RGDPX skew (9)	**0.00**	**0.30**	RGDPX skew (9)	0.10	0.06
Bull-Bear (10)	0.34	0.41	Bull-Bear (10)	0.00	0.00	Bull-Bear (10)	0.63	0.53	Bull-Bear (10)	0.63	0.53	Bull-Bear (10)	**0.00**	**0.79**	Bull-Bear (10)	0.68	0.69	Bull-Bear (10)	**0.00**	**0.56**	Bull-Bear (10)	0.65	0.64
Bull-Neurtal (11)	0.82	0.75	Bull-Neurtal (11)	0.63	0.53	Bull-Neurtal (11)	0.00	0.00	Bull-Neurtal (11)	0.63	0.53	Bull-Neurtal (11)	**0.00**	**0.78**	Bull-Neurtal (11)	0.82	0.69	Bull-Neurtal (11)	**0.00**	**0.93**	Bull-Neurtal (11)	0.92	0.80
Bear-Neutral (12)	**0.00**	**0.14**	Bear-Neutral (12)	0.63	0.53	Bear-Neutral (12)	0.63	0.53	Bear-Neutral (12)	0.00	0.00	Bear-Neutral (12)	**0.00**	**0.97**	Bear-Neutral (12)	0.40	0.84	Bear-Neutral (12)	**0.00**	**0.95**	Bear-Neutral (12)	0.15	0.63
BTX (13)	**0.00**	**0.93**	BTX (13)	**0.00**	**0.79**	BTX (13)	**0.00**	**0.78**	BTX (13)	**0.00**	**0.97**	BTX (13)	0.00	0.00	BTX (13)	**0.00**	**0.69**	BTX (13)	0.00	0.00	BTX (13)	**0.00**	**0.67**
MACRO (14)	0.90	0.61	MACRO (14)	0.68	0.69	MACRO (14)	0.82	0.69	MACRO (14)	0.40	0.84	MACRO (14)	**0.00**	**0.69**	MACRO (14)	0.00	0.00	MACRO (14)	**0.00**	**0.53**	MACRO (14)	0.00	0.00
VIX (15)	**0.00**	**0.30**	VIX (15)	**0.00**	**0.56**	VIX (15)	**0.00**	**0.93**	VIX (15)	**0.00**	**0.95**	VIX (15)	0.00	0.00	VIX (15)	**0.00**	**0.53**	VIX (15)	0.00	0.00	VIX (15)	**0.00**	**0.16**
ANX (16)	0.10	0.06	ANX (16)	0.65	0.64	ANX (16)	0.92	0.80	ANX (16)	0.15	0.63	ANX (16)	**0.00**	**0.67**	ANX (16)	0.00	0.00	ANX (16)	**0.00**	**0.16**	ANX (16)	0.00	0.00
CRASH (17)	0.00	0.03	CRASH (17)	0.31	0.62	CRASH (17)	0.43	0.92	CRASH (17)	0.50	0.86	CRASH (17)	**0.00**	**0.25**	CRASH (17)	0.37	0.59	CRASH (17)	0.00	0.05	CRASH (17)	0.42	0.46
VRP (18)	**0.00**	**0.36**	VRP (18)	**0.00**	**0.70**	VRP (18)	**0.00**	**0.95**	VRP (18)	**0.00**	**0.97**	VRP (18)	0.00	0.00	VRP (18)	**0.00**	**0.69**	VRP (18)	0.00	0.00	VRP (18)	**0.00**	**0.41**
KJ (19)	**0.00**	**0.60**	KJ (19)	**0.00**	**0.77**	KJ (19)	**0.00**	**0.51**	KJ (19)	**0.00**	**0.49**	KJ (19)	0.00	0.00	KJ (19)	**0.00**	**0.63**	KJ (19)	0.00	0.00	KJ (19)	**0.00**	**0.56**
CATFIN (20)	**0.00**	**0.47**	CATFIN (20)	**0.00**	**0.70**	CATFIN (20)	**0.00**	**0.52**	CATFIN (20)	**0.00**	**0.48**	CATFIN (20)	0.00	0.00	CATFIN (20)	**0.00**	**0.55**	CATFIN (20)	0.00	0.00	CATFIN (20)	**0.00**	**0.36**
TAIL (21)	**0.00**	**0.55**	TAIL (21)	**0.00**	**0.73**	TAIL (21)	**0.00**	**0.48**	TAIL (21)	**0.00**	**0.58**	TAIL (21)	0.00	0.00	TAIL (21)	**0.00**	**0.69**	TAIL (21)	0.00	0.00	TAIL (21)	**0.00**	**0.49**
FFHS 2 (22)	**0.00**	**0.72**	FFHS 2 (22)	**0.00**	**0.83**	FFHS 2 (22)	**0.00**	**0.95**	FFHS (22)	0.00	0.00	FFHS 2 (22)	**0.00**	**0.86**	FFHS 2 (22)	0.00	0.01	FFHS 2 (22)	**0.00**	**0.46**			
FFHS 3 (23)	**0.00**	**0.72**	FFHS 3 (23)	**0.00**	**0.83**	FFHS 3 (23)	**0.00**	**0.95**	FFHS 3 (23)	**0.00**	**0.99**	FFHS 3 (23)	0.00	0.00	FFHS 3 (23)	**0.00**	**0.86**	FFHS 3 (23)	0.00	0.01	FFHS 3 (23)	**0.00**	**0.46**
FVaR (24)	**0.00**	**0.76**	FVaR (24)	**0.00**	**0.57**	FVaR (24)	**0.00**	**0.54**	FVaR (24)	**0.00**	**0.97**	FVaR (24)	0.00	0.00	FVaR (24)	**0.00**	**0.93**	FVaR (24)	0.00	0.03	FVaR (24)	**0.00**	**0.85**
FVaR 10 (25)	**0.00**	**0.77**	FVaR 10 (25)	**0.00**	**0.59**	FVaR 10 (25)	**0.00**	**0.54**	FVaR 10 (25)	**0.00**	**0.96**	FFVaR 10 (25)	0.00	0.00	FVaR 10 (25)	**0.00**	**0.94**	FVaR 10 (25)	0.00	0.03	FVaR 10 (25)	**0.00**	**0.86**

CRASH (17)	r0	r1	VRP (18)	r0	r1	KJ (19)	r0	r1	CATFIN (20)	r0	r1	TAIL (21)	r0	r1	FFHS 2 (22)	r0	r1	FFHS 3 (23)	r0	r1	FVaR (24)	r0	r1
MEAN (1)	0.60	1.00	MEAN (1)	0.00	1.00	MEAN (1)	**0.00**	**1.00**	MEAN (1)	**0.00**	**1.00**	MEAN (1)	**0.00**	**1.00**	MEAN (1)	0.00	0.00	MEAN (1)	0.00	0.00	MEAN (1)	**0.00**	**0.84**
UP (2)	0.82	0.99	UP (2)	**0.00**	**0.99**	UP (2)	**0.00**	**0.81**	UP (2)	**0.00**	**0.85**	UP (2)	**0.00**	**0.81**	UP (2)	0.00	0.00	UP (2)	0.00	0.00	UP (2)	**0.00**	**0.83**
LOW (3)	0.33	0.91	LOW (3)	**0.00**	**0.97**	LOW (3)	**0.00**	**0.91**	LOW (3)	**0.00**	**0.87**	LOW (3)	**0.00**	**0.72**	LOW (3)	**0.00**	**0.22**	LOW (3)	**0.00**	**0.22**	LOW (3)	**0.00**	**0.75**
DEVST (4)	0.43	0.51	DEVST (4)	**0.00**	**0.56**	DEVST (4)	**0.00**	**0.71**	DEVST (4)	**0.00**	**0.68**	DEVST (4)	**0.00**	**0.55**	DEVST (4)	**0.00**	**0.34**	DEVST (4)	**0.00**	**0.34**	DEVST (4)	**0.00**	**0.47**
UF (5)	0.09	0.70	UF (5)	**0.00**	**0.83**	UF (5)	**0.00**	**0.59**	UF (5)	**0.00**	**0.69**	UF (5)	**0.00**	**0.64**	UF (5)	**0.00**	**0.87**	UF (5)	**0.00**	**0.87**	UF (5)	**0.00**	**0.94**
UM (6)	0.61	0.80	UM (6)	**0.00**	**0.79**	UM (6)	**0.00**	**0.05**	UM (6)	**0.00**	**0.06**	UM (6)	0.00	0.05	UM (6)	**0.00**	**0.94**	UM (6)	**0.00**	**0.95**	UM (6)	**0.00**	**0.99**
UM-MD (7)	0.48	0.40	UM-MD (7)	**0.00**	**0.38**	UM-MD (7)	**0.00**	**0.10**	UM-MD (7)	**0.00**	**0.06**	UM-MD (7)	0.00	0.07	UM-MD (7)	**0.00**	**0.11**	UM-MD (7)	**0.00**	**0.11**	UM-MD (7)	**0.00**	**0.15**
LIV skew (8)	0.07	0.06	LIV skew (8)	**0.00**	**0.06**	LIV skew (8)	**0.00**	**0.14**	LIV skew (8)	**0.00**	**0.12**	LIV skew (8)	0.00	0.09	LIV skew (8)	**0.00**	**0.50**	LIV skew (8)	**0.00**	**0.50**	LIV skew (8)	**0.00**	**0.55**
RGDPX skew (9)	0.00	0.03	RGDPX skew (9)	**0.00**	**0.36**	RGDPX skew (9)	**0.00**	**0.60**	RGDPX skew (9)	**0.00**	**0.47**	RGDPX skew (9)	**0.00**	**0.55**	RGDPX skew (9)	**0.00**	**0.72**	RGDPX skew (9)	**0.00**	**0.72**	RGDPX skew (9)	**0.00**	**0.76**
Bull-Bear (10)	0.31	0.62	Bull-Bear (10)	**0.00**	**0.70**	Bull-Bear (10)	**0.00**	**0.77**	Bull-Bear (10)	**0.00**	**0.70**	Bull-Bear (10)	**0.00**	**0.73**	Bull-Bear (10)	**0.00**	**0.83**	Bull-Bear (10)	**0.00**	**0.83**	Bull-Bear (10)	**0.00**	**0.57**
Bull-Neurtal (11)	0.43	0.92	Bull-Neurtal (11)	**0.00**	**0.95**	Bull-Neurtal (11)	**0.00**	**0.51**	Bull-Neurtal (11)	**0.00**	**0.52**	Bull-Neurtal (11)	**0.00**	**0.48**	Bull-Neurtal (11)	**0.00**	**0.95**	Bull-Neurtal (11)	**0.00**	**0.95**	Bull-Neurtal (11)	**0.00**	**0.54**
Bear-Neutral (12)	0.50	0.86	Bear-Neutral (12)	**0.00**	**0.97**	Bear-Neutral (12)	**0.00**	**0.49**	Bear-Neutral (12)	**0.00**	**0.48**	Bear-Neutral (12)	**0.00**	**0.58**	Bear-Neutral (12)	**0.00**	**0.99**	Bear-Neutral (12)	**0.00**	**0.99**	Bear-Neutral (12)	**0.00**	**0.97**
BTX (13)	**0.00**	**0.25**	BTX (13)	0.00	0.00	BTX (13)	0.00	0.00	BTX (13)	0.00	0.00	BTX (13)	0.00	0.00	BTX (13)	0.00	0.00	BTX (13)	0.00	0.00	BTX (13)	0.00	0.00
MACRO (14)	0.37	0.59	MACRO (14)	**0.00**	**0.69**	MACRO (14)	**0.00**	**0.63**	MACRO (14)	**0.00**	**0.55**	MACRO (14)	**0.00**	**0.69**	MACRO (14)	**0.00**	**0.86**	MACRO (14)	**0.00**	**0.86**	MACRO (14)	**0.00**	**0.93**
VIX (15)	0.00	0.05	VIX (15)	0.00	0.00	VIX (15)	0.00	0.00	VIX (15)	0.00	0.00	VIX (15)	0.00	0.00	VIX (15)	0.00	0.01	VIX (15)	0.00	0.01	VIX (15)	0.00	0.03
ANX (16)	0.42	0.46	ANX (16)	**0.00**	**0.41**	ANX (16)	**0.00**	**0.56**	ANX (16)	**0.00**	**0.36**	ANX (16)	**0.00**	**0.49**	ANX (16)	**0.00**	**0.46**	ANX (16)	**0.00**	**0.46**	ANX (16)	**0.00**	**0.85**
CRASH (17)	0.00	0.00	CRASH (17)	**0.00**	**0.10**	CRASH (17)	**0.00**	**0.27**	CRASH (17)	**0.00**	**0.14**	CRASH (17)	**0.00**	**0.15**	CRASH (17)	**0.00**	**0.19**	CRASH (17)	**0.00**	**0.19**	CRASH (17)	**0.00**	**0.22**
VRP (18)	**0.00**	**0.10**	VRP (18)	0.00	0.00	VRP (18)	0.00	0.00	VRP (18)	0.00	0.00	VRP (18)	0.00	0.00	VRP (18)	0.00	0.00	VRP (18)	0.00	0.00	VRP (18)	0.00	0.00
KJ (19)	**0.00**	**0.27**	KJ (19)	0.00	0.00	KJ (19)	0.00	0.00	KJ (19)	0.00	0.00	KJ (19)	0.00	0.00	KJ (19)	0.00	0.00	KJ (19)	0.00	0.00	KJ (19)	0.00	0.00
CATFIN (20)	**0.00**	**0.14**	CATFIN (20)	0.00	0.00	CATFIN (20)	0.00	0.00	CATFIN (20)	0.00	0.00	CATFIN (20)	0.00	0.00	CATFIN (20)	0.00	0.00	CATFIN (20)	0.00	0.00	CATFIN (20)	0.00	0.02
TAIL (21)	**0.00**	**0.15**	TAIL (21)	0.00	0.00	TAIL (21)	0.00	0.00	TAIL (21)	0.00	0.00	TAIL (21)	0.00	0.00	TAIL (21)	0.00	0.00	TAIL (21)	0.00	0.00	TAIL (21)	0.00	0.00
FFHS 2 (22)	**0.00**	**0.19**	FFHS 2 (22)	0.00	0.00	FFHS 2 (22)	0.00	0.00	FFHS 2 (22)	0.00	0.00	FFHS 2 (22)	0.00	0.00	FFHS 2 (22)	0.00	0.00	FFHS 2 (22)	0.00	0.00	FFHS 2 (22)	0.00	0.00
FFHS 3 (23)	**0.00**	**0.19**	FFHS 3 (23)	0.00	0.00	FFHS 3 (23)	0.00	0.00	FFHS 3 (23)	0.00	0.00	FFHS 3 (23)	0.00	0.00	FFHS 3 (23)	0.00	0.00	FFHS 3 (23)	0.00	0.00	FFHS 3 (23)	0.00	0.00
FVaR (24)	**0.00**	**0.22**	FVaR (24)	0.00	0.00	FVaR (24)	0.00	0.00	FVaR (24)	0.00	0.02	FVaR (24)	0.00	0.00	FVaR (24)	0.00	0.00	FVaR (24)	0.00	0.00	FVaR L15-L15 (24)	0.00	0.00
FVaR 10 (25)	**0.00**	**0.22**	FVaR 10 (25)	0.00	0.00	FVaR 10 (25)	0.00	0.00	FVaR 10 (25)	0.00	0.02	FVaR 10 (25)	0.00	0.00	FVaR 10 (25)	0.00	0.00	FVaR 10 (25)	0.00	0.00	FVaR 10 (25)	0.00	0.00

Table 2.27: In this table we report the Granger causality tests of the time series listed in table 14. The methodology employed is the same of Table 8. At first 12 legs are chosen as default initial size and the AIC criteria is employed to identify the best number of legs. The table report the difference between the value of the F-statistic and the critical value from the F-distribution. If F>critical value, we reject the null hypothesis that y does not Grangr Cause x.

MEAN (1)	caused by	causes	UP (2)	caused by	causes	LOW (3)	caused by	causes	DEVST (4)	caused by	causes	UF (5)	caused by	causes	UM (6)	caused by	causes	UM-MD (7)	caused by	causes	LIV skew (8)	caused by	causes
MEAN (1)	0.00	0.00	MEAN (1)	24.50	5.52	MEAN (1)	8.48	1.68	MEAN (1)	**-1.17**	**1.42**	MEAN (1)	0.92	1.07	MEAN (1)	0.42	6.14	MEAN (1)	16.25	0.59	MEAN (1)	-3.77	-1.22
UP (2)	5.52	24.50	UP (2)	0.00	0.00	UP (2)	1.99	21.44	UP (2)	**-2.97**	**6.23**	UP (2)	-0.62	-1.16	UP (2)	-1.39	-0.41	UP (2)	14.49	11.47	UP (2)	**-3.48**	**10.17**
LOW (3)	1.68	8.48	LOW (3)	21.44	1.99	LOW (3)	0.00	0.00	LOW (3)	**-0.22**	**3.95**	LOW (3)	1.22	8.91	LOW (3)	1.99	18.14	LOW (3)	**15.18**	**-3.23**	LOW (3)	-3.74	-2.10
DEVST (4)	**1.42**	**-1.17**	DEVST (4)	**6.23**	**-2.97**	DEVST (4)	**3.95**	**-0.22**	DEVST (4)	0.00	0.00	DEVST (4)	**-3.84**	**4.96**	DEVST (4)	**-3.08**	**5.94**	DEVST (4)	**13.25**	**-0.75**	DEVST (4)	-2.27	-2.49
UF (5)	1.07	0.92	UF (5)	-1.16	-0.62	UF (5)	8.91	1.22	UF (5)	**4.96**	**-3.84**	UF (5)	0.00	0.00	UF (5)	-2.85	-2.16	UF (5)	**13.88**	**-3.77**	UF (5)	-3.05	-3.82
UM (6)	6.14	0.42	UM (6)	-0.41	-1.39	UM (6)	18.14	1.99	UM (6)	**5.94**	**-3.08**	UM (6)	-2.16	-2.85	UM (6)	0.00	0.00	UM (6)	**13.75**	**-3.32**	UM (6)	-3.31	-3.85
UM-MD (7)	0.59	16.25	UM-MD (7)	11.47	14.49	UM-MD (7)	**-3.23**	**15.18**	UM-MD (7)	-0.75	13.25	UM-MD (7)	**-3.77**	**13.88**	UM-MD (7)	**-3.32**	**13.75**	UM-MD (7)	0.00	0.00	UM-MD (7)	**-3.84**	**13.27**
LIV skew (8)	-1.22	-3.77	LIV skew (8)	**10.17**	**-3.48**	LIV skew (8)	-2.10	-3.74	LIV skew (8)	-2.49	-2.27	LIV skew (8)	-3.82	-3.05	LIV skew (8)	-3.85	-3.31	LIV skew (8)	**13.27**	**-3.84**	LIV skew (8)	0.00	0.00
RGDPX skew (9)	**-3.34**	**1.05**	RGDPX skew (9)	10.69	0.53	RGDPX skew (9)	**-3.49**	**2.18**	RGDPX skew (9)	**1.62**	**-2.21**	RGDPX skew (9)	-3.85	-3.72	RGDPX skew (9)	-1.58	-3.27	RGDPX skew (9)	13.93	6.29	RGDPX skew (9)	-3.72	-3.66
Bull-Bear (10)	**4.13**	**-3.03**	Bull-Bear (10)	**11.57**	**-3.24**	Bull-Bear (10)	**3.42**	**-2.82**	Bull-Bear (10)	-2.08	-3.56	Bull-Bear (10)	**-2.55**	**2.69**	Bull-Bear (10)	**-3.74**	**0.39**	Bull-Bear (10)	**13.93**	**-3.09**	Bull-Bear (10)	-2.40	-3.58
Bull-Neurtal (11)	-3.60	-1.56	Bull-Neurtal (11)	**11.92**	**-1.10**	Bull-Neurtal (11)	-3.72	-1.86	Bull-Neurtal (11)	-0.52	-2.56	Bull-Neurtal (11)	-2.16	-2.79	Bull-Neurtal (11)	-2.25	-2.23	Bull-Neurtal (11)	14.37	0.91	Bull-Neurtal (11)	-2.24	-1.77
Bear-Neutral (12)	-0.53	-3.02	Bear-Neutral (12)	**10.10**	**-2.71**	Bear-Neutral (12)	-0.43	-3.21	Bear-Neutral (12)	-2.00	-3.36	Bear-Neutral (12)	**-3.82**	**1.02**	Bear-Neutral (12)	**-2.61**	**6.28**	Bear-Neutral (12)	**13.33**	**-1.63**	Bear-Neutral (12)	-3.84	-2.16
BTX (13)	-0.31	-3.85	BTX (13)	-1.48	-3.85	BTX (13)	**2.32**	**-3.85**	BTX (13)	-0.09	-3.55	BTX (13)	13.86	18.02	BTX (13)	13.21	11.27	BTX (13)	-1.52	-3.38	BTX (13)	**6.95**	**-3.69**
MACRO (14)	2.41	1.20	MACRO (14)	-1.93	-2.79	MACRO (14)	9.84	1.28	MACRO (14)	-1.00	-3.55	MACRO (14)	**-3.85**	**17.54**	MACRO (14)	0.48	31.69	MACRO (14)	-2.74	-3.17	MACRO (14)	**20.41**	**-0.69**
VIX (15)	7.26	3.13	VIX (15)	-2.16	3.42	VIX (15)	21.54	0.45	VIX (15)	**6.33**	**-1.50**	VIX (15)	38.63	68.10	VIX (15)	1.76	12.07	VIX (15)	-2.03	-2.44	VIX (15)	-2.56	-3.39
ANX (16)	**4.66**	**-3.59**	ANX (16)	**10.04**	**-3.64**	ANX (16)	**14.96**	**-3.46**	ANX (16)	-1.08	-3.87	ANX (16)	**-3.82**	**10.53**	ANX (16)	**-3.40**	**9.40**	ANX (16)	**12.81**	**-3.32**	ANX (16)	**1.61**	**-1.80**
CRASH (17)	-1.57	-2.88	CRASH (17)	-3.54	-3.17	CRASH (17)	**0.06**	**-2.65**	CRASH (17)	-2.30	-3.29	CRASH (17)	**-2.70**	**7.34**	CRASH (17)	**-3.10**	**1.55**	CRASH (17)	-3.76	1.47	CRASH (17)	-3.82	-2.53
VRP (18)	5.52	0.48	VRP (18)	4.30	1.01	VRP (18)	-1.70	-1.72	VRP (18)	-3.79	-3.83	VRP (18)	**-2.54**	**5.98**	VRP (18)	2.38	1.42	VRP (18)	**5.22**	**-3.17**	VRP (18)	**1.64**	**-2.69**
KJ (19)	4.36	1.27	KJ (19)	5.63	0.12	KJ (19)	1.47	0.24	KJ (19)	**5.44**	**-2.14**	KJ (19)	13.44	7.01	KJ (19)	14.11	3.80	KJ (19)	**17.09**	**-3.42**	KJ (19)	-2.98	-3.67
CATFIN (20)	0.59	-3.77	CATFIN (20)	-1.25	-3.58	CATFIN (20)	**0.72**	**-3.82**	CATFIN (20)	-1.38	-3.80	CATFIN (20)	**-1.92**	**12.56**	CATFIN (20)	1.08	4.25	CATFIN (20)	**13.16**	**-3.50**	CATFIN (20)	-3.38	-3.83
TAIL (21)	-1.20	-3.48	TAIL (21)	-0.36	-3.25	TAIL (21)	**0.49**	**-3.85**	TAIL (21)	1.09	1.03	TAIL (21)	9.81	24.31	TAIL (21)	6.40	10.60	TAIL (21)	**12.89**	**-3.75**	TAIL (21)	-1.83	-3.39
FFHS 2 (22)	-2.86	-2.61	FFHS 2 (22)	-3.68	-3.69	FFHS 2 (22)	-2.48	-1.62	FFHS 2 (22)	-3.11	-3.65	FFHS 2 (22)	-3.06	-0.33	FFHS 2 (22)	-2.32	-3.48	FFHS 2 (22)	-1.45	-3.88	FFHS 2 (22)	**-3.75**	**0.37**
FFHS 3 (23)	-3.44	-3.43	FFHS 3 (23)	-3.29	-3.89	FFHS 3 (23)	-3.54	-2.58	FFHS 3 (23)	-3.33	-2.97	FFHS 3 (23)	-3.11	-3.00	FFHS 3 (23)	-2.13	-3.88	FFHS 3 (23)	-1.40	-3.89	FFHS 3 (23)	-3.65	-1.95
FVaR (24)	**-3.55**	**1.67**	FVaR (24)	**-1.47**	**0.61**	FVaR (24)	-2.61	-0.50	FVaR (24)	**0.06**	**-2.17**	FVaR (24)	**-2.40**	**0.95**	FVaR (24)	**4.57**	**-3.65**	FVaR (24)	**-2.89**	**0.22**	FVaR (24)	-3.79	-2.44
FVaR 10 (25)	**-3.63**	**3.61**	FVaR 10 (25)	**-3.01**	**1.23**	FVaR 10 (25)	**-3.24**	**0.94**	FVaR 10 (25)	-1.76	-0.90	FVaR 10 (25)	0.04	0.49	FVaR 10 (25)	**6.71**	**-3.74**	FVaR 10 (25)	**-3.01**	**0.94**	FVaR 10 (25)	-3.74	-2.62

RGDPX skew (9)	caused by	causes	Bull-Bear (10)	caused by	causes	Bull-Neurtal (11)	caused by	causes	Bear-Neutral (12)	caused by	causes	BTX (13)	caused by	causes	MACRO (14)	caused by	causes	VIX (15)	caused by	causes	ANX (16)	caused by	causes
MEAN (1)	**1.05**	**-3.34**	MEAN (1)	**-3.03**	**4.13**	MEAN (1)	-1.56	-3.60	MEAN (1)	-3.02	-0.53	MEAN (1)	-3.85	-0.31	MEAN (1)	1.20	2.41	MEAN (1)	3.13	7.26	MEAN (1)	**-3.59**	**4.66**
UP (2)	0.53	10.69	UP (2)	**-3.24**	**11.57**	UP (2)	**-1.10**	**11.92**	UP (2)	**-2.71**	**10.10**	UP (2)	-3.85	-1.48	UP (2)	-2.79	-1.93	UP (2)	**3.42**	**-2.16**	UP (2)	**-3.64**	**10.04**
LOW (3)	**2.18**	**-3.49**	LOW (3)	**-2.82**	**3.42**	LOW (3)	-1.86	-3.72	LOW (3)	-3.21	-0.43	LOW (3)	**-3.85**	**2.32**	LOW (3)	1.28	9.84	LOW (3)	0.45	21.54	LOW (3)	**-3.46**	**14.96**
DEVST (4)	**-2.21**	**1.62**	DEVST (4)	-3.56	-2.08	DEVST (4)	-2.56	-0.52	DEVST (4)	-3.36	-2.00	DEVST (4)	-3.55	-0.09	DEVST (4)	-3.55	-1.00	DEVST (4)	**-1.50**	**6.33**	DEVST (4)	-3.87	-1.08
UF (5)	-3.72	-3.85	UF (5)	**2.69**	**-2.55**	UF (5)	-2.79	-2.16	UF (5)	**1.02**	**-3.82**	UF (5)	18.02	13.86	UF (5)	**17.54**	**-3.85**	UF (5)	68.10	38.63	UF (5)	**10.53**	**-3.82**
UM (6)	-3.27	-1.58	UM (6)	**0.39**	**-3.74**	UM (6)	-2.23	-2.25	UM (6)	**6.28**	**-2.61**	UM (6)	11.27	13.21	UM (6)	31.69	0.48	UM (6)	12.07	1.76	UM (6)	**9.40**	**-3.40**
UM-MD (7)	6.29	13.93	UM-MD (7)	**-3.09**	**13.93**	UM-MD (7)	0.91	14.37	UM-MD (7)	-1.63	13.33	UM-MD (7)	-3.38	-1.52	UM-MD (7)	-3.17	-2.74	UM-MD (7)	-2.44	-2.03	UM-MD (7)	**-3.32**	**12.81**
LIV skew (8)	-3.66	-3.72	LIV skew (8)	-3.58	-2.40	LIV skew (8)	-1.77	-2.24	LIV skew (8)	-2.16	-3.84	LIV skew (8)	**-3.69**	**6.95**	LIV skew (8)	**-0.69**	**20.41**	LIV skew (8)	-3.39	-2.56	LIV skew (8)	**-1.80**	**1.61**
RGDPX skew (9)	0.00	0.00	RGDPX skew (9)	-2.51	-0.58	RGDPX skew (9)	-2.75	-3.76	RGDPX skew (9)	**0.59**	**-1.19**	RGDPX skew (9)	-3.79	-3.05	RGDPX skew (9)	-3.61	-1.68	RGDPX skew (9)	-3.33	-3.26	RGDPX skew (9)	-2.85	-3.23
Bull-Bear (10)	-0.58	-2.51	Bull-Bear (10)	0.00	0.00	Bull-Bear (10)	-0.50	-3.67	Bull-Bear (10)	-3.38	-3.67	Bull-Bear (10)	-1.20	-2.34	Bull-Bear (10)	0.89	1.72	Bull-Bear (10)	**-3.50**	**3.17**	Bull-Bear (10)	**-1.98**	**2.56**
Bull-Neurtal (11)	-3.76	-2.75	Bull-Neurtal (11)	-3.67	-0.50	Bull-Neurtal (11)	0.00	0.00	Bull-Neurtal (11)	-3.38	-0.50	Bull-Neurtal (11)	-3.16	-0.38	Bull-Neurtal (11)	-3.66	-3.41	Bull-Neurtal (11)	**-2.03**	**2.75**	Bull-Neurtal (11)	-3.80	-1.96
Bear-Neutral (12)	**-1.19**	**0.59**	Bear-Neutral (12)	-3.67	-3.38	Bear-Neutral (12)	-0.50	-3.38	Bear-Neutral (12)	0.00	0.00	Bear-Neutral (12)	-2.97	-3.38	Bear-Neutral (12)	**2.21**	**-2.88**	Bear-Neutral (12)	**-2.47**	**1.45**	Bear-Neutral (12)	**-1.38**	**4.34**
BTX (13)	-3.05	-3.79	BTX (13)	-2.34	-1.20	BTX (13)	-0.38	-3.16	BTX (13)	-3.38	-2.97	BTX (13)	0.00	0.00	BTX (13)	15.57	0.23	BTX (13)	**-3.10**	**16.86**	BTX (13)	**-3.81**	**0.80**
MACRO (14)	-1.68	-3.61	MACRO (14)	1.72	0.89	MACRO (14)	-3.41	-3.66	MACRO (14)	**-2.88**	**2.21**	MACRO (14)	0.23	15.57	MACRO (14)	0.00	0.00	MACRO (14)	**-0.43**	**14.50**	MACRO (14)	**-3.84**	**27.48**
VIX (15)	-3.26	-3.33	VIX (15)	**3.17**	**-3.50**	VIX (15)	**2.75**	**-2.03**	VIX (15)	**1.45**	**-2.47**	VIX (15)	**16.86**	**-3.10**	VIX (15)	**14.50**	**-0.43**	VIX (15)	0.00	0.00	VIX (15)	**9.84**	**-1.80**
ANX (16)	-3.23	-2.85	ANX (16)	**2.56**	**-1.98**	ANX (16)	-1.96	-3.80	ANX (16)	**4.34**	**-1.38**	ANX (16)	**0.80**	**-3.81**	ANX (16)	**27.48**	**-3.84**	ANX (16)	**-1.80**	**9.84**	ANX (16)	0.00	0.00
CRASH (17)	-2.60	-2.60	CRASH (17)	**1.99**	**-3.31**	CRASH (17)	-3.59	-2.41	CRASH (17)	-1.11	-2.65	CRASH (17)	-3.32	3.00	CRASH (17)	-0.49	-3.80	CRASH (17)	**-2.96**	**9.65**	CRASH (17)	6.47	3.41
VRP (18)	-3.72	-3.85	VRP (18)	**2.13**	**-3.57**	VRP (18)	**2.13**	**-3.33**	VRP (18)	**3.24**	**-2.56**	VRP (18)	3.12	9.05	VRP (18)	23.45	5.05	VRP (18)	2.80	7.50	VRP (18)	**7.77**	**-1.37**
KJ (19)	-3.74	-3.68	KJ (19)	-3.69	-3.29	KJ (19)	-2.78	-3.63	KJ (19)	-3.41	-3.55	KJ (19)	-3.74	-3.07	KJ (19)	**3.55**	**-3.69**	KJ (19)	-3.44	-2.36	KJ (19)	-3.84	-3.51
CATFIN (20)	-2.78	-3.86	CATFIN (20)	**4.31**	**-2.91**	CATFIN (20)	-1.01	-3.79	CATFIN (20)	-2.03	-3.57	CATFIN (20)	16.00	2.97	CATFIN (20)	**20.97**	**-2.89**	CATFIN (20)	**-2.42**	**3.42**	CATFIN (20)	**19.08**	**-2.97**
TAIL (21)	-3.79	-3.16	TAIL (21)	**1.46**	**-1.45**	TAIL (21)	-1.68	-1.62	TAIL (21)	**-2.96**	**4.59**	TAIL (21)	**13.21**	**-0.69**	TAIL (21)	8.44	9.19	TAIL (21)	29.60	3.80	TAIL (21)	1.01	2.77
FFHS 2 (22)	-3.81	-3.29	FFHS 2 (22)	**1.18**	**-2.65**	FFHS 2 (22)	**3.15**	**-3.83**	FFHS 2 (22)	**0.69**	**-2.24**	FFHS 2 (22)	-2.63	-3.80	FFHS 2 (22)	**6.11**	**-3.60**	FFHS 2 (22)	-3.86	-3.85	FFHS 2 (22)	-3.24	-3.52
FFHS 3 (23)	-3.81	-3.57	FFHS 3 (23)	**0.79**	**-3.80**	FFHS 3 (23)	**3.16**	**-3.81**	FFHS 3 (23)	**0.67**	**-3.63**	FFHS 3 (23)	-2.68	-3.38	FFHS 3 (23)	-3.29	-3.09	FFHS 3 (23)	-3.86	-3.40	FFHS 3 (23)	-3.60	-3.80
FVaR (24)	**-3.65**	**1.11**	FVaR (24)	-1.63	-2.73	FVaR (24)	-3.73	-1.74	FVaR (24)	**4.23**	**-3.72**	FVaR (24)	1.37	0.21	FVaR (24)	**2.56**	**-1.31**	FVaR L15-L15 (24)	1.83	1.14	FVaR L15-L15 (24)	**-1.91**	**0.16**
FVaR 10 (25)	**-3.49**	**1.01**	FVaR 10 (25)	-1.56	-3.30	FVaR 10 (25)	-3.56	-0.35	FVaR 10 (25)	**3.80**	**-3.73**	FVaR 10 (25)	**0.82**	**-2.27**	FVaR 10 (25)	7.68	0.54	FVaR 10 (25)	**-1.85**	**0.86**	FVaR 10 (25)	-2.07	-2.89

CRASH (17)	caused by	causes	VRP (18)	caused by	causes	KJ (19)	caused by	causes	CATFIN (20)	caused by	causes	TAIL (21)	caused by	causes	FFHS 2 (22)	caused by	causes	FFHS 3 (23)	caused by	causes	FVaR (24)	caused by	causes
MEAN (1)	-2.88	-1.57	MEAN (1)	0.48	5.52	MEAN (1)	1.27	4.36	MEAN (1)	**-3.77**	**0.59**	MEAN (1)	-3.48	-1.20	MEAN (1)	-2.61	-2.86	MEAN (1)	-3.43	-3.44	MEAN (1)	**1.67**	**-3.55**
UP (2)	-3.17	-3.54	UP (2)	1.01	4.30	UP (2)	0.12	5.63	UP (2)	-3.58	-1.25	UP (2)	-3.25	-0.36	UP (2)	-3.69	-3.68	UP (2)	-3.89	-3.29	UP (2)	**0.61**	**-1.47**
LOW (3)	**-2.65**	**0.06**	LOW (3)	-1.72	-1.70	LOW (3)	0.24	1.47	LOW (3)	**-3.82**	**0.72**	LOW (3)	-3.85	0.49	LOW (3)	-1.62	-2.48	LOW (3)	-2.58	-3.54	LOW (3)	-0.50	-2.61
DEVST (4)	-3.29	-2.30	DEVST (4)	-3.83	-3.79	DEVST (4)	**-2.14**	**5.44**	DEVST (4)	-3.80	-1.38	DEVST (4)	1.03	1.09	DEVST (4)	-3.65	-3.11	DEVST (4)	-2.97	-3.33	DEVST (4)	**-2.17**	**0.06**
UF (5)	**7.34**	**-2.70**	UF (5)	**5.98**	**-2.54**	UF (5)	7.01	13.44	UF (5)	**12.56**	**-1.92**	UF (5)	24.31	9.81	UF (5)	-0.33	-3.06	UF (5)	-3.00	-3.11	UF (5)	**0.95**	**-2.40**
UM (6)	**1.55**	**-3.10**	UM (6)	1.42	2.38	UM (6)	3.80	14.11	UM (6)	4.25	1.08	UM (6)	10.60	6.40	UM (6)	-3.48	-2.32	UM (6)	-3.88	-2.13	UM (6)	**-3.65**	**4.57**
UM-MD (7)	**1.47**	**-3.76**	UM-MD (7)	**-3.17**	**5.22**	UM-MD (7)	**-3.42**	**17.09**	UM-MD (7)	**-3.50**	**13.16**	UM-MD (7)	-3.75	12.89	UM-MD (7)	-3.88	-1.45	UM-MD (7)	-3.89	-1.40	UM-MD (7)	**0.22**	**-2.89**
LIV skew (8)	-2.53	-3.82	LIV skew (8)	**-2.69**	**1.64**	LIV skew (8)	-3.67	-2.98	LIV skew (8)	-3.83	-3.38	LIV skew (8)	-3.39	-1.83	LIV skew (8)	**0.37**	**-3.75**	LIV skew (8)	-1.95	-3.65	LIV skew (8)	-2.44	-3.79
RGDPX skew (9)	-2.60	-2.60	RGDPX skew (9)	-3.85	-3.72	RGDPX skew (9)	-3.68	-3.74	RGDPX skew (9)	-3.86	-2.78	RGDPX skew (9)	-3.16	-3.79	RGDPX skew (9)	-3.29	-3.81	RGDPX skew (9)	-3.57	-3.81	RGDPX skew (9)	**1.11**	**-3.65**
Bull-Bear (10)	**-3.31**	**1.99**	Bull-Bear (10)	**-3.57**	**2.13**	Bull-Bear (10)	-3.29	-3.69	Bull-Bear (10)	**-2.91**	**4.31**	Bull-Bear (10)	-1.45	1.46	Bull-Bear (10)	**-2.65**	**1.18**	Bull-Bear (10)	**-3.80**	**0.79**	Bull-Bear (10)	-2.73	-1.63
Bull-Neurtal (11)	-2.41	-3.59	Bull-Neurtal (11)	**-3.33**	**2.13**	Bull-Neurtal (11)	-3.63	-2.78	Bull-Neurtal (11)	-3.79	-1.01	Bull-Neurtal (11)	-1.62	-1.68	Bull-Neurtal (11)	**-3.83**	**3.15**	Bull-Neurtal (11)	**-3.81**	**3.16**	Bull-Neurtal (11)	-1.74	-3.73
Bear-Neutral (12)	-2.65	-1.11	Bear-Neutral (12)	**-2.56**	**3.24**	Bear-Neutral (12)	-3.55	-3.41	Bear-Neutral (12)	-3.57	-2.03	Bear-Neutral (12)	4.59	-2.96	Bear-Neutral (12)	**-2.24**	**0.69**	Bear-Neutral (12)	**-3.63**	**0.67**	Bear-Neutral (12)	**-3.72**	**4.23**
BTX (13)	**3.00**	**-3.32**	BTX (13)	9.05	3.12	BTX (13)	-3.07	-3.74	BTX (13)	2.97	16.00	BTX (13)	-0.69	13.21	BTX (13)	**-3.80**	**-2.63**	BTX (13)	-3.38	-2.68	BTX (13)	0.21	1.37
MACRO (14)	-3.80	-0.49	MACRO (14)	5.05	23.45	MACRO (14)	**-3.69**	**3.55**	MACRO (14)	**-2.89**	**20.97**	MACRO (14)	9.19	8.44	MACRO (14)	**-3.60**	**6.11**	MACRO (14)	-3.09	-3.29	MACRO (14)	**-1.31**	**2.56**
VIX (15)	**9.65**	**-2.96**	VIX (15)	7.50	2.80	VIX (15)	-2.36	-3.44	VIX (15)	**3.42**	**-2.42**	VIX (15)	3.80	29.60	VIX (15)	-3.85	-3.86	VIX (15)	-3.40	-3.86	VIX (15)	1.14	1.83
ANX (16)	3.41	6.47	ANX (16)	**-1.37**	**7.77**	ANX (16)	-3.51	-3.84	ANX (16)	**-2.97**	**19.08**	ANX (16)	2.77	1.01	ANX (16)	-3.52	-3.24	ANX (16)	-3.80	-3.60	ANX (16)	**0.16**	**-1.91**
CRASH (17)	0.00	0.00	CRASH (17)	12.28	0.42	CRASH (17)	-3.41	-3.01	CRASH (17)	**-3.10**	**13.59**	CRASH (17)	-2.67	2.53	CRASH (17)	**-3.60**	**5.47**	CRASH (17)	**-2.89**	**2.64**	CRASH (17)	**-2.15**	**3.85**
VRP (18)	0.42	12.28	VRP (18)	0.00	0.00	VRP (18)	-3.76	-1.26	VRP (18)	2.49	1.36	VRP (18)	-1.85	4.73	VRP (18)	-3.10	-3.02	VRP (18)	-3.04	-3.21	VRP (18)	-2.71	-2.86
KJ (19)	-3.01	-3.41	KJ (19)	-1.26	-3.76	KJ (19)	0.00	0.00	KJ (19)	-2.41	-3.76	KJ (19)	4.16	6.75	KJ (19)	-3.86	-2.46	KJ (19)	-3.76	-3.28	KJ (19)	**1.91**	**-2.70**
CATFIN (20)	**13.59**	**-3.10**	CATFIN (20)	1.36	2.49	CATFIN (20)	-3.76	-2.41	CATFIN (20)	0.00	0.00	CATFIN (20)	1.82	27.04	CATFIN (20)	-3.81	-3.64	CATFIN (20)	-3.79	-3.64	CATFIN (20)	-2.93	-3.65
TAIL (21)	**2.53**	**-2.67**	TAIL (21)	**4.73**	**-1.85**	TAIL (21)	6.75	4.16	TAIL (21)	27.04	1.82	TAIL (21)	0.00	0.00	TAIL (21)	**2.35**	**-2.63**	TAIL (21)	-2.00	-1.35	TAIL (21)	**-3.45**	**2.29**
FFHS 2 (22)	**5.47**	**-3.60**	FFHS 2 (22)	-3.02	-3.10	FFHS 2 (22)	-2.46	-3.86	FFHS 2 (22)	-3.64	-3.81	FFHS 2 (22)	-2.63	2.35	FFHS 2 (22)	0.00	0.00	FFHS 2 (22)	5.37	24.28	FFHS 2 (22)	**-3.58**	**0.74**
FFHS 3 (23)	**2.64**	**-2.89**	FFHS 3 (23)	-3.21	-3.04	FFHS 3 (23)	-3.28	-3.76	FFHS 3 (23)	-3.64	-3.79	FFHS 3 (23)	-1.35	-2.00	FFHS 3 (23)	24.28	5.37	FFHS 3 (23)	0.00	0.00	FFHS 3 (23)	**-3.36**	**1.19**
FVaR (24)	**3.85**	**-2.15**	FVaR (24)	-2.86	-2.71	FVaR (24)	**-2.70**	**1.91**	FVaR (24)	-3.65	-2.93	FVaR (24)	2.29	-3.45	FVaR (24)	**0.74**	**-3.58**	FVaR (24)	**1.19**	**-3.36**	FVaR (24)	0.00	0.00
FVaR 10 (25)	**2.96**	**-1.32**	FVaR 10 (25)	-3.76	-3.58	FVaR 10 (25)	**-3.29**	**2.36**	FVaR 10 (25)	-3.53	-2.34	FVaR 10 (25)	0.93	-2.80	FVaR 10 (25)	2.26	3.45	FVaR 10 (25)	**3.88**	**-3.13**	FVaR 10 (25)	-3.60	-3.77

Table 2.28: Long term predictive power of sentiment indexes. This table shows the Δ Utility and the R^2_{OS} metrics for forecasts of the S&P500 returns at months t+2, t+3, t+6 and t+12 using fear predictors at month t.

t+2

Δ Utility	Tot	Bull	Bear	R^2_{OS}	Tot	pval	Bull	pval	Bear	pval
UM-MD	-0.21	14.70	-16.44	UM-MD	0.78	0.07	**10.16**	0.00	-4.77	0.72
LIV skew	-0.69	0.89	-2.52	LIV skew	-0.41	0.86	0.80	0.06	-1.13	0.99
RGDPX skew	0.58	10.84	-10.80	RGDPX skew	**0.57**	0.02	**10.13**	0.00	-5.09	0.71
Bull-Bear	-1.70	1.84	-5.87	Bull-Bear	-1.04	0.75	0.89	0.10	-2.18	0.95
Bull-Neurtal	3.87	-5.53	15.13	Bull-Neurtal	0.73	0.07	-10.87	1.00	**7.60**	0.00
Bear-Neutral	2.73	-4.00	10.73	Bear-Neutral	-0.87	0.44	-17.03	1.00	**8.69**	0.00
BTX	-1.08	0.23	-3.13	BTX	-12.11	0.84	-7.18	0.46	-15.76	0.86
MACRO	2.75	3.66	1.49	MACRO	-17.57	0.35	-70.00	0.95	**21.27**	0.04
VIX	-4.72	2.74	-13.93	VIX	-3.70	0.91	**4.55**	0.01	-8.59	1.00
ANX	0.29	1.07	-0.65	ANX	-1.24	0.58	-6.36	0.87	1.80	0.20
CRASH	-0.24	4.10	-5.51	CRASH	-0.67	0.57	**3.74**	0.00	-3.29	1.00
VRP	3.63	2.20	5.51	VRP	**5.20**	0.03	5.74	0.06	4.89	0.07
KJ	0.04	2.45	-3.25	KJ	0.16	0.20	0.36	0.23	0.00	0.34
CATFIN	-2.67	3.22	-10.68	CATFIN	-1.26	0.66	**2.52**	0.02	-4.34	0.99
TAIL	-4.78	0.24	-11.64	TAIL	-3.35	0.99	-0.40	0.57	-5.75	1.00
FFHS 2	-2.18	1.94	-7.94	FFHS 2	-0.89	0.90	0.88	0.06	-2.27	0.99
FFHS 3	-0.71	1.40	-3.67	FFHS 3	-0.65	0.86	0.02	0.44	-1.17	0.91
FVaR	3.15	6.43	-2.78	FVaR	**7.27**	0.00	**8.90**	0.00	3.51	0.25
VaR 10	2.30	4.83	-2.30	VaR 10	**4.38**	0.00	**6.31**	0.00	-0.07	0.43

t+3

Δ Utility	Tot	Bull	Bear	R^2_{OS}	Tot	pval	Bull	pval	Bear	pval
UM-MD	-0.04	13.81	-15.20	UM-MD	**1.29**	0.05	**8.64**	0.00	-3.06	0.56
LIV skew	-0.23	0.42	-0.98	LIV skew	-0.23	0.78	0.31	0.20	-0.55	0.94
RGDPX skew	0.66	10.28	-10.04	RGDPX skew	**0.87**	0.02	**9.68**	0.00	-4.33	0.68
Bull-Bear	-2.19	1.40	-6.43	Bull-Bear	-1.33	0.86	0.36	0.22	-2.33	0.97
Bull-Neurtal	3.61	-5.49	14.52	Bull-Neurtal	0.48	0.10	-10.90	1.00	**7.21**	0.00
Bear-Neutral	2.88	-4.69	11.91	Bear-Neutral	-0.89	0.42	-19.21	1.00	**9.94**	0.00
BTX	-1.60	-2.41	-0.55	BTX	-12.77	0.91	-10.56	0.93	-14.41	0.85
MACRO	3.13	5.44	-0.12	MACRO	-12.70	0.35	-55.18	0.93	**18.77**	0.05
VIX	-4.28	1.50	-11.50	VIX	-2.87	0.95	0.25	0.36	-4.71	1.00
ANX	1.40	0.44	2.64	ANX	-0.47	0.45	-7.12	0.90	3.47	0.09
CRASH	0.39	5.08	-5.29	CRASH	-0.20	0.23	**5.09**	0.00	-3.34	1.00
VRP	3.20	2.14	4.62	VRP	**6.95**	0.01	**8.86**	0.03	5.82	0.06
KJ	0.02	2.96	-3.97	KJ	0.11	0.20	0.04	0.27	0.17	0.27
CATFIN	-0.25	1.35	-2.44	CATFIN	-0.16	0.44	0.17	0.35	-0.43	0.55
TAIL	-6.63	1.89	-18.08	TAIL	-6.27	1.00	-0.47	0.43	-10.98	1.00
FFHS 2	-0.33	0.22	-1.10	FFHS 2	0.06	0.34	0.34	0.17	-0.15	0.82
FFHS 3	-0.47	0.41	-1.70	FFHS 3	0.32	0.17	**1.01**	0.04	-0.21	0.64
FVaR	1.42	3.05	-1.57	FVaR	0.30	0.26	0.96	0.08	-1.25	0.83
VaR 10	2.88	6.51	-3.68	VaR 10	**4.08**	0.00	**6.97**	0.00	-2.59	0.70

t+6

Δ Utility	Tot	Bull	Bear	R^2_{OS}	Tot	pval	Bull	pval	Bear	pval
UM-MD	1.33	14.01	-12.65	UM-MD	**1.58**	0.01	-0.04	0.04	2.53	0.08
LIV skew	0.88	1.25	0.49	LIV skew	0.33	0.15	**1.54**	0.00	-0.39	0.77
RGDPX skew	0.85	10.07	-9.42	RGDPX skew	**1.10**	0.02	**9.01**	0.00	-3.57	0.61
Bull-Bear	-2.02	1.44	-6.04	Bull-Bear	-1.74	0.94	0.89	0.16	-3.30	1.00
Bull-Neurtal	1.55	-3.73	7.80	Bull-Neurtal	-0.61	0.40	-6.95	1.00	**3.14**	0.00
Bear-Neutral	2.79	-4.49	11.45	Bear-Neutral	-0.90	0.41	-19.09	1.00	**9.86**	0.00
BTX	-1.01	5.25	-10.02	BTX	-0.40	0.39	**5.17**	0.00	-4.53	0.90
MACRO	2.89	4.60	0.49	MACRO	-13.42	0.57	-49.52	0.96	**13.32**	0.06
VIX	1.77	0.73	3.12	VIX	1.78	0.10	-2.12	0.67	**4.09**	0.02
ANX	3.22	0.61	6.55	ANX	0.06	0.29	-13.88	0.94	**8.33**	0.02
CRASH	-0.01	2.34	-2.88	CRASH	0.00	0.35	**2.57**	0.00	-1.52	1.00
VRP	-2.54	0.89	-6.79	VRP	-2.46	1.00	-1.75	0.84	-2.88	1.00
KJ	-0.03	5.13	-6.95	KJ	-0.08	0.16	-0.25	0.24	0.06	0.24
CATFIN	0.28	4.93	-5.97	CATFIN	0.24	0.20	**5.43**	0.00	-3.98	0.98
TAIL	2.86	4.37	0.80	TAIL	**3.88**	0.00	**1.95**	0.01	**5.45**	0.01
FFHS 2	-2.52	4.46	-12.13	FFHS 2	-0.36	0.63	**5.27**	0.00	-4.72	1.00
FFHS 3	-2.70	4.19	-12.18	FFHS 3	-0.70	0.75	**4.21**	0.00	-4.51	1.00
FVaR	-4.64	-3.07	-7.60	FVaR	-16.00	1.00	-19.43	1.00	-8.04	0.73
FVaR 10	-3.72	-3.42	-4.31	FVaR 10	-11.52	1.00	-15.53	1.00	-2.23	0.56

t+12

Δ Utility	Tot	Bull	Bear	R^2_{OS}	Tot	pval	Bull	pval	Bear	pval
UM-MD	1.22	3.40	-1.31	UM-MD	2.09	0.06	-7.60	0.85	**7.83**	0.01
LIV skew	-0.25	-0.99	0.58	LIV skew	-0.22	0.78	-1.55	1.00	**0.57**	0.03
RGDPX skew	1.05	7.57	-6.30	RGDPX skew	**1.55**	0.02	**8.20**	0.00	-2.39	0.71
Bull-Bear	-1.93	1.65	-6.08	Bull-Bear	-1.10	0.85	**1.74**	0.03	-2.78	0.99
Bull-Neurtal	-0.83	-1.24	-0.33	Bull-Neurtal	-2.80	0.94	-1.96	0.79	-3.30	0.91
Bear-Neutral	1.57	-1.41	5.07	Bear-Neutral	-0.92	0.53	-9.35	0.99	**4.07**	0.04
BTX	0.32	1.59	-1.65	BTX	-10.85	0.69	0.22	0.15	-19.04	0.91
MACRO	3.43	6.02	-0.22	MACRO	-0.52	0.26	2.21	0.11	-2.54	0.79
VIX	-2.58	1.91	-8.15	VIX	-1.31	0.97	0.10	0.42	-2.14	1.00
ANX	0.69	2.03	-0.93	ANX	-0.40	0.57	0.06	0.42	-0.67	0.68
CRASH	-0.11	7.91	-9.66	CRASH	-1.00	0.21	**7.95**	0.00	-6.31	1.00
VRP	0.29	4.00	-4.24	VRP	1.20	0.13	**5.62**	0.00	-1.42	0.73
KJ	0.01	4.08	-5.49	KJ	0.55	0.12	**2.40**	0.02	-0.95	0.65
CATFIN	-1.71	3.87	-9.27	CATFIN	-0.29	0.63	**2.51**	0.00	-2.57	1.00
TAIL	1.13	4.20	-3.01	TAIL	**1.02**	0.04	**3.31**	0.00	-0.85	0.77
FFHS 2	-1.00	7.78	-13.03	FFHS 2	1.12	0.10	**11.04**	0.00	-6.58	1.00
FFHS 3	-3.57	9.16	-20.76	FFHS 3	-0.25	0.33	**12.72**	0.00	-10.30	1.00
FVaR	6.17	14.05	-7.75	FVaR	**9.82**	0.00	**14.08**	0.00	-0.05	0.32
FVaR 10	5.38	12.08	-6.54	FVaR 10	**7.71**	0.00	**12.94**	0.00	-4.38	0.54

Table 2.29: Regression of the level and deltas of the uncertainty and Fear indexes at month t on the SP500 excess return at month t+1, t+3, t+6 and t+12

	t+1		t+3		t+6		t+12	
Level	b	t-stat	b	t-stat	b	t-stat	b	t-stat
MEAN (1)	**-0.0020**	**-1.96**	**-0.0020**	**-1.97**	**-0.0020**	**-1.94**	-0.0017	-1.64
UP (2)	**-0.0015**	**-1.96**	**-0.0015**	**-2.05**	**-0.0019**	**-2.44**	-0.0014	-1.79
LOW (3)	-0.0020	-1.79	-0.0021	-1.85	-0.0016	-1.42	-0.0017	-1.44
DEVST (4)	-0.0017	-0.66	-0.0023	-0.92	-0.0042	-1.64	-0.0021	-0.80
UF (5)	**-0.0483**	**-3.15**	-0.0233	-1.51	-0.0092	-0.60	-0.0119	-0.77
UM (6)	**-0.0710**	**-2.75**	-0.0367	-1.42	-0.0121	-0.46	-0.0153	-0.59
UM-MD (7)	**-0.0093**	**-2.06**	**-0.0114**	**-2.51**	**-0.0147**	**-3.22**	-0.0053	-1.13
LIV skew (8)	-0.0133	-1.02	-0.0089	-0.68	-0.0087	-0.66	0.0038	0.29
RGDPX skew (9)	**-0.0495**	**-2.30**	**-0.0531**	**-2.46**	**-0.0468**	**-2.15**	**-0.0432**	**-1.97**
Bull-Bear (10)	-0.0196	-0.83	-0.0156	-0.66	-0.0128	-0.54	-0.0210	-0.87
Bull-Neurtal (11)	-0.0413	-1.88	**-0.0441**	**-1.98**	-0.0387	-1.71	-0.0246	-1.04
Bear-Neutral (12)	-0.0218	-1.04	-0.0268	-1.27	-0.0235	-1.11	-0.0036	-0.17
BTX (13)	0.0006	0.08	0.0088	1.21	**0.0158**	**2.20**	0.0102	1.43
MACRO (14)	-0.0007	-0.54	0.0004	0.27	0.0002	0.14	0.0009	0.65
VIX (15)	0.0000	0.13	0.0001	0.41	0.0004	1.28	0.0001	0.16
ANX (16)	-0.0002	-1.00	0.0000	-0.20	-0.0001	-0.71	0.0000	0.25
CRASH (17)	0.0000	0.14	-0.0001	-0.32	-0.0001	-0.30	0.0000	-0.11
VRP (18)	**0.0005**	**4.23**	**0.0004**	**3.60**	-0.0001	-0.85	0.0001	0.55
KJ (19)	0.0041	1.10	0.0044	1.19	0.0040	1.08	0.0060	1.63
CATFIN (20)	-0.0224	-1.12	-0.0130	-0.65	0.0083	0.42	0.0145	0.73
TAIL (21)	**-40.5764**	**-7.02**	6.6113	1.08	5.0678	0.83	-1.1121	-0.18
FFHS 2 (22)	0.0000	-0.56	0.0000	-0.61	0.0000	0.50	0.0000	-1.77
FFHS 3 (23)	0.0000	-0.21	0.0000	-1.04	0.0000	0.87	**0.0000**	**-2.00**
FVaR (24)	**0.0006**	**2.82**	0.0000	-0.07	-0.0002	-0.92	0.0003	1.45
FVaR 10 (25)	**0.0002**	**2.12**	0.0001	0.58	-0.0001	-0.82	0.0002	1.50

	t+1		t+3		t+6		t+12	
Delta	b	t-stat	b	t-stat	b	t-stat	b	t-stat
MEAN (1)	-0.0045	-0.35	0.0156	1.22	-0.0129	-1.01	0.0030	0.23
UP (2)	0.0018	0.35	0.0096	1.83	-0.0031	-0.59	-0.0026	-0.49
LOW (3)	-0.0043	-0.53	-0.0015	-0.19	-0.0122	-1.51	0.0078	0.96
DEVST (4)	0.0068	0.56	0.0176	1.44	0.0041	0.34	-0.0080	-0.65
UF (5)	**-0.5340**	**-6.40**	**-0.2470**	**-2.85**	0.0668	0.76	-0.0841	-0.96
UM (6)	**-0.8377**	**-4.62**	-0.3341	-1.80	-0.1436	-0.77	-0.0195	-0.11
UM-MD (7)	0.0230	1.63	0.0020	0.14	**-0.0363**	**-2.58**	0.0100	0.70
LIV skew (8)	-0.0376	-0.91	0.0112	0.27	0.0007	0.02	0.0109	0.26
RGDPX skew (9)	0.1006	1.05	-0.0453	-0.47	-0.0212	-0.22	-0.0525	-0.55
Bull-Bear (10)	-0.0164	-0.12	0.0985	0.74	-0.0575	-0.43	-0.0143	-0.11
Bull-Neurtal (11)	0.0034	0.02	0.1411	0.85	-0.1890	-1.13	-0.2296	-1.37
Bear-Neutral (12)	0.0398	0.21	-0.0207	-0.11	-0.1318	-0.68	-0.2808	-1.44
BTX (13)	-0.0112	-1.44	-0.0005	-0.06	0.0141	1.81	0.0024	0.31
MACRO (14)	-0.0092	-1.46	0.0019	0.30	-0.0010	-0.16	-0.0037	-0.58
VIX (15)	-0.0010	-1.82	-0.0002	-0.27	0.0010	1.88	-0.0003	-0.55
ANX (16)	**-0.0017**	**-2.22**	-0.0002	-0.22	0.0001	0.12	0.0003	0.37
CRASH (17)	0.0010	1.00	0.0003	0.31	0.0004	0.46	-0.0010	-1.01
VRP (18)	0.0001	1.43	0.0001	0.70	0.0000	0.00	0.0000	0.07
KJ (19)	0.0084	1.33	0.0039	0.61	-0.0112	-1.79	-0.0029	-0.46
CATFIN (20)	-0.0418	-1.56	-0.0398	-1.49	0.0383	1.44	-0.0109	-0.41
TAIL (21)	**-30.4340**	**-5.49**	1.9190	0.33	3.7233	0.65	1.4804	0.26
FFHS 2 (22)	0.0000	-0.96	0.0000	0.31	0.0000	0.47	0.0000	-1.08
FFHS 3 (23)	0.0000	-0.81	0.0000	-0.21	0.0000	1.02	0.0000	-1.32
FVaR (24)	0.0003	1.68	0.0000	-0.14	-0.0003	-1.50	-0.0001	-0.39
FVaR 10 (25)	0.0001	1.21	0.0000	-0.09	-0.0002	-1.86	0.0000	-0.36

Table 2.30: Anomalies during periods of high and low investor Sentiment (PLS 6). The table reports values in months following high and low levels of investor Sentiment, as identified on the base of the median level of PLS 6 Sentiment proxy. Also reported is the performance on a strategy which equally combines the strategies available within a given month (Combination). For each anomaly we make use of all data available. Details of the length of the time series can be found in the section dedicated on Data. We report conditional Excess Returns, Standard Deviation, Skewness, Kurtosis, Sharpe Ratio and Cornish-Fisher Ratio for the Long and short leg and for the Spread of the anomalies. We even report their difference.

Sentiment PLS 6		**Long Leg**			**Short Leg**			**Long-Short**		
Excess Returns		High Sent	Low Sent	High-Low	High Sent	Low Sent	High-Low	High Sent	Low Sent	High-Low
	(1) Asset Growth	-0.18	0.84	-1.01	-0.96	0.41	-1.37	1.28	0.72	0.57
	(2) Gross Profitability	-0.26	0.73	-0.99	-0.66	0.43	-1.08	0.90	0.59	0.30
	(3) Investment to Assets	-0.13	0.85	-0.98	-0.97	0.32	-1.30	1.35	0.82	0.53
	(4) Net Stock Issues	-0.24	0.64	-0.88	-0.85	0.47	-1.32	1.11	0.46	0.65
	(5) Net Operating Assets	-0.34	0.76	-1.10	-0.93	0.29	-1.22	1.10	0.76	0.33
	(6) Total Accruals	-0.12	0.62	-0.74	-1.08	0.13	-1.21	1.47	0.78	0.68
	(7) Ohlson's O	-0.44	0.57	-1.02	-0.59	0.26	-0.86	0.65	0.61	0.05
	(8) Return on Assets	-0.80	0.48	-1.28	-1.12	-0.02	-1.11	0.83	0.75	0.07
	(9) Failure Probability	0.16	0.88	-0.72	-2.01	-0.39	-1.62	2.68	1.53	1.15
	(10) Momentum	-0.33	0.72	-1.05	-0.88	0.24	-1.12	1.05	0.78	0.28
	(11) Composite Equity Issues	-0.03	0.72	-0.74	-1.08	0.21	-1.29	1.55	0.80	0.75
	(12) Size	0.33	1.42	-1.08	0.23	0.90	-0.67	0.60	0.81	-0.21
	(13) Book to Market	0.84	1.56	-0.73	-0.17	1.07	-1.24	1.51	0.79	0.72
	(14) Operating Profitability	0.46	1.26	-0.80	0.20	1.43	-1.23	0.76	0.13	0.63
	(15) Investments	0.68	1.65	-0.97	-0.13	1.08	-1.21	1.31	0.86	0.46
	(16) Earning to Price	0.88	1.34	-0.46	0.09	1.21	-1.13	1.29	0.42	0.87
	(17) Cash Flows to Price	0.88	1.41	-0.53	0.05	1.17	-1.13	1.34	0.54	0.80
	(18) Dividend Yield	0.77	0.93	-0.16	0.44	1.18	-0.73	0.82	0.04	0.78
	Combination	0.12	0.96	-0.85	-0.58	0.58	-1.16	1.20	0.68	0.52
Standard Deviation										
	(1) Asset Growth	6.36	4.60	1.77	7.44	5.04	2.41	2.34	1.62	0.72
	(2) Gross Profitability	6.80	4.73	2.07	5.87	4.31	1.56	2.69	2.14	0.55
	(3) Investment to Assets	6.46	4.71	1.75	7.44	4.97	2.48	2.24	1.45	0.79
	(4) Net Stock Issues	5.94	4.11	1.82	6.86	4.88	1.98	2.39	1.57	0.82
	(5) Net Operating Assets	6.70	4.80	1.90	6.98	4.81	2.17	1.96	1.57	0.39
	(6) Total Accruals	6.37	4.76	1.62	7.03	4.96	2.07	2.52	2.40	0.12
	(7) Ohlson's O	6.74	4.67	2.07	6.52	4.76	1.76	2.73	2.08	0.65
	(8) Return on Assets	6.79	4.36	2.43	6.50	4.46	2.04	2.67	2.28	0.39
	(9) Failure Probability	7.13	4.76	2.38	6.85	4.28	2.57	4.69	2.85	1.84
	(10) Momentum	6.93	4.70	2.22	7.12	4.94	2.18	4.38	3.06	1.32
	(11) Composite Equity Issues	5.66	3.78	1.88	6.96	4.65	2.32	2.98	1.63	1.35
	(12) Size	7.38	5.38	1.99	5.56	4.09	1.47	4.42	3.62	0.80
	(13) Book to Market	6.45	5.00	1.46	7.89	5.24	2.64	3.63	2.25	1.38
	(14) Operating Profitability	6.63	4.70	1.93	7.68	5.63	2.05	3.26	2.37	0.89
	(15) Investments	7.29	5.47	1.81	7.61	5.28	2.33	2.14	1.87	0.27
	(16) Earning to Price	5.98	4.62	1.35	7.15	4.80	2.35	2.83	1.70	1.13
	(17) Cash Flows to Price	6.23	4.73	1.50	7.05	4.73	2.31	2.53	1.74	0.79
	(18) Dividend Yield	4.73	3.62	1.10	6.26	4.48	1.78	2.95	2.02	0.93
	Combination	6.48	4.64	1.84	6.93	4.79	2.14	2.96	2.12	0.84
Sharpe Ratio										
	(1) Asset Growth	-2.75	18.17	-20.93	-12.89	8.16	-21.05	54.87	44.22	10.64
	(2) Gross Profitability	-3.85	15.34	-19.19	-11.18	9.94	-21.12	33.25	27.66	5.60
	(3) Investment to Assets	-1.98	18.03	-20.01	-13.08	6.47	-19.56	60.19	56.60	3.59
	(4) Net Stock Issues	-4.11	15.48	-19.58	-12.43	9.62	-22.05	46.41	29.40	17.01
	(5) Net Operating Assets	-5.01	15.85	-20.86	-13.35	6.08	-19.43	56.01	48.52	7.49
	(6) Total Accruals	-1.81	13.12	-14.93	-15.32	2.62	-17.95	58.14	32.49	25.65
	(7) Ohlson's O	-6.59	12.26	-18.84	-9.12	5.47	-14.59	23.86	29.10	-5.24
	(8) Return on Assets	-11.85	10.96	-22.81	-17.31	-0.35	-16.96	30.97	33.10	-2.13
	(9) Failure Probability	2.26	18.51	-16.25	-29.38	-9.16	-20.22	57.17	53.68	3.49
	(10) Momentum	-4.75	15.33	-20.08	-12.40	4.79	-17.19	24.08	25.43	-1.35
	(11) Composite Equity Issues	-0.47	18.97	-19.44	-15.47	4.55	-20.02	51.99	48.90	3.10
	(12) Size	4.49	26.30	-21.81	4.13	21.98	-17.84	13.61	22.36	-8.75
	(13) Book to Market	12.96	31.28	-18.32	-2.19	20.44	-22.63	41.59	34.89	6.70
	(14) Operating Profitability	6.89	26.81	-19.92	2.56	25.30	-22.75	23.36	5.43	17.92
	(15) Investments	9.35	30.10	-20.75	-1.71	20.53	-22.24	61.23	45.70	15.53
	(16) Earning to Price	14.66	28.89	-14.23	1.22	25.28	-24.05	45.56	24.49	21.07
	(17) Cash Flows to Price	14.20	29.89	-15.69	0.66	24.78	-24.11	52.98	30.90	22.08
	(18) Dividend Yield	16.21	25.62	-9.41	7.09	26.33	-19.23	27.86	2.15	25.71
	Combination	2.10	20.61	-18.50	-8.34	11.82	-20.17	42.40	33.06	9.34

		Long Leg			**Short Leg**			**Long-Short**		
Skewness		High Sent	Low Sent	High-Low	High Sent	Low Sent	High-Low	High Sent	Low Sent	High-Low
	(1) Asset Growth	-1.04	0.11	-1.15	-0.93	-0.15	-0.79	0.29	0.64	-0.35
	(2) Gross Profitability	-1.00	-0.01	-0.99	-1.07	-0.07	-1.00	-0.27	-0.05	-0.22
	(3) Investment to Assets	-1.04	0.12	-1.16	-0.97	-0.06	-0.91	0.20	0.47	-0.27
	(4) Net Stock Issues	-1.18	0.12	-1.31	-0.97	-0.04	-0.93	-0.02	0.01	-0.03
	(5) Net Operating Assets	-0.90	-0.05	-0.85	-1.06	-0.06	-1.00	0.37	-0.12	0.50
	(6) Total Accruals	-1.11	0.03	-1.14	-1.10	-0.18	-0.93	0.52	0.09	0.43
	(7) Ohlson's O	-1.13	-0.04	-1.08	-0.88	0.05	-0.93	1.04	-0.02	1.06
	(8) Return on Assets	-1.15	-0.45	-0.70	-1.09	-0.39	-0.69	-0.30	-0.29	0.00
	(9) Failure Probability	-0.77	-0.15	-0.62	-1.34	-0.60	-0.73	0.49	0.61	-0.12
	(10) Momentum	-1.27	-0.59	-0.68	-0.43	0.20	-0.63	-0.85	-0.89	0.04
	(11) Composite Equity Issues	-1.30	-0.18	-1.12	-0.93	-0.35	-0.58	1.07	0.23	0.84
	(12) Size	-0.10	0.72	-0.82	-0.46	0.18	-0.65	0.97	0.85	0.12
	(13) Book to Market	-0.23	1.10	-1.33	-0.18	0.26	-0.44	-0.03	0.16	-0.19
	(14) Operating Profitability	-0.55	0.40	-0.94	0.00	0.82	-0.82	-1.90	-1.03	-0.87
	(15) Investments	-0.07	0.83	-0.90	-0.25	0.43	-0.68	0.39	1.21	-0.83
	(16) Earning to Price	-0.44	0.92	-1.36	-0.39	0.34	-0.73	-0.18	-0.23	0.06
	(17) Cash Flows to Price	-0.45	0.83	-1.28	-0.42	0.37	-0.79	-0.09	-0.23	0.14
	(18) Dividend Yield	-0.46	1.23	-1.69	-0.74	0.28	-1.02	0.17	0.14	0.02
	Combination	-0.79	0.28	-1.06	-0.73	0.06	-0.79	0.10	0.09	0.02
Kurtosis										
	(1) Asset Growth	5.90	4.07	1.83	5.32	3.99	1.33	3.62	4.10	-0.49
	(2) Gross Profitability	5.81	4.07	1.74	5.69	4.16	1.54	3.52	3.71	-0.20
	(3) Investment to Assets	5.91	3.95	1.97	5.63	4.14	1.49	4.12	3.85	0.27
	(4) Net Stock Issues	6.56	4.74	1.82	5.23	3.96	1.27	5.88	4.92	0.96
	(5) Net Operating Assets	5.21	3.70	1.51	6.11	4.27	1.84	8.38	4.65	3.73
	(6) Total Accruals	6.61	3.90	2.70	6.71	3.48	3.22	6.54	3.81	2.73
	(7) Ohlson's O	6.54	4.13	2.41	5.28	3.84	1.44	9.73	3.21	6.52
	(8) Return on Assets	6.67	3.63	3.04	6.45	3.57	2.89	3.41	3.59	-0.18
	(9) Failure Probability	5.63	4.17	1.46	8.34	3.35	4.99	8.24	4.58	3.66
	(10) Momentum	7.03	3.48	3.55	4.87	4.66	0.21	7.11	5.63	1.48
	(11) Composite Equity Issues	7.27	4.21	3.06	5.01	3.67	1.34	11.13	3.68	7.45
	(12) Size	4.66	6.28	-1.62	4.36	4.39	-0.03	6.02	6.74	-0.72
	(13) Book to Market	5.30	9.54	-4.25	4.54	4.45	0.08	4.79	5.11	-0.32
	(14) Operating Profitability	5.04	6.35	-1.31	4.84	6.83	-1.98	15.21	7.24	7.97
	(15) Investments	4.81	6.56	-1.75	4.63	5.85	-1.22	4.35	8.94	-4.58
	(16) Earning to Price	5.56	9.62	-4.07	4.28	5.16	-0.88	3.52	5.80	-2.28
	(17) Cash Flows to Price	5.76	8.71	-2.96	4.34	5.52	-1.18	3.56	5.10	-1.54
	(18) Dividend Yield	5.50	11.56	-6.06	5.09	5.26	-0.17	3.57	4.60	-1.03
	Combination	5.88	5.71	0.17	5.37	4.48	0.90	6.26	4.96	1.30
Cornis-Fisher Ratio										
	(1) Asset Growth	-0.88	8.81	-9.69	-0.88	3.47	-4.35	35.06	31.23	3.82
	(2) Gross Profitability	-1.24	7.05	-8.29	-1.24	4.36	-5.60	15.15	13.25	1.91
	(3) Investment to Assets	-0.64	8.77	-9.40	-0.64	2.81	-3.44	38.14	40.00	-1.87
	(4) Net Stock Issues	-1.27	7.44	-8.71	-1.27	4.25	-5.52	24.73	14.54	10.19
	(5) Net Operating Assets	-1.65	7.19	-8.84	-1.65	2.63	-4.28	37.53	25.11	12.42
	(6) Total Accruals	-0.57	6.04	-6.61	-0.57	1.08	-1.65	42.69	16.82	25.87
	(7) Ohlson's O	-2.05	5.48	-7.53	-2.05	2.45	-4.50	18.05	14.19	3.86
	(8) Return on Assets	-3.61	4.30	-7.91	-3.61	-0.13	-3.47	13.86	14.97	-1.11
	(9) Failure Probability	0.79	8.22	-7.44	0.79	-3.20	3.99	40.93	39.99	0.94
	(10) Momentum	-1.44	5.89	-7.32	-1.44	2.24	-3.68	8.90	9.34	-0.44
	(11) Composite Equity Issues	-0.14	8.37	-8.51	-0.14	1.79	-1.93	50.98	29.30	21.68
	(12) Size	1.91	17.18	-15.27	1.91	11.14	-9.23	9.22	15.14	-5.92
	(13) Book to Market	5.48	25.97	-20.50	5.48	10.58	-5.11	21.56	18.79	2.77
	(14) Operating Profitability	2.59	15.17	-12.58	2.59	17.19	-14.60	6.69	1.79	4.90
	(15) Investments	4.09	21.26	-17.17	4.09	11.35	-7.26	42.85	46.79	-3.94
	(16) Earning to Price	5.86	21.28	-15.41	5.86	13.85	-7.99	22.75	10.87	11.88
	(17) Cash Flows to Price	5.65	21.13	-15.48	5.65	13.69	-8.04	28.38	14.11	14.27
	(18) Dividend Yield	6.48	21.98	-15.50	6.48	14.18	-7.69	14.47	0.98	13.49
	Combination	1.08	12.31	-11.23	1.08	6.32	-5.24	26.22	19.84	6.37

Table 2.31: Anomalies during periods of high and low macroeconomic uncertainty (UM). The table reports values in months following high and low levels of macroeconomic uncertainty, as identified on the base of the median level of the UM uncertainty proxy. Also reported is the performance on a strategy which equally combines the strategies available within a given month (Combination). For each anomaly we make use of all data available. Details of the length of the time series can be found in the section dedicated on Data. We report conditional Excess Returns, Standard Deviation, Skewness, Kurtosis, Sharpe Ratio and Cornish-Fisher Ratio for the Long and short Leg and for the Spread of the anomalies. We even report their difference. Excess Returns, Standard Deviation, Sharpe Ratio and Cornish-Fisher Ratio are reported in percentage.

UM		Long Leg			Short Leg			Long-Short		
Excess Returns		High Unc	Low Unc	High-Low	High Unc	Low Unc	High-Low	High Unc	Low Unc	High-Low
	(1) Asset Growth	0.31	0.56	-0.24	-0.28	-0.10	-0.18	0.97	0.92	0.05
	(2) Gross Profitability	0.44	0.31	0.13	-0.20	0.19	-0.39	1.03	0.39	0.64
	(3) Investment to Assets	0.32	0.49	-0.16	-0.16	-0.28	0.11	0.87	1.03	-0.16
	(4) Net Stock Issues	0.29	0.40	-0.12	-0.14	-0.03	-0.11	0.81	0.70	0.11
	(5) Net Operating Assets	0.24	0.36	-0.12	-0.18	-0.22	0.04	0.80	0.85	-0.05
	(6) Total Accruals	0.34	0.30	0.04	-0.20	-0.38	0.18	0.93	0.95	-0.02
	(7) Ohlson's O	0.26	0.10	0.16	-0.17	0.05	-0.21	0.81	0.32	0.49
	(8) Return on Assets	-0.11	-0.10	-0.01	-0.77	-0.25	-0.52	1.04	0.42	0.62
	(9) Failure Probability	0.51	0.50	0.01	-1.32	-0.99	-0.33	2.22	1.76	0.46
	(10) Momentum	-0.13	0.54	-0.67	-0.28	-0.10	-0.18	0.54	0.91	-0.37
	(11) Composite Equity Issues	0.27	0.71	-0.44	-0.63	-0.11	-0.53	1.29	1.09	0.20
	(12) Size	0.70	0.95	-0.25	0.51	1.00	-0.49	0.57	0.22	0.36
	(13) Book to Market	1.04	1.40	-0.36	0.34	0.56	-0.22	1.08	1.11	-0.03
	(14) Operating Profitability	0.81	1.01	-0.20	0.58	0.90	-0.32	0.61	0.37	0.24
	(15) Investments	1.05	1.32	-0.27	0.30	0.57	-0.28	1.14	1.02	0.12
	(16) Earning to Price	1.04	1.20	-0.15	0.51	0.85	-0.34	0.92	0.61	0.31
	(17) Cash Flows to Price	1.13	1.16	-0.04	0.47	0.86	-0.39	1.05	0.58	0.47
	(18) Dividend Yield	0.86	1.01	-0.15	0.73	1.02	-0.30	0.51	0.26	0.26
	Combination	0.52	0.68	-0.16	-0.05	0.20	-0.25	0.95	0.75	0.20
Standard Deviation										
	(1) Asset Growth	5.55	4.91	0.64	6.30	5.50	0.80	2.21	1.62	0.59
	(2) Gross Profitability	5.84	5.15	0.69	5.49	4.77	0.72	2.34	2.12	0.22
	(3) Investment to Assets	5.61	4.83	0.78	6.43	5.39	1.05	2.22	1.58	0.64
	(4) Net Stock Issues	4.77	4.14	0.63	6.12	5.44	0.68	2.49	2.02	0.47
	(5) Net Operating Assets	6.03	5.14	0.89	5.92	5.22	0.70	2.06	1.75	0.32
	(6) Total Accruals	5.67	5.11	0.56	5.80	5.39	0.41	2.71	2.27	0.44
	(7) Ohlson's O	5.67	4.94	0.73	6.27	5.13	1.14	2.81	1.98	0.83
	(8) Return on Assets	5.95	5.33	0.62	6.09	5.21	0.89	2.66	2.27	0.39
	(9) Failure Probability	6.73	5.40	1.33	5.68	5.38	0.30	4.80	2.79	2.01
	(10) Momentum	6.61	4.35	2.25	6.72	4.79	1.92	4.51	2.68	1.83
	(11) Composite Equity Issues	5.15	3.23	1.92	6.63	4.72	1.91	3.26	2.19	1.07
	(12) Size	6.95	4.86	2.10	5.77	3.78	2.00	4.15	3.36	0.79
	(13) Book to Market	6.08	4.27	1.81	7.73	5.14	2.59	3.64	2.29	1.35
	(14) Operating Profitability	6.17	4.05	2.11	7.58	5.29	2.29	3.76	2.51	1.25
	(15) Investments	7.25	5.16	2.08	7.31	4.88	2.43	2.28	1.85	0.43
	(16) Earning to Price	5.67	3.77	1.89	6.55	4.40	2.15	2.76	1.71	1.05
	(17) Cash Flows to Price	5.96	3.96	1.99	6.44	4.29	2.15	2.45	1.69	0.75
	(18) Dividend Yield	4.74	2.88	1.86	5.71	3.74	1.97	2.66	1.74	0.92
	Combination	5.91	4.53	1.38	6.36	4.91	1.45	2.99	2.13	0.85
Sharpe Ratio										
	(1) Asset Growth	5.62	11.31	-5.69	-4.41	-1.76	-2.65	44.02	56.60	-12.58
	(2) Gross Profitability	7.53	6.00	1.53	-3.72	3.91	-7.63	43.87	18.42	25.44
	(3) Investment to Assets	5.76	10.08	-4.33	-2.52	-5.12	2.60	39.18	65.37	-26.19
	(4) Net Stock Issues	6.04	9.77	-3.73	-2.24	-0.53	-1.70	32.49	34.67	-2.18
	(5) Net Operating Assets	3.93	7.03	-3.10	-3.05	-4.26	1.21	38.83	48.77	-9.94
	(6) Total Accruals	6.02	5.93	0.09	-3.49	-7.03	3.54	34.18	41.83	-7.65
	(7) Ohlson's O	4.51	1.99	2.53	-2.68	0.89	-3.57	28.71	16.19	12.52
	(8) Return on Assets	-1.85	-1.81	-0.04	-12.59	-4.80	-7.80	39.18	18.56	20.62
	(9) Failure Probability	7.62	9.30	-1.68	-23.31	-18.46	-4.84	46.24	63.21	-16.97
	(10) Momentum	-1.89	12.44	-14.34	-4.23	-2.19	-2.04	12.04	34.18	-22.14
	(11) Composite Equity Issues	5.23	22.05	-16.83	-9.56	-2.31	-7.26	39.48	49.77	-10.29
	(12) Size	10.11	19.56	-9.45	8.88	26.53	-17.65	13.84	6.42	7.42
	(13) Book to Market	17.12	32.78	-15.66	4.43	10.86	-6.44	29.76	48.37	-18.61
	(14) Operating Profitability	13.12	24.83	-11.71	7.69	17.10	-9.41	16.23	14.77	1.46
	(15) Investments	14.54	25.64	-11.10	4.04	11.74	-7.69	49.96	54.93	-4.98
	(16) Earning to Price	18.43	31.70	-13.27	7.77	19.36	-11.59	33.29	35.76	-2.47
	(17) Cash Flows to Price	18.94	29.40	-10.46	7.24	19.95	-12.71	42.72	34.04	8.69
	(18) Dividend Yield	18.09	35.12	-17.03	12.73	27.33	-14.60	19.30	14.70	4.60
	Combination	8.83	16.29	-7.46	-1.06	5.07	-6.12	33.52	36.48	-2.96

		Long Leg			Short Leg			Long-Short		
Skewness		High Unc	Low Unc	High-Low	High Unc	Low Unc	High-Low	High Unc	Low Unc	High-Low
	(1) Asset Growth	-0.44	-2.18	1.73	-0.53	-2.19	1.66	0.54	0.65	-0.11
	(2) Gross Profitability	-0.42	-2.18	1.76	-0.62	-1.95	1.33	0.08	-0.15	0.23
	(3) Investment to Assets	-0.48	-2.10	1.62	-0.62	-2.30	1.68	0.52	0.53	-0.01
	(4) Net Stock Issues	-0.60	-2.83	2.24	-0.54	-1.98	1.44	0.01	0.40	-0.39
	(5) Net Operating Assets	-0.48	-1.92	1.44	-0.66	-2.39	1.73	0.51	0.01	0.50
	(6) Total Accruals	-0.47	-1.89	1.42	-0.33	-2.27	1.94	0.17	0.06	0.11
	(7) Ohlson's O	-0.66	-2.43	1.77	-0.43	-1.74	1.31	1.39	-0.24	1.63
	(8) Return on Assets	-0.45	-2.16	1.70	-0.33	-2.09	1.77	-0.39	-0.17	-0.22
	(9) Failure Probability	-0.18	-1.65	1.47	-0.21	-2.53	2.32	0.62	0.31	0.31
	(10) Momentum	-1.35	-1.19	-0.16	-0.36	-0.88	0.52	-0.99	-0.51	-0.48
	(11) Composite Equity Issues	-1.74	-1.05	-0.69	-1.03	-1.30	0.27	1.28	0.62	0.67
	(12) Size	0.00	-0.20	0.20	-0.43	-0.73	0.29	1.08	1.16	-0.09
	(13) Book to Market	-0.42	-0.09	-0.33	-0.06	-0.58	0.53	0.09	0.05	0.04
	(14) Operating Profitability	-0.61	-0.77	0.16	0.09	-0.13	0.22	-1.66	-1.29	-0.37
	(15) Investments	0.04	0.09	-0.05	-0.21	-0.74	0.53	0.55	1.45	-0.89
	(16) Earning to Price	-0.61	-0.54	-0.08	-0.39	-0.77	0.38	0.03	0.34	-0.30
	(17) Cash Flows to Price	-0.61	-0.51	-0.10	-0.42	-0.81	0.38	0.07	-0.03	0.10
	(18) Dividend Yield	-0.47	-0.20	-0.27	-0.77	-0.86	0.09	0.33	0.75	-0.42
	Combination	-0.55	-1.32	0.77	-0.44	-1.46	1.02	0.23	0.22	0.02
Kurtosis										
	(1) Asset Growth	3.54	15.18	-11.64	3.85	14.20	-10.35	4.06	3.62	0.44
	(2) Gross Profitability	3.50	14.68	-11.17	4.08	12.27	-8.19	3.51	2.95	0.56
	(3) Investment to Assets	4.01	14.75	-10.74	4.63	15.28	-10.65	4.89	4.31	0.58
	(4) Net Stock Issues	4.42	21.55	-17.13	3.68	12.22	-8.55	5.83	5.69	0.14
	(5) Net Operating Assets	3.66	12.28	-8.61	4.92	15.90	-10.98	9.17	5.03	4.15
	(6) Total Accruals	4.38	13.30	-8.92	3.50	15.56	-12.05	5.04	3.56	1.48
	(7) Ohlson's O	4.91	17.45	-12.54	3.83	11.84	-8.01	11.07	2.98	8.09
	(8) Return on Assets	3.48	14.86	-11.38	3.53	13.55	-10.02	3.53	3.72	-0.20
	(9) Failure Probability	4.03	11.38	-7.35	3.22	17.95	-14.73	8.33	5.20	3.13
	(10) Momentum	8.17	7.21	0.96	5.64	6.04	-0.40	7.46	5.16	2.29
	(11) Composite Equity Issues	10.79	6.54	4.25	5.77	7.30	-1.53	11.18	5.13	6.05
	(12) Size	5.61	5.47	0.13	4.63	5.06	-0.43	8.00	9.11	-1.11
	(13) Book to Market	5.81	6.17	-0.36	5.29	5.11	0.18	5.09	3.60	1.49
	(14) Operating Profitability	6.37	5.30	1.07	5.55	5.41	0.14	12.46	7.16	5.30
	(15) Investments	5.19	5.84	-0.65	5.52	5.31	0.21	4.27	10.92	-6.65
	(16) Earning to Price	6.29	5.27	1.02	5.32	5.13	0.19	3.52	4.15	-0.63
	(17) Cash Flows to Price	6.80	5.17	1.63	5.46	5.12	0.34	3.21	3.75	-0.54
	(18) Dividend Yield	6.23	4.02	2.21	6.32	6.08	0.24	3.50	5.65	-2.15
	Combination	5.40	10.36	-4.96	4.71	9.96	-5.26	6.34	5.09	1.25
Cornis-Fisher Ratio										
	(1) Asset Growth	2.17	2.96	-0.80	2.17	-0.44	2.61	29.58	44.16	-14.59
	(2) Gross Profitability	2.95	1.55	1.39	2.95	1.05	1.89	23.94	8.17	15.77
	(3) Investment to Assets	2.20	2.67	-0.48	2.20	-1.26	3.46	25.20	50.86	-25.66
	(4) Net Stock Issues	2.23	2.27	-0.03	2.23	-0.14	2.37	16.29	20.53	-4.24
	(5) Net Operating Assets	1.49	1.92	-0.43	1.49	-1.03	2.52	24.81	26.64	-1.83
	(6) Total Accruals	2.31	1.62	0.68	2.31	-1.73	4.03	18.37	22.47	-4.09
	(7) Ohlson's O	1.63	0.48	1.15	1.63	0.25	1.38	28.21	6.91	21.30
	(8) Return on Assets	-0.69	-0.46	-0.23	-0.69	-1.23	0.53	17.61	8.18	9.43
	(9) Failure Probability	3.20	2.70	0.50	3.20	-4.22	7.42	32.84	43.11	-10.27
	(10) Momentum	-0.57	4.04	-4.61	-0.57	-0.73	0.16	4.11	14.49	-10.39
	(11) Composite Equity Issues	1.47	7.67	-6.20	1.47	-0.70	2.17	40.01	36.17	3.84
	(12) Size	4.55	8.59	-4.05	4.55	10.22	-5.68	9.91	4.57	5.34
	(13) Book to Market	6.95	15.88	-8.93	6.95	4.11	2.84	15.14	26.74	-11.60
	(14) Operating Profitability	4.96	9.39	-4.43	4.96	7.61	-2.65	4.79	4.72	0.07
	(15) Investments	6.76	12.79	-6.03	6.76	4.26	2.50	35.20	77.03	-41.83
	(16) Earning to Price	7.11	13.18	-6.07	7.11	7.17	-0.07	16.92	20.79	-3.87
	(17) Cash Flows to Price	7.32	12.20	-4.88	7.32	7.34	-0.01	23.14	16.95	6.19
	(18) Dividend Yield	7.26	16.56	-9.30	7.26	10.17	-2.92	10.21	9.04	1.17
	Combination	3.52	6.45	-2.93	3.52	2.26	1.25	20.90	24.53	-3.63

Table 2.32: Anomalies during periods of high and low Volatility (VIX). The table reports values in months following high and low levels of Volatility, as identified on the base of the median level of the VIX index. Also reported is the performance on a strategy which equally combines the strategies available within a given month (Combination). For each anomaly we make use of all data available. Details of the length of the time series can be found in the section dedicated on Data. We report conditional Excess Returns, Standard Deviation, Skewness, Kurtosis, Sharpe Ratio and Cornish-Fisher Ratio for the long and short leg and for the Spread of the anomalies. We even report their difference. Excess Returns, Standard Deviation, Sharpe Ratio and Cornish-Fisher Ratio are reported in percentage.

VIX		Long Leg			Short Leg			Long-Short		
Excess Returns		High VIX	Low VIX	High-Low	High VIX	Low VIX	High-Low	High VIX	Low VIX	High-Low
	(1) Asset Growth	0.77	0.20	0.57	0.03	-0.29	0.32	0.98	0.71	0.27
	(2) Gross Profitability	0.67	0.06	0.61	0.06	-0.05	0.11	0.85	0.33	0.52
	(3) Investment to Assets	0.68	0.16	0.52	0.17	-0.46	0.63	0.76	0.84	-0.09
	(4) Net Stock Issues	0.46	0.27	0.19	0.18	-0.23	0.41	0.52	0.72	-0.20
	(5) Net Operating Assets	0.51	0.09	0.43	0.11	-0.33	0.44	0.64	0.64	0.00
	(6) Total Accruals	0.62	0.03	0.59	-0.07	-0.38	0.31	0.93	0.63	0.30
	(7) Ohlson's O	0.56	-0.11	0.66	0.12	-0.12	0.24	0.69	0.24	0.45
	(8) Return on Assets	0.20	-0.18	0.38	-0.13	-0.64	0.51	0.57	0.68	-0.11
	(9) Failure Probability	1.09	0.14	0.95	-0.84	-0.93	0.09	2.18	1.29	0.88
	(10) Momentum	0.08	0.29	-0.21	-0.04	-0.26	0.22	0.36	0.77	-0.41
	(11) Composite Equity Issues	0.56	0.46	0.11	-0.44	-0.30	-0.13	1.24	0.98	0.26
	(12) Size	1.18	0.74	0.44	0.91	0.54	0.37	0.51	0.42	0.09
	(13) Book to Market	1.36	1.13	0.23	0.97	0.21	0.76	0.64	1.15	-0.51
	(14) Operating Profitability	1.19	0.74	0.44	1.20	0.60	0.60	0.23	0.37	-0.14
	(15) Investments	1.73	0.89	0.83	0.66	0.38	0.28	1.31	0.73	0.58
	(16) Earning to Price	1.24	0.96	0.28	1.03	0.60	0.43	0.45	0.58	-0.13
	(17) Cash Flows to Price	1.26	0.99	0.27	1.02	0.56	0.47	0.48	0.66	-0.18
	(18) Dividend Yield	1.00	0.81	0.19	1.03	0.75	0.28	0.22	0.28	-0.06
	Combination	0.84	0.43	0.42	0.33	-0.02	0.35	0.75	0.67	0.08
Standard Deviation										
	(1) Asset Growth	6.06	3.99	2.07	6.87	4.37	2.50	2.35	1.57	0.79
	(2) Gross Profitability	6.33	4.10	2.24	6.14	4.08	2.05	2.45	2.17	0.28
	(3) Investment to Assets	6.04	4.03	2.00	7.00	4.25	2.75	2.34	1.47	0.87
	(4) Net Stock Issues	4.97	3.20	1.77	6.95	4.33	2.62	3.09	1.63	1.46
	(5) Net Operating Assets	6.73	4.18	2.54	6.49	4.13	2.36	2.52	1.41	1.10
	(6) Total Accruals	6.26	4.11	2.15	6.31	4.26	2.05	3.03	2.27	0.75
	(7) Ohlson's O	6.09	3.99	2.10	6.88	4.02	2.86	3.09	1.88	1.21
	(8) Return on Assets	6.29	4.26	2.03	6.81	4.22	2.60	2.86	2.21	0.65
	(9) Failure Probability	7.45	4.20	3.26	6.09	4.37	1.72	5.34	2.35	2.99
	(10) Momentum	6.78	3.83	2.95	7.62	3.72	3.90	5.08	2.36	2.72
	(11) Composite Equity Issues	5.04	2.88	2.16	7.28	3.84	3.44	3.90	1.93	1.97
	(12) Size	7.77	3.86	3.91	6.22	2.85	3.37	5.01	2.41	2.60
	(13) Book to Market	6.85	3.48	3.37	8.48	4.08	4.40	3.90	2.17	1.73
	(14) Operating Profitability	6.37	3.34	3.02	8.61	4.12	4.49	4.49	1.90	2.59
	(15) Investments	8.31	3.97	4.34	8.02	3.90	4.12	2.71	1.48	1.23
	(16) Earning to Price	6.14	3.20	2.93	6.88	3.50	3.38	2.72	1.53	1.19
	(17) Cash Flows to Price	6.55	3.28	3.27	6.68	3.48	3.20	2.46	1.53	0.93
	(18) Dividend Yield	4.94	2.71	2.22	5.83	3.11	2.72	2.69	1.49	1.20
	Combination	6.39	3.70	2.69	6.95	3.92	3.03	3.33	1.88	1.46
Sharpe Ratio										
	(1) Asset Growth	12.70	5.05	7.65	0.49	-6.54	7.04	41.62	45.39	-3.77
	(2) Gross Profitability	10.54	1.36	9.19	0.97	-1.30	2.27	34.77	15.28	19.50
	(3) Investment to Assets	11.29	4.08	7.21	2.41	-10.74	13.15	32.33	57.32	-24.99
	(4) Net Stock Issues	9.23	8.34	0.89	2.57	-5.30	7.87	16.95	44.13	-27.18
	(5) Net Operating Assets	7.62	2.09	5.53	1.75	-7.96	9.72	25.52	45.19	-19.67
	(6) Total Accruals	9.95	0.85	9.10	-1.08	-8.85	7.77	30.88	27.93	2.94
	(7) Ohlson's O	9.19	-2.64	11.82	1.71	-3.03	4.74	22.20	12.78	9.42
	(8) Return on Assets	3.18	-4.18	7.37	-1.91	-15.13	13.23	20.07	30.95	-10.88
	(9) Failure Probability	14.69	3.33	11.35	-13.76	-21.30	7.53	40.76	55.02	-14.26
	(10) Momentum	1.18	7.46	-6.28	-0.49	-7.01	6.52	7.11	32.63	-25.52
	(11) Composite Equity Issues	11.15	15.85	-4.70	-6.01	-7.89	1.88	31.87	50.94	-19.07
	(12) Size	15.13	19.16	-4.03	14.67	19.08	-4.42	10.13	17.41	-7.28
	(13) Book to Market	19.86	32.60	-12.75	11.41	5.14	6.28	16.29	52.86	-36.57
	(14) Operating Profitability	18.67	22.27	-3.60	13.94	14.51	-0.57	5.16	19.48	-14.31
	(15) Investments	20.76	22.51	-1.75	8.23	9.82	-1.59	48.25	49.54	-1.30
	(16) Earning to Price	20.14	29.83	-9.69	15.03	17.22	-2.19	16.38	37.66	-21.28
	(17) Cash Flows to Price	19.23	30.31	-11.08	15.34	16.05	-0.71	19.51	43.13	-23.62
	(18) Dividend Yield	20.21	29.68	-9.48	17.57	24.01	-6.44	8.06	18.90	-10.85
	Combination	13.04	12.66	0.38	4.60	0.60	4.00	23.77	36.47	-12.70

		Long Leg			Short Leg			Long-Short		
Skewness		High VIX	Low VIX	High-Low	High VIX	Low VIX	High-Low	High VIX	Low VIX	High-Low
	(1) Asset Growth	-0.78	-0.55	-0.24	-0.97	-0.67	-0.30	0.60	0.72	-0.12
	(2) Gross Profitability	-0.80	-0.57	-0.23	-0.85	-0.64	-0.21	0.14	-0.01	0.14
	(3) Investment to Assets	-0.77	-0.49	-0.27	-1.06	-0.65	-0.41	0.65	0.42	0.23
	(4) Net Stock Issues	-0.99	-0.70	-0.29	-0.92	-0.64	-0.29	0.23	0.84	-0.60
	(5) Net Operating Assets	-0.73	-0.64	-0.09	-1.12	-0.75	-0.36	0.49	0.04	0.46
	(6) Total Accruals	-0.68	-0.55	-0.13	-0.67	-0.56	-0.11	0.14	0.25	-0.11
	(7) Ohlson's O	-1.05	-0.59	-0.46	-0.74	-0.32	-0.41	1.29	0.00	1.30
	(8) Return on Assets	-0.90	-0.62	-0.28	-0.68	-0.75	0.07	-0.23	0.09	-0.32
	(9) Failure Probability	-0.54	-0.61	0.07	-0.62	-0.60	-0.02	0.57	0.17	0.40
	(10) Momentum	-0.87	-0.40	-0.47	-0.35	-0.60	0.25	-0.87	0.43	-1.29
	(11) Composite Equity Issues	-1.24	-0.69	-0.56	-0.87	-0.43	-0.44	1.07	0.48	0.59
	(12) Size	0.08	-0.08	0.16	-0.50	-0.64	0.14	1.14	0.37	0.77
	(13) Book to Market	-0.15	0.08	-0.23	-0.08	-0.43	0.35	0.21	0.86	-0.65
	(14) Operating Profitability	-0.50	-0.29	-0.21	0.14	-0.18	0.32	-1.32	-0.25	-1.07
	(15) Investments	0.13	-0.12	0.25	-0.17	-0.29	0.12	0.83	0.35	0.48
	(16) Earning to Price	-0.45	-0.05	-0.39	-0.34	-0.35	0.01	0.15	1.06	-0.91
	(17) Cash Flows to Price	-0.40	-0.04	-0.36	-0.35	-0.40	0.05	0.30	0.39	-0.08
	(18) Dividend Yield	-0.29	-0.48	0.19	-0.68	-0.25	-0.44	0.50	0.31	0.19
	Combination	-0.61	-0.41	-0.20	-0.60	-0.51	-0.09	0.33	0.36	-0.03
Kurtosis										
	(1) Asset Growth	3.97	3.33	0.65	4.69	3.73	0.96	4.09	3.65	0.44
	(2) Gross Profitability	4.14	3.53	0.61	4.10	3.33	0.78	3.53	3.10	0.42
	(3) Investment to Assets	4.34	3.32	1.02	5.38	3.72	1.67	5.33	3.17	2.16
	(4) Net Stock Issues	5.26	4.20	1.05	4.37	3.24	1.13	4.22	4.16	0.05
	(5) Net Operating Assets	3.83	3.30	0.53	5.87	4.01	1.86	6.42	3.54	2.88
	(6) Total Accruals	4.34	3.06	1.28	3.87	3.46	0.41	4.37	3.40	0.98
	(7) Ohlson's O	5.47	3.58	1.90	4.03	3.07	0.97	10.04	3.24	6.81
	(8) Return on Assets	4.41	3.77	0.64	3.83	3.68	0.15	3.09	3.25	-0.16
	(9) Failure Probability	4.28	3.51	0.77	3.85	3.39	0.46	7.18	5.06	2.13
	(10) Momentum	4.04	2.77	1.27	4.09	3.92	0.17	5.92	5.67	0.25
	(11) Composite Equity Issues	6.23	4.93	1.30	3.66	2.76	0.90	7.53	3.97	3.56
	(12) Size	4.00	2.92	1.08	3.52	3.60	-0.08	6.66	3.35	3.32
	(13) Book to Market	3.94	3.82	0.12	3.88	2.85	1.04	4.82	4.20	0.62
	(14) Operating Profitability	4.47	2.95	1.52	3.89	2.73	1.15	8.18	4.00	4.18
	(15) Investments	3.64	2.92	0.72	3.92	2.76	1.15	5.07	3.01	2.06
	(16) Earning to Price	4.55	4.01	0.54	3.47	2.92	0.55	3.84	5.22	-1.38
	(17) Cash Flows to Price	4.79	3.25	1.54	3.53	3.08	0.45	3.53	3.43	0.11
	(18) Dividend Yield	5.20	6.32	-1.13	4.51	3.20	1.31	3.51	2.94	0.57
	Combination	4.49	3.64	0.86	4.14	3.30	0.83	5.41	3.80	1.61
Cornis-Fisher Ratio										
	(1) Asset Growth	4.58	1.89	2.69	4.58	-2.27	6.85	28.31	33.83	-5.52
	(2) Gross Profitability	3.75	0.50	3.26	3.75	-0.46	4.22	18.50	7.01	11.49
	(3) Investment to Assets	4.07	1.54	2.52	4.07	-3.69	7.76	21.20	39.60	-18.40
	(4) Net Stock Issues	3.12	3.02	0.09	3.12	-1.86	4.98	8.54	34.78	-26.24
	(5) Net Operating Assets	2.73	0.75	1.98	2.73	-2.69	5.42	14.94	24.46	-9.52
	(6) Total Accruals	3.65	0.31	3.34	3.65	-3.13	6.78	16.12	14.99	1.13
	(7) Ohlson's O	3.06	-0.95	4.00	3.06	-1.17	4.23	19.26	5.81	13.45
	(8) Return on Assets	1.08	-1.48	2.56	1.08	-5.00	6.08	8.74	15.84	-7.10
	(9) Failure Probability	5.70	1.22	4.48	5.70	-7.14	12.84	27.13	33.31	-6.17
	(10) Momentum	0.40	2.93	-2.53	0.40	-2.47	2.87	2.46	19.34	-16.88
	(11) Composite Equity Issues	3.56	5.93	-2.37	3.56	-2.90	6.46	26.11	34.80	-8.69
	(12) Size	7.15	8.73	-1.58	7.15	7.33	-0.18	7.31	9.26	-1.95
	(13) Book to Market	8.87	16.80	-7.94	8.87	1.99	6.88	8.12	45.37	-37.25
	(14) Operating Profitability	7.46	9.62	-2.16	7.46	6.27	1.19	1.59	8.41	-6.82
	(15) Investments	10.27	10.29	-0.01	10.27	4.02	6.25	39.07	31.43	7.64
	(16) Earning to Price	8.21	14.43	-6.22	8.21	7.14	1.07	7.98	32.15	-24.17
	(17) Cash Flows to Price	7.93	14.77	-6.84	7.93	6.52	1.41	10.22	26.76	-16.54
	(18) Dividend Yield	8.65	12.44	-3.80	8.65	10.59	-1.95	4.28	9.90	-5.62
	Combination	5.23	5.71	-0.47	5.23	0.62	4.62	14.99	23.72	-8.73

Table 2.33: Anomalies during periods of high and low Variance Risk Premium (VRP). The table reports values in months following high and low levels of Variance, as identified on the base of the median level of the VRP index. Also reported is the performance on a strategy which equally combines the strategies available within a given month (Combination). For each anomaly we make use of all data available. Details of the length of the time series can be found in the section dedicated on Data. We report conditional Excess Returns, Standard Deviation, Skewness, Kurtosis, Sharpe Ratio and Cornish-Fisher Ratio for the long and short Leg and for the Spread of the anomalies. We even report their difference. Excess Returns, Standard Deviation, Sharpe Ratio and Cornish-Fisher Ratio are reported in percentage.

VRP		Long Leg			Short Leg			Long-Short		
Excess Returns		High VRP	Low VRP	High-Low	High VRP	Low VRP	High-Low	High VRP	Low VRP	High-Low
	(1) Asset Growth	0.84	0.13	0.72	0.11	-0.36	0.47	0.99	0.70	0.28
	(2) Gross Profitability	0.77	-0.05	0.82	0.02	-0.01	0.03	1.00	0.18	0.83
	(3) Investment to Assets	0.79	0.06	0.73	0.21	-0.50	0.71	0.83	0.77	0.06
	(4) Net Stock Issues	0.62	0.10	0.52	0.24	-0.29	0.53	0.64	0.61	0.03
	(5) Net Operating Assets	0.59	0.01	0.58	0.09	-0.31	0.40	0.75	0.53	0.23
	(6) Total Accruals	0.53	0.12	0.41	-0.06	-0.38	0.32	0.85	0.72	0.13
	(7) Ohlson's O	0.56	-0.10	0.66	0.35	-0.35	0.70	0.46	0.46	0.00
	(8) Return on Assets	0.28	-0.25	0.53	-0.07	-0.70	0.63	0.60	0.66	-0.06
	(9) Failure Probability	1.10	0.13	0.97	-0.82	-0.95	0.14	2.17	1.30	0.87
	(10) Momentum	0.82	-0.45	1.27	0.56	-0.86	1.41	0.51	0.62	-0.11
	(11) Composite Equity Issues	1.08	-0.06	1.15	0.30	-1.04	1.34	1.04	1.19	-0.15
	(12) Size	1.85	0.06	1.79	1.37	0.09	1.28	0.74	0.19	0.55
	(13) Book to Market	2.09	0.40	1.70	1.52	-0.34	1.86	0.83	0.95	-0.12
	(14) Operating Profitability	1.68	0.25	1.43	1.88	-0.08	1.97	0.05	0.55	-0.50
	(15) Investments	2.37	0.25	2.11	1.33	-0.28	1.61	1.29	0.75	0.54
	(16) Earning to Price	1.85	0.34	1.50	1.55	0.08	1.47	0.55	0.48	0.07
	(17) Cash Flows to Price	1.85	0.41	1.44	1.56	0.02	1.54	0.54	0.60	-0.05
	(18) Dividend Yield	1.54	0.26	1.28	1.51	0.26	1.25	0.28	0.22	0.06
	Combination	1.18	0.09	1.09	0.65	-0.33	0.98	0.78	0.64	0.15
Standard Deviation										
	(1) Asset Growth	5.68	4.51	1.17	6.60	4.77	1.83	2.35	1.57	0.77
	(2) Gross Profitability	6.08	4.45	1.63	5.77	4.58	1.19	2.41	2.17	0.24
	(3) Investment to Assets	5.59	4.61	0.98	6.66	4.76	1.90	2.31	1.52	0.80
	(4) Net Stock Issues	4.60	3.70	0.90	6.57	4.89	1.68	2.97	1.85	1.12
	(5) Net Operating Assets	6.34	4.73	1.61	6.18	4.58	1.60	2.32	1.71	0.62
	(6) Total Accruals	5.76	4.79	0.98	6.01	4.67	1.34	2.80	2.56	0.24
	(7) Ohlson's O	5.74	4.47	1.27	6.52	4.55	1.97	2.90	2.18	0.73
	(8) Return on Assets	6.08	4.55	1.54	6.46	4.73	1.73	2.67	2.44	0.23
	(9) Failure Probability	6.93	5.01	1.92	5.86	4.67	1.19	4.86	3.23	1.63
	(10) Momentum	5.81	5.10	0.71	6.67	5.14	1.53	4.40	3.48	0.92
	(11) Composite Equity Issues	4.37	3.73	0.64	6.20	5.32	0.88	2.98	3.17	-0.19
	(12) Size	6.95	5.05	1.90	5.46	4.03	1.43	4.85	2.69	2.16
	(13) Book to Market	6.17	4.42	1.75	7.43	5.64	1.79	3.40	2.92	0.48
	(14) Operating Profitability	5.76	4.19	1.57	7.58	5.66	1.92	3.97	2.81	1.17
	(15) Investments	7.35	5.37	1.98	7.10	5.28	1.81	2.55	1.75	0.80
	(16) Earning to Price	5.54	4.02	1.52	6.12	4.60	1.53	2.37	2.03	0.33
	(17) Cash Flows to Price	5.88	4.26	1.62	5.97	4.48	1.49	2.16	1.93	0.22
	(18) Dividend Yield	4.42	3.38	1.04	5.27	3.90	1.38	2.48	1.81	0.66
	Combination	5.84	4.46	1.37	6.36	4.79	1.56	3.04	2.32	0.72
Sharpe Ratio										
	(1) Asset Growth	14.87	2.81	12.05	1.65	-7.57	9.22	42.06	44.67	-2.61
	(2) Gross Profitability	12.70	-1.09	13.79	0.34	-0.28	0.62	41.71	8.25	33.46
	(3) Investment to Assets	14.10	1.24	12.86	3.14	-10.44	13.58	35.98	50.70	-14.72
	(4) Net Stock Issues	13.59	2.73	10.85	3.66	-5.95	9.62	21.45	32.84	-11.39
	(5) Net Operating Assets	9.33	0.16	9.17	1.47	-6.68	8.15	32.43	30.94	1.49
	(6) Total Accruals	9.27	2.57	6.70	-1.07	-8.14	7.07	30.43	28.09	2.34
	(7) Ohlson's O	9.72	-2.33	12.05	5.33	-7.73	13.06	15.96	21.24	-5.29
	(8) Return on Assets	4.56	-5.61	10.16	-1.05	-14.79	13.74	22.39	27.07	-4.68
	(9) Failure Probability	15.89	2.67	13.22	-13.92	-20.41	6.49	44.63	40.27	4.36
	(10) Momentum	14.06	-8.85	22.91	8.36	-16.63	24.99	11.65	17.79	-6.13
	(11) Composite Equity Issues	24.77	-1.74	26.51	4.81	-19.52	24.33	34.72	37.50	-2.78
	(12) Size	26.68	1.23	25.45	25.04	2.19	22.85	15.23	7.01	8.23
	(13) Book to Market	33.97	9.02	24.94	20.41	-6.02	26.43	24.43	32.66	-8.23
	(14) Operating Profitability	29.20	5.98	23.23	24.85	-1.49	26.33	1.32	19.56	-18.25
	(15) Investments	32.19	4.71	27.48	18.68	-5.35	24.02	50.69	42.82	7.88
	(16) Earning to Price	33.36	8.57	24.79	25.39	1.81	23.58	23.01	23.41	-0.39
	(17) Cash Flows to Price	31.46	9.51	21.95	26.14	0.52	25.62	25.12	30.86	-5.74
	(18) Dividend Yield	34.89	7.73	27.16	28.71	6.65	22.06	11.33	11.94	-0.62
	Combination	20.26	2.19	18.07	10.11	-6.66	16.76	26.92	28.20	-1.28

		Long Leg			Short Leg			Long-Short		
Skewness		High VRP	Low VRP	High-Low	High VRP	Low VRP	High-Low	High VRP	Low VRP	High-Low
	(1) Asset Growth	-0.86	-0.50	-0.37	-1.08	-0.57	-0.51	0.59	0.74	-0.15
	(2) Gross Profitability	-0.85	-0.58	-0.27	-1.00	-0.45	-0.55	0.16	-0.06	0.22
	(3) Investment to Assets	-0.88	-0.44	-0.44	-1.14	-0.65	-0.49	0.58	0.49	0.09
	(4) Net Stock Issues	-1.11	-0.76	-0.34	-1.06	-0.51	-0.55	0.23	0.36	-0.13
	(5) Net Operating Assets	-0.86	-0.47	-0.39	-1.23	-0.64	-0.59	0.59	-0.04	0.63
	(6) Total Accruals	-0.70	-0.53	-0.17	-0.69	-0.57	-0.12	0.34	0.06	0.28
	(7) Ohlson's O	-1.16	-0.51	-0.66	-0.87	-0.32	-0.56	1.47	0.60	0.88
	(8) Return on Assets	-0.99	-0.55	-0.43	-0.74	-0.63	-0.11	-0.02	-0.31	0.29
	(9) Failure Probability	-0.59	-0.39	-0.20	-0.66	-0.57	-0.08	0.90	-0.06	0.96
	(10) Momentum	-0.84	-1.16	0.32	-0.25	-0.99	0.74	-1.35	-0.11	-1.25
	(11) Composite Equity Issues	-0.85	-2.13	1.28	-0.88	-1.18	0.30	-0.05	2.28	-2.33
	(12) Size	0.24	-0.62	0.86	-0.40	-1.21	0.82	1.18	0.15	1.03
	(13) Book to Market	0.02	-0.99	1.00	0.09	-0.65	0.74	-0.39	1.18	-1.57
	(14) Operating Profitability	-0.30	-1.29	0.99	0.30	-0.44	0.73	-1.85	-0.15	-1.70
	(15) Investments	0.27	-0.34	0.61	-0.02	-0.89	0.87	0.97	0.60	0.38
	(16) Earning to Price	-0.18	-1.46	1.28	-0.25	-0.84	0.60	-0.27	1.10	-1.38
	(17) Cash Flows to Price	-0.10	-1.49	1.39	-0.27	-0.87	0.60	-0.11	0.83	-0.94
	(18) Dividend Yield	0.11	-1.67	1.78	-0.48	-1.46	0.98	0.55	0.26	0.28
	Combination	-0.54	-0.88	0.35	-0.59	-0.75	0.16	0.20	0.44	-0.24
Kurtosis										
	(1) Asset Growth	4.65	3.31	1.34	5.30	3.53	1.78	4.09	3.78	0.31
	(2) Gross Profitability	4.58	3.60	0.98	4.83	3.07	1.76	3.57	3.01	0.56
	(3) Investment to Assets	5.12	3.57	1.55	6.14	3.96	2.18	5.41	3.46	1.94
	(4) Net Stock Issues	6.30	4.54	1.76	5.10	3.32	1.78	4.68	4.29	0.39
	(5) Net Operating Assets	4.44	3.35	1.09	6.69	4.06	2.63	7.79	4.83	2.96
	(6) Total Accruals	5.00	3.68	1.33	4.26	3.54	0.72	4.56	4.18	0.38
	(7) Ohlson's O	6.36	3.68	2.69	4.70	3.44	1.26	12.51	4.64	7.86
	(8) Return on Assets	4.81	3.77	1.04	4.39	3.54	0.85	3.15	3.59	-0.44
	(9) Failure Probability	4.95	4.47	0.48	4.26	3.17	1.09	9.69	5.08	4.61
	(10) Momentum	4.79	5.37	-0.58	4.93	6.25	-1.32	9.09	5.43	3.66
	(11) Composite Equity Issues	4.97	12.16	-7.19	4.43	5.35	-0.91	6.12	13.11	-6.99
	(12) Size	4.68	5.32	-0.65	3.62	7.87	-4.25	7.14	4.36	2.78
	(13) Book to Market	4.26	6.50	-2.25	4.81	5.13	-0.32	4.51	8.30	-3.79
	(14) Operating Profitability	4.60	7.45	-2.85	4.73	5.29	-0.56	11.20	8.11	3.08
	(15) Investments	4.27	5.54	-1.28	4.77	5.15	-0.37	6.07	3.88	2.19
	(16) Earning to Price	4.75	7.66	-2.90	3.96	5.19	-1.22	3.44	7.78	-4.35
	(17) Cash Flows to Price	4.87	8.80	-3.93	4.00	5.17	-1.17	3.03	5.76	-2.72
	(18) Dividend Yield	5.41	8.41	-3.00	4.40	8.31	-3.91	4.12	3.72	0.40
	Combination	4.93	5.62	-0.69	4.74	4.74	0.00	6.12	5.41	0.71
Cornis-Fisher Ratio										
	(1) Asset Growth	5.29	1.06	4.23	5.29	-2.69	7.97	28.59	33.42	-4.83
	(2) Gross Profitability	4.50	-0.40	4.89	4.50	-0.11	4.60	23.24	3.60	19.63
	(3) Investment to Assets	4.98	0.47	4.51	4.98	-3.59	8.57	23.40	34.83	-11.43
	(4) Net Stock Issues	4.52	0.96	3.57	4.52	-2.16	6.68	11.04	18.94	-7.89
	(5) Net Operating Assets	3.26	0.06	3.20	3.26	-2.33	5.60	20.64	15.11	5.53
	(6) Total Accruals	3.38	0.96	2.42	3.38	-2.88	6.26	17.16	14.01	3.15
	(7) Ohlson's O	3.15	-0.85	4.01	3.15	-2.93	6.09	14.72	12.68	2.04
	(8) Return on Assets	1.52	-2.01	3.52	1.52	-5.03	6.55	10.57	11.84	-1.27
	(9) Failure Probability	6.10	1.03	5.07	6.10	-6.91	13.01	36.71	20.50	16.21
	(10) Momentum	5.02	-2.71	7.73	5.02	-5.17	10.18	3.64	7.99	-4.35
	(11) Composite Equity Issues	9.15	-0.45	9.60	9.15	-5.76	14.92	17.22	136.21	-118.99
	(12) Size	14.17	0.44	13.73	14.17	0.69	13.49	11.67	3.27	8.40
	(13) Book to Market	17.21	3.05	14.16	17.21	-2.10	19.31	10.31	28.85	-18.54
	(14) Operating Profitability	12.94	1.86	11.08	12.94	-0.56	13.50	0.36	8.73	-8.37
	(15) Investments	17.84	1.86	15.98	17.84	-1.76	19.61	45.89	29.33	16.56
	(16) Earning to Price	15.67	2.59	13.09	15.67	0.62	15.05	10.02	18.27	-8.26
	(17) Cash Flows to Price	15.08	2.86	12.22	15.08	0.18	14.90	11.67	21.94	-10.27
	(18) Dividend Yield	18.37	2.22	16.15	18.37	2.00	16.38	6.26	5.94	0.32
	Combination	9.01	0.72	8.29	9.01	-2.25	11.26	16.84	23.64	-6.80

Table 2.34: Anomalies during periods of high and low Fear (FVaR). The table reports values in months following high and low levels of Fear, as identified on the base of the median level of the FVaR index. Also reported is the performance on a strategy which equally combines the strategies available within a given month (Combination). For each anomaly we make use of all data available. Details of the length of the time series can be found in the section dedicated on Data. We report conditional Excess Returns, Standard Deviation, Skewness, Kurtosis, Sharpe Ratio and Cornish-Fisher Ratio for the long and short leg and for the Spread of the anomalies. We even report their difference. Excess Returns, Standard Deviation, Sharpe Ratio and Cornish-Fisher Ratio are reported in percentage.

FVaR		**Long Leg**			**Short Leg**			**Long-Short**		
Excess Returns		High Fear	Low Fear	High-Low	High Fear	Low Fear	High-Low	High Fear	Low Fear	High-Low
	(1) Asset Growth	0.28	0.08	0.20	-0.02	-0.20	0.18	0.36	0.44	-0.07
	(2) Gross Profitability	0.31	0.04	0.27	0.09	0.09	0.00	0.29	0.11	0.18
	(3) Investment to Assets	0.17	0.03	0.14	-0.02	-0.17	0.15	0.25	0.35	-0.10
	(4) Net Stock Issues	0.22	-0.02	0.25	0.09	-0.14	0.24	0.20	0.28	-0.08
	(5) Net Operating Assets	0.30	0.12	0.18	0.10	-0.11	0.22	0.26	0.39	-0.13
	(6) Total Accruals	-0.24	0.52	-0.76	-0.01	0.12	-0.13	-0.16	0.55	-0.72
	(7) Ohlson's O	0.20	0.06	0.15	-0.12	-0.03	-0.09	0.39	0.24	0.15
	(8) Return on Assets	0.31	0.16	0.14	-0.19	-0.61	0.42	0.56	0.93	-0.37
	(9) Failure Probability	0.40	0.68	-0.28	-0.10	-0.79	0.69	0.57	1.63	-1.06
	(10) Momentum	0.64	-0.95	1.60	0.75	-1.04	1.79	-0.04	0.24	-0.28
	(11) Composite Equity Issues	0.98	-0.80	1.78	0.50	-1.09	1.59	0.55	0.45	0.10
	(12) Size	1.39	-0.28	1.67	1.59	-0.28	1.88	-0.14	0.16	-0.30
	(13) Book to Market	1.62	-0.37	1.99	1.40	-0.26	1.66	0.29	0.05	0.24
	(14) Operating Profitability	1.67	-0.18	1.85	1.40	-0.29	1.69	0.34	0.27	0.07
	(15) Investments	1.80	-0.27	2.07	1.21	-0.32	1.54	0.65	0.21	0.44
	(16) Earning to Price	1.68	-0.37	2.05	1.48	-0.11	1.59	0.27	-0.10	0.37
	(17) Cash Flows to Price	1.84	-0.21	2.05	1.40	-0.18	1.59	0.50	0.12	0.38
	(18) Dividend Yield	1.61	-0.51	2.12	1.49	-0.24	1.74	0.18	-0.11	0.29
	Combination	0.84	-0.13	0.97	0.61	-0.31	0.93	0.30	0.34	-0.05
Standard Deviation										
	(1) Asset Growth	5.67	5.51	0.16	5.78	5.58	0.20	1.59	1.36	0.23
	(2) Gross Profitability	5.22	5.49	-0.27	5.61	5.17	0.44	1.94	1.93	0.00
	(3) Investment to Assets	5.94	5.85	0.09	6.31	5.97	0.34	1.86	1.42	0.44
	(4) Net Stock Issues	4.86	4.80	0.06	5.92	5.88	0.04	1.65	1.53	0.12
	(5) Net Operating Assets	5.83	5.50	0.33	6.05	5.74	0.30	1.46	1.46	0.00
	(6) Total Accruals	6.19	5.67	0.52	5.30	5.29	0.01	2.77	2.92	-0.15
	(7) Ohlson's O	6.05	5.44	0.61	5.65	5.13	0.52	1.58	2.02	-0.44
	(8) Return on Assets	5.56	5.14	0.42	5.61	6.00	-0.40	2.63	2.41	0.22
	(9) Failure Probability	5.93	6.79	-0.86	5.09	5.15	-0.06	3.20	4.49	-1.29
	(10) Momentum	4.58	6.36	-1.78	5.77	6.60	-0.82	4.31	3.70	0.61
	(11) Composite Equity Issues	4.09	5.53	-1.44	4.61	6.19	-1.58	1.72	1.47	0.24
	(12) Size	5.40	6.27	-0.87	4.51	5.51	-0.99	2.62	2.01	0.61
	(13) Book to Market	5.43	6.11	-0.68	5.12	6.27	-1.15	2.32	2.12	0.19
	(14) Operating Profitability	5.15	6.05	-0.90	5.53	6.46	-0.93	2.06	1.71	0.35
	(15) Investments	6.03	6.40	-0.37	5.19	6.49	-1.30	1.98	1.42	0.56
	(16) Earning to Price	4.96	6.23	-1.26	4.73	5.85	-1.11	1.41	1.63	-0.22
	(17) Cash Flows to Price	5.30	6.62	-1.32	4.70	5.74	-1.04	1.69	1.78	-0.09
	(18) Dividend Yield	4.49	5.44	-0.95	4.71	5.91	-1.20	2.31	2.51	-0.20
	Combination	5.37	5.84	-0.47	5.34	5.83	-0.49	2.17	2.10	0.07
Sharpe Ratio										
	(1) Asset Growth	4.91	1.47	3.44	-0.34	-3.59	3.25	22.95	32.27	-9.32
	(2) Gross Profitability	5.98	0.77	5.21	1.57	1.68	-0.11	15.01	5.78	9.22
	(3) Investment to Assets	2.85	0.49	2.36	-0.26	-2.77	2.51	13.57	24.76	-11.19
	(4) Net Stock Issues	4.63	-0.50	5.12	1.57	-2.45	4.02	12.07	18.11	-6.04
	(5) Net Operating Assets	5.16	2.21	2.95	1.71	-1.95	3.66	18.04	26.73	-8.69
	(6) Total Accruals	-3.81	9.16	-12.97	-0.15	2.29	-2.45	-5.81	19.00	-24.81
	(7) Ohlson's O	3.37	1.05	2.32	-2.10	-0.57	-1.53	24.68	12.06	12.62
	(8) Return on Assets	5.55	3.19	2.36	-3.34	-10.15	6.81	21.40	38.63	-17.23
	(9) Failure Probability	6.69	10.02	-3.33	-2.04	-15.33	13.30	17.73	36.25	-18.52
	(10) Momentum	14.03	-14.99	29.02	12.99	-15.79	28.78	-0.93	6.62	-7.55
	(11) Composite Equity Issues	24.09	-14.45	38.54	10.85	-17.62	28.47	32.14	30.46	1.69
	(12) Size	25.72	-4.45	30.17	35.27	-5.16	40.43	-5.16	8.07	-13.22
	(13) Book to Market	29.82	-6.08	35.91	27.35	-4.17	31.52	12.40	2.18	10.22
	(14) Operating Profitability	32.40	-2.97	35.37	25.26	-4.48	29.74	16.48	15.59	0.89
	(15) Investments	29.80	-4.23	34.03	23.39	-4.96	28.35	32.78	14.71	18.07
	(16) Earning to Price	33.88	-5.93	39.81	31.17	-1.88	33.06	19.26	-6.29	25.55
	(17) Cash Flows to Price	34.64	-3.23	37.87	29.90	-3.16	33.06	29.60	6.99	22.61
	(18) Dividend Yield	35.88	-9.37	45.24	31.72	-4.08	35.80	7.87	-4.46	12.33
	Combination	16.42	-2.10	18.52	12.47	-5.23	17.70	15.78	15.97	-0.19

		Long Leg			**Short Leg**			**Long-Short**		
Skewness		High Fear	Low Fear	High-Low	High Fear	Low Fear	High-Low	High Fear	Low Fear	High-Low
	(1) Asset Growth	-1.20	-0.08	-1.12	-1.92	0.10	-2.02	0.50	-0.09	0.60
	(2) Gross Profitability	-1.48	0.07	-1.55	-1.60	-0.29	-1.31	-0.46	0.72	-1.18
	(3) Investment to Assets	-1.30	0.09	-1.39	-1.97	0.23	-2.19	0.56	-1.06	1.63
	(4) Net Stock Issues	-1.67	0.01	-1.68	-1.68	-0.09	-1.59	0.59	-0.03	0.62
	(5) Net Operating Assets	-1.60	0.19	-1.79	-1.97	0.14	-2.11	0.43	-0.15	0.58
	(6) Total Accruals	-1.40	0.41	-1.81	-1.39	0.17	-1.56	0.30	0.49	-0.19
	(7) Ohlson's O	-1.76	-0.06	-1.70	-1.62	0.45	-2.08	-0.03	-0.41	0.38
	(8) Return on Assets	-1.81	0.14	-1.95	-1.17	0.11	-1.27	-0.64	-0.13	-0.50
	(9) Failure Probability	-1.56	0.61	-2.17	-1.08	-0.55	-0.53	-0.13	1.01	-1.14
	(10) Momentum	-0.81	-1.04	0.23	1.06	-0.93	2.00	-2.42	-1.06	-1.36
	(11) Composite Equity Issues	-0.45	-1.48	1.03	-0.54	-1.16	0.62	-0.08	0.39	-0.47
	(12) Size	0.45	-0.86	1.31	-0.05	-0.96	0.91	0.31	0.06	0.25
	(13) Book to Market	0.80	-1.03	1.83	0.18	-0.78	0.96	0.86	-0.28	1.14
	(14) Operating Profitability	0.78	-0.95	1.74	0.26	-0.83	1.09	-0.98	-1.44	0.46
	(15) Investments	0.79	-0.87	1.66	0.23	-0.78	1.01	1.67	-0.42	2.09
	(16) Earning to Price	1.00	-0.88	1.87	0.41	-0.84	1.25	0.29	-0.30	0.59
	(17) Cash Flows to Price	1.09	-1.01	2.09	0.35	-0.79	1.14	0.23	-0.20	0.42
	(18) Dividend Yield	0.81	-0.76	1.57	0.09	-0.84	0.93	1.08	0.38	0.71
	Combination	-0.52	-0.42	-0.10	-0.69	-0.42	-0.27	0.12	-0.14	0.26
Kurtosis										
	(1) Asset Growth	5.16	3.02	2.15	8.47	3.35	5.12	3.44	3.07	0.37
	(2) Gross Profitability	6.49	3.66	2.83	6.76	3.17	3.58	3.04	3.52	-0.47
	(3) Investment to Assets	5.46	3.55	1.90	8.87	4.14	4.73	4.93	6.72	-1.79
	(4) Net Stock Issues	7.23	3.60	3.63	6.84	3.31	3.54	3.36	3.31	0.05
	(5) Net Operating Assets	6.42	3.10	3.32	9.01	3.98	5.02	3.87	3.58	0.29
	(6) Total Accruals	5.68	3.74	1.95	5.90	4.05	1.86	2.81	5.77	-2.96
	(7) Ohlson's O	8.07	3.27	4.80	6.62	3.57	3.05	3.69	3.01	0.68
	(8) Return on Assets	7.37	3.27	4.10	5.30	4.26	1.05	3.85	3.55	0.29
	(9) Failure Probability	6.58	5.24	1.33	3.85	2.87	0.98	6.33	4.61	1.71
	(10) Momentum	3.70	4.38	-0.68	9.18	5.38	3.80	15.88	4.79	11.08
	(11) Composite Equity Issues	4.93	7.01	-2.08	3.18	5.31	-2.13	3.03	4.13	-1.10
	(12) Size	5.19	4.82	0.38	6.10	5.81	0.29	3.12	4.18	-1.06
	(13) Book to Market	6.40	4.84	1.56	5.36	5.14	0.22	3.89	2.98	0.91
	(14) Operating Profitability	7.29	5.41	1.88	4.77	4.88	-0.11	4.78	6.73	-1.95
	(15) Investments	6.15	4.67	1.48	5.52	4.94	0.57	8.39	3.05	5.33
	(16) Earning to Price	7.55	4.67	2.88	5.76	5.10	0.67	3.98	4.53	-0.55
	(17) Cash Flows to Price	8.41	5.12	3.29	5.93	5.00	0.93	4.56	3.49	1.06
	(18) Dividend Yield	7.53	4.67	2.87	4.94	5.60	-0.66	5.20	3.71	1.50
	Combination	6.42	4.33	2.09	6.24	4.44	1.81	4.90	4.15	0.74
Cornis-Fisher Ratio										
	(1) Asset Growth	1.56	0.62	0.94	1.56	-1.57	3.12	13.29	15.57	-2.28
	(2) Gross Profitability	1.78	0.34	1.44	1.78	0.67	1.11	5.96	3.32	2.64
	(3) Investment to Assets	0.88	0.22	0.66	0.88	-1.26	2.14	7.64	8.65	-1.02
	(4) Net Stock Issues	1.32	-0.21	1.53	1.32	-1.01	2.33	6.80	8.34	-1.54
	(5) Net Operating Assets	1.50	1.02	0.47	1.50	-0.87	2.36	9.84	12.32	-2.48
	(6) Total Accruals	-1.12	4.74	-5.86	-1.12	1.05	-2.18	-2.68	10.71	-13.40
	(7) Ohlson's O	0.94	0.45	0.49	0.94	-0.28	1.23	11.75	4.81	6.94
	(8) Return on Assets	1.54	1.46	0.08	1.54	-4.32	5.86	8.29	18.96	-10.67
	(9) Failure Probability	1.96	5.64	-3.68	1.96	-5.31	7.28	7.89	29.75	-21.85
	(10) Momentum	5.04	-4.62	9.67	5.04	-4.98	10.03	-0.23	2.18	-2.40
	(11) Composite Equity Issues	9.98	-4.06	14.04	9.98	-5.25	15.23	15.57	17.53	-1.96
	(12) Size	14.77	-1.48	16.26	14.77	-1.67	16.45	-2.40	3.67	-6.07
	(13) Book to Market	20.73	-1.94	22.67	20.73	-1.42	22.15	7.91	0.87	7.05
	(14) Operating Profitability	22.70	-0.97	23.67	22.70	-1.50	24.20	5.72	4.83	0.89
	(15) Investments	20.61	-1.41	22.01	20.61	-1.68	22.29	42.58	5.91	36.67
	(16) Earning to Price	27.02	-1.96	28.98	27.02	-0.64	27.66	10.03	-2.41	12.44
	(17) Cash Flows to Price	29.30	-1.04	30.35	29.30	-1.08	30.38	15.88	2.91	12.97
	(18) Dividend Yield	26.12	-3.14	29.26	26.12	-1.36	27.48	5.43	-2.13	7.56
	Combination	10.37	-0.35	10.72	10.37	-1.81	12.17	9.40	8.10	1.30

Table 2.35: Anomalies during periods of high and low level of Fear (FVaR L15-R15). The table reports values in months following high and low levels of Fear, as identified on the base of the median level of the Fear (FVAR L15-R15). Also reported is the performance on a strategy which equally combines the strategies available within a given month (Combination). For each anomaly we make use of all data available. Details of the length of the time series can be found in the section dedicated on Data. We report conditional Excess Returns, Standard Deviation, Skewness, Kurtosis, Sharpe Ratio and Cornish-Fisher Ratio for the long and short leg and for the Spread of the anomalies. We even report their difference. Excess Returns, Standard Deviation, Sharpe Ratio and Cornish-Fisher Ratio are reported in percentage.

FVaR L15-R15		Long Leg			Short Leg			Long-Short		
Excess Returns		High Fear	Low Fear	High-Low	High Fear	Low Fear	High-Low	High Fear	Low Fear	High-Low
	(1) Asset Growth	0.71	-0.47	1.18	0.41	-0.68	1.09	0.48	0.26	0.23
	(2) Gross Profitability	0.71	-0.28	1.00	0.53	-0.48	1.01	0.36	0.24	0.12
	(3) Investment to Assets	0.67	-0.54	1.20	0.64	-0.87	1.50	0.21	0.37	-0.16
	(4) Net Stock Issues	0.48	-0.30	0.77	0.49	-0.61	1.10	0.17	0.35	-0.18
	(5) Net Operating Assets	0.65	-0.27	0.92	0.64	-0.70	1.34	0.19	0.47	-0.27
	(6) Total Accruals	0.86	-0.85	1.71	0.61	-0.67	1.28	0.44	-0.14	0.58
	(7) Ohlson's O	0.69	-0.61	1.30	0.21	-0.36	0.58	0.66	-0.20	0.87
	(8) Return on Assets	0.66	-0.12	0.78	0.22	-1.20	1.43	0.62	1.13	-0.51
	(9) Failure Probability	1.16	-0.26	1.42	-0.21	-0.64	0.43	1.56	0.42	1.13
	(10) Momentum	1.16	-1.52	2.68	1.87	-2.11	3.99	-0.53	0.64	-1.17
	(11) Composite Equity Issues	1.54	-1.30	2.84	1.12	-1.74	2.87	0.59	0.49	0.11
	(12) Size	2.31	-1.27	3.58	2.13	-0.80	2.93	0.36	-0.42	0.78
	(13) Book to Market	2.58	-1.37	3.95	2.04	-0.95	3.00	0.71	-0.37	1.09
	(14) Operating Profitability	2.58	-1.08	3.66	2.25	-1.27	3.52	0.51	0.23	0.28
	(15) Investments	2.78	-1.29	4.08	2.05	-1.24	3.29	0.92	-0.01	0.93
	(16) Earning to Price	2.53	-1.23	3.76	2.19	-0.84	3.02	0.53	-0.35	0.87
	(17) Cash Flows to Price	2.83	-1.24	4.07	2.07	-0.86	2.93	0.94	-0.34	1.28
	(18) Dividend Yield	2.11	-0.96	3.07	2.11	-0.85	2.96	0.19	-0.06	0.25
	Combination	1.50	-0.83	2.33	1.19	-0.94	2.12	0.49	0.15	0.35
Standard Deviation										
	(1) Asset Growth	4.93	6.05	-1.11	4.70	6.34	-1.64	1.44	1.51	-0.07
	(2) Gross Profitability	4.60	5.91	-1.30	4.53	5.97	-1.45	1.89	2.08	-0.18
	(3) Investment to Assets	5.10	6.47	-1.37	5.23	6.64	-1.41	1.58	1.69	-0.12
	(4) Net Stock Issues	4.04	5.35	-1.30	4.90	6.58	-1.67	1.43	1.72	-0.29
	(5) Net Operating Assets	5.00	6.24	-1.24	4.89	6.53	-1.64	1.35	1.69	-0.34
	(6) Total Accruals	5.10	6.37	-1.27	4.65	5.81	-1.16	2.28	3.22	-0.94
	(7) Ohlson's O	4.72	6.50	-1.78	4.80	5.90	-1.10	1.75	1.90	-0.15
	(8) Return on Assets	4.71	5.84	-1.13	4.97	6.22	-1.25	2.60	2.35	0.24
	(9) Failure Probability	5.37	6.87	-1.50	4.55	5.54	-0.99	3.59	3.81	-0.22
	(10) Momentum	4.30	6.19	-1.89	5.21	6.46	-1.25	4.28	3.49	0.78
	(11) Composite Equity Issues	3.49	5.46	-1.97	4.08	6.23	-2.15	1.51	1.75	-0.24
	(12) Size	5.22	5.98	-0.76	3.75	5.59	-1.84	2.27	2.43	-0.16
	(13) Book to Market	5.11	5.72	-0.61	4.87	6.21	-1.34	1.92	2.36	-0.44
	(14) Operating Profitability	4.73	5.85	-1.12	5.31	6.23	-0.92	1.69	2.01	-0.32
	(15) Investments	5.84	6.16	-0.32	4.88	6.24	-1.36	1.92	1.44	0.48
	(16) Earning to Price	4.76	5.72	-0.95	4.41	5.73	-1.32	1.35	1.61	-0.26
	(17) Cash Flows to Price	5.08	6.04	-0.96	4.31	5.67	-1.36	1.46	1.75	-0.30
	(18) Dividend Yield	4.23	5.03	-0.80	4.19	5.90	-1.71	1.98	2.70	-0.72
	Combination	4.80	5.98	-1.19	4.68	6.10	-1.42	2.02	2.20	-0.18
Sharpe Ratio										
	(1) Asset Growth	14.49	-7.70	22.19	8.72	-10.75	19.48	33.65	16.99	16.67
	(2) Gross Profitability	15.45	-4.82	20.27	11.74	-8.04	19.78	18.99	11.40	7.59
	(3) Investment to Assets	13.06	-8.32	21.38	12.17	-13.05	25.22	13.26	21.87	-8.61
	(4) Net Stock Issues	11.80	-5.56	17.35	10.02	-9.22	19.24	11.56	20.33	-8.77
	(5) Net Operating Assets	13.06	-4.34	17.40	13.10	-10.66	23.76	14.33	27.70	-13.37
	(6) Total Accruals	16.93	-13.34	30.27	13.03	-11.51	24.55	19.16	-4.34	23.50
	(7) Ohlson's O	14.71	-9.38	24.09	4.43	-6.17	10.59	37.84	-10.77	48.61
	(8) Return on Assets	14.07	-1.99	16.06	4.46	-19.35	23.81	23.90	47.95	-24.05
	(9) Failure Probability	21.65	-3.80	25.45	-4.70	-11.60	6.90	43.31	11.09	32.22
	(10) Momentum	27.06	-24.48	51.54	35.97	-32.73	68.70	-12.34	18.30	-30.64
	(11) Composite Equity Issues	44.09	-23.75	67.84	27.53	-27.94	55.47	39.47	27.75	11.72
	(12) Size	44.31	-21.20	65.51	56.88	-14.38	71.26	15.95	-17.38	33.33
	(13) Book to Market	50.44	-23.95	74.39	41.97	-15.37	57.34	37.13	-15.82	52.95
	(14) Operating Profitability	54.62	-18.51	73.13	42.46	-20.37	62.82	29.98	11.27	18.71
	(15) Investments	47.68	-20.95	68.63	41.88	-19.87	61.75	47.75	-0.69	48.45
	(16) Earning to Price	53.20	-21.43	74.63	49.61	-14.63	64.23	39.05	-21.53	60.58
	(17) Cash Flows to Price	55.63	-20.54	76.16	47.99	-15.12	63.10	64.38	-19.45	83.83
	(18) Dividend Yield	49.95	-19.00	68.94	50.30	-14.44	64.74	9.38	-2.33	11.72
	Combination	31.23	-14.06	45.29	25.98	-15.29	41.26	27.04	6.80	20.25

		Long Leg			Short Leg			Long-Short		
Skewness		High Fear	Low Fear	High-Low	High Fear	Low Fear	High-Low	High Fear	Low Fear	High-Low
	(1) Asset Growth	-0.04	-0.80	0.75	-0.07	-1.18	1.11	0.18	0.30	-0.12
	(2) Gross Profitability	0.32	-0.93	1.26	-0.31	-1.16	0.86	0.41	0.01	0.40
	(3) Investment to Assets	0.14	-0.79	0.93	0.05	-1.39	1.45	0.30	-0.02	0.32
	(4) Net Stock Issues	-0.02	-1.04	1.02	-0.20	-1.02	0.82	0.23	0.31	-0.08
	(5) Net Operating Assets	-0.09	-0.94	0.86	0.14	-1.35	1.49	-0.13	0.30	-0.43
	(6) Total Accruals	-0.05	-0.76	0.71	-0.01	-0.82	0.80	0.81	0.46	0.35
	(7) Ohlson's O	-0.07	-1.16	1.08	-0.18	-0.97	0.79	-0.35	-0.21	-0.14
	(8) Return on Assets	-0.34	-1.16	0.82	0.34	-0.75	1.09	-0.69	-0.24	-0.45
	(9) Failure Probability	0.78	-0.66	1.44	-0.56	-0.81	0.26	0.95	0.71	0.24
	(10) Momentum	-0.91	-0.73	-0.18	1.76	-0.65	2.41	-2.99	0.15	-3.14
	(11) Composite Equity Issues	0.17	-1.15	1.32	-0.41	-0.70	0.29	0.05	0.04	0.01
	(12) Size	0.71	-0.76	1.47	1.06	-0.68	1.74	0.35	0.13	0.22
	(13) Book to Market	1.08	-0.96	2.05	0.60	-0.56	1.16	1.09	0.36	0.73
	(14) Operating Profitability	1.20	-0.65	1.85	0.60	-0.73	1.33	-0.49	-1.45	0.95
	(15) Investments	0.92	-0.66	1.58	0.76	-0.68	1.45	1.70	-0.47	2.17
	(16) Earning to Price	1.31	-0.86	2.17	0.71	-0.54	1.25	0.99	-0.33	1.32
	(17) Cash Flows to Price	1.37	-0.98	2.35	0.84	-0.53	1.37	0.91	0.01	0.90
	(18) Dividend Yield	1.55	-1.02	2.57	0.51	-0.51	1.02	0.53	0.68	-0.15
	Combination	0.45	-0.89	1.34	0.31	-0.84	1.15	0.21	0.04	0.17
Kurtosis										
	(1) Asset Growth	3.34	3.94	-0.60	3.74	5.86	-2.12	2.70	3.90	-1.20
	(2) Gross Profitability	3.77	4.57	-0.80	2.96	5.35	-2.39	3.09	3.15	-0.06
	(3) Investment to Assets	3.49	4.21	-0.72	4.48	6.82	-2.34	4.34	6.51	-2.17
	(4) Net Stock Issues	4.25	5.09	-0.84	3.21	4.82	-1.61	3.23	2.96	0.28
	(5) Net Operating Assets	3.47	4.89	-1.42	4.24	6.45	-2.22	4.53	2.87	1.66
	(6) Total Accruals	4.67	4.86	-0.19	4.55	4.31	0.24	4.40	3.93	0.47
	(7) Ohlson's O	3.50	5.84	-2.33	3.37	5.85	-2.49	4.15	3.19	0.96
	(8) Return on Assets	3.77	5.87	-2.11	5.03	3.77	1.26	3.89	3.63	0.26
	(9) Failure Probability	7.02	4.71	2.31	3.03	3.13	-0.10	9.21	4.05	5.15
	(10) Momentum	3.59	4.12	-0.52	10.45	4.54	5.91	14.98	3.65	11.33
	(11) Composite Equity Issues	4.20	6.01	-1.82	3.08	4.33	-1.25	3.30	2.97	0.33
	(12) Size	4.75	4.17	0.58	6.74	4.84	1.90	3.43	3.16	0.27
	(13) Book to Market	6.37	4.23	2.14	5.01	4.44	0.57	4.77	2.80	1.98
	(14) Operating Profitability	7.82	4.82	2.99	4.42	4.11	0.31	3.26	6.28	-3.02
	(15) Investments	5.62	4.16	1.46	5.25	4.33	0.91	7.95	2.58	5.37
	(16) Earning to Price	7.58	4.30	3.28	5.92	4.53	1.38	4.04	3.55	0.48
	(17) Cash Flows to Price	8.20	4.90	3.30	6.06	4.37	1.69	4.59	3.35	1.24
	(18) Dividend Yield	7.85	4.24	3.61	5.16	4.82	0.35	3.07	4.40	-1.33
	Combination	5.18	4.72	0.46	4.82	4.82	0.00	4.94	3.72	1.22
Cornis-Fisher Ratio										
	(1) Asset Growth	6.55	-2.58	9.12	6.55	-3.25	9.80	18.13	8.77	9.37
	(2) Gross Profitability	7.99	-1.57	9.56	7.99	-2.46	10.45	10.35	5.17	5.18
	(3) Investment to Assets	6.23	-2.78	9.01	6.23	-3.75	9.98	6.72	10.31	-3.59
	(4) Net Stock Issues	5.30	-1.77	7.07	5.30	-2.91	8.21	5.66	10.72	-5.06
	(5) Net Operating Assets	5.78	-1.42	7.20	5.78	-3.11	8.90	6.29	15.14	-8.85
	(6) Total Accruals	7.71	-4.42	12.12	7.71	-3.79	11.49	12.44	-2.13	14.58
	(7) Ohlson's O	6.59	-2.87	9.46	6.59	-1.99	8.58	17.16	-4.16	21.32
	(8) Return on Assets	5.77	-0.62	6.40	5.77	-6.30	12.07	9.20	23.71	-14.51
	(9) Failure Probability	14.09	-1.33	15.42	14.09	-3.81	17.90	36.34	6.55	29.79
	(10) Momentum	9.93	-7.88	17.81	9.93	-10.45	20.38	-2.66	9.02	-11.67
	(11) Composite Equity Issues	25.02	-6.96	31.98	25.02	-8.95	33.97	20.81	13.73	7.08
	(12) Size	32.55	-6.84	39.39	32.55	-4.84	37.39	8.36	-7.24	15.60
	(13) Book to Market	49.17	-7.31	56.48	49.17	-5.32	54.49	32.21	-7.12	39.33
	(14) Operating Profitability	60.87	-6.19	67.06	60.87	-6.64	67.52	12.55	3.44	9.11
	(15) Investments	40.53	-6.93	47.46	40.53	-6.56	47.09	79.39	-0.26	79.64
	(16) Earning to Price	64.02	-6.76	70.77	64.02	-5.10	69.12	32.34	-7.72	40.06
	(17) Cash Flows to Price	73.12	-6.31	79.43	73.12	-5.27	78.39	63.63	-7.74	71.37
	(18) Dividend Yield	72.40	-5.82	78.21	72.40	-5.07	77.47	5.09	-1.26	6.35
	Combination	27.42	-4.46	31.89	27.42	-4.98	32.40	20.78	3.83	16.95

Table 2.36: Anomalies during periods of high and low level of Fear (FCVaR). The table reports values in months following high and low levels of Fear, as identified on the base of the median level of the Fear (FCVaR). Also reported is the performance on a strategy which equally combines the strategies available within a given month (Combination). For each anomaly we make use of all data available. Details of the length of the time series can be found in the section dedicated on Data. We report conditional Excess Returns, Standard Deviation, Skewness, Kurtosis, Sharpe Ratio and Cornish-Fisher Ratio for the long and short leg and for the Spread of the anomalies. We even report their difference. Excess Returns, Standard Deviation, Sharpe Ratio and Cornish-Fisher Ratio are reported in percentage.

FCVaR		Long Leg			Short Leg			Long-Short		
Excess Returns		High FCVaR	Low FCVaR	High-Low	High FCVaR	Low FCVaR	High-Low	High FCVaR	Low FCVaR	High-Low
	(1) Asset Growth	0.05	0.26	-0.21	-0.28	0.07	-0.36	0.52	0.23	0.29
	(2) Gross Profitability	0.10	0.40	-0.31	-0.13	0.20	-0.33	0.41	0.24	0.17
	(3) Investment to Assets	-0.06	0.27	-0.33	-0.18	0.04	-0.22	0.30	0.27	0.03
	(4) Net Stock Issues	-0.03	0.28	-0.31	-0.27	0.19	-0.46	0.42	0.13	0.29
	(5) Net Operating Assets	-0.05	0.48	-0.53	-0.13	0.15	-0.29	0.26	0.36	-0.10
	(6) Total Accruals	-0.10	0.25	-0.35	-0.05	0.02	-0.08	0.13	0.26	-0.13
	(7) Ohlson's O	-0.08	0.26	-0.33	-0.39	0.34	-0.73	0.50	-0.04	0.54
	(8) Return on Assets	0.12	0.53	-0.41	-0.54	-0.44	-0.11	0.84	1.00	-0.16
	(9) Failure Probability	0.14	0.80	-0.65	-0.46	-0.33	-0.13	0.79	1.17	-0.38
	(10) Momentum	1.54	-1.83	3.37	1.38	-1.56	2.94	0.34	-0.24	0.58
	(11) Composite Equity Issues	1.43	-1.13	2.56	1.24	-1.78	3.03	0.37	0.70	-0.32
	(12) Size	1.99	-0.87	2.86	1.98	-0.59	2.56	0.20	-0.24	0.44
	(13) Book to Market	2.21	-0.91	3.12	1.81	-0.65	2.46	0.59	-0.22	0.81
	(14) Operating Profitability	2.23	-0.66	2.88	1.97	-0.91	2.88	0.44	0.29	0.15
	(15) Investments	2.40	-0.82	3.22	1.76	-0.90	2.66	0.82	0.12	0.70
	(16) Earning to Price	2.09	-0.68	2.77	1.97	-0.57	2.54	0.30	-0.08	0.38
	(17) Cash Flows to Price	2.36	-0.68	3.04	1.85	-0.57	2.41	0.70	-0.07	0.77
	(18) Dividend Yield	1.75	-0.52	2.27	1.99	-0.66	2.65	-0.06	0.18	-0.23
	Combination	1.00	-0.25	1.26	0.75	-0.44	1.19	0.44	0.23	0.21
Standard Deviation										
	(1) Asset Growth	4.66	6.30	-1.64	4.36	6.61	-2.25	1.40	1.55	-0.15
	(2) Gross Profitability	4.12	6.26	-2.15	4.50	6.03	-1.53	1.86	1.98	-0.12
	(3) Investment to Assets	4.72	6.78	-2.07	4.80	7.01	-2.21	1.41	1.83	-0.42
	(4) Net Stock Issues	3.66	5.62	-1.96	4.65	6.79	-2.14	1.47	1.66	-0.19
	(5) Net Operating Assets	4.67	6.51	-1.84	4.46	6.87	-2.41	1.02	1.90	-0.87
	(6) Total Accruals	4.74	6.71	-1.97	4.28	6.14	-1.86	2.42	3.13	-0.71
	(7) Ohlson's O	4.51	6.71	-2.20	4.47	6.10	-1.63	1.84	1.88	-0.04
	(8) Return on Assets	4.40	6.06	-1.67	4.45	6.69	-2.24	2.40	2.46	-0.06
	(9) Failure Probability	4.37	7.60	-3.23	4.60	5.50	-0.90	2.77	4.51	-1.74
	(10) Momentum	3.90	6.33	-2.43	3.55	7.76	-4.22	2.24	5.10	-2.86
	(11) Composite Equity Issues	2.95	5.88	-2.93	3.58	6.54	-2.96	1.41	1.82	-0.41
	(12) Size	4.06	7.04	-2.98	2.80	6.24	-3.44	2.14	2.59	-0.45
	(13) Book to Market	3.94	6.86	-2.92	3.81	7.05	-3.24	1.92	2.42	-0.50
	(14) Operating Profitability	3.47	6.90	-3.43	4.21	7.22	-3.01	1.65	2.06	-0.40
	(15) Investments	4.62	7.40	-2.78	3.66	7.20	-3.54	1.86	1.59	0.27
	(16) Earning to Price	3.49	6.87	-3.38	3.30	6.57	-3.26	1.23	1.80	-0.57
	(17) Cash Flows to Price	3.62	7.32	-3.70	3.28	6.47	-3.20	1.33	2.00	-0.67
	(18) Dividend Yield	3.09	6.02	-2.93	3.27	6.56	-3.29	1.71	2.88	-1.17
	Combination	4.05	6.62	-2.57	4.00	6.63	-2.63	1.78	2.40	-0.61
Sharpe Ratio										
	(1) Asset Growth	1.07	4.13	-3.06	-6.51	1.09	-7.60	36.90	14.65	22.25
	(2) Gross Profitability	2.36	6.47	-4.10	-2.98	3.32	-6.30	22.24	12.27	9.97
	(3) Investment to Assets	-1.27	3.99	-5.25	-3.76	0.53	-4.30	21.49	14.80	6.69
	(4) Net Stock Issues	-0.74	5.04	-5.78	-5.77	2.77	-8.54	28.89	8.08	20.81
	(5) Net Operating Assets	-1.12	7.36	-8.48	-3.01	2.22	-5.23	25.81	19.24	6.57
	(6) Total Accruals	-2.21	3.70	-5.91	-1.22	0.38	-1.61	5.37	8.40	-3.04
	(7) Ohlson's O	-1.70	3.85	-5.55	-8.78	5.50	-14.28	27.13	-2.07	29.20
	(8) Return on Assets	2.66	8.68	-6.01	-12.17	-6.52	-5.65	35.00	40.72	-5.71
	(9) Failure Probability	3.30	10.51	-7.21	-10.02	-6.03	-3.98	28.41	25.91	2.51
	(10) Momentum	39.48	-28.91	68.39	38.88	-20.05	58.93	15.29	-4.61	19.90
	(11) Composite Equity Issues	48.62	-19.15	67.77	34.73	-27.26	61.99	26.59	38.29	-11.70
	(12) Size	49.01	-12.34	61.35	70.44	-9.41	79.85	9.28	-9.40	18.67
	(13) Book to Market	56.15	-13.27	69.42	47.44	-9.28	56.72	30.59	-8.97	39.56
	(14) Operating Profitability	64.16	-9.52	73.68	46.84	-12.61	59.45	26.53	14.22	12.31
	(15) Investments	51.84	-11.09	62.94	48.14	-12.47	60.61	43.83	7.28	36.56
	(16) Earning to Price	59.82	-9.95	69.77	59.68	-8.68	68.36	24.57	-4.19	28.76
	(17) Cash Flows to Price	65.13	-9.31	74.44	56.34	-8.78	65.12	52.49	-3.75	56.24
	(18) Dividend Yield	56.58	-8.71	65.29	60.73	-10.08	70.81	-3.27	6.10	-9.37
	Combination	27.40	-3.81	31.21	22.72	-6.41	29.13	25.40	9.83	15.57

		Long Leg			Short Leg			Long-Short		
Skewness		High FCVaR	Low FCVaR	High-Low	High FCVaR	Low FCVaR	High-Low	High FCVaR	Low FCVaR	High-Low
	(1) Asset Growth	-0.46	-0.67	0.21	-0.62	-1.06	0.43	0.17	0.33	-0.15
	(2) Gross Profitability	-0.38	-0.69	0.31	-0.53	-1.19	0.66	0.34	0.42	-0.08
	(3) Investment to Assets	-0.44	-0.64	0.20	-0.63	-1.12	0.49	0.53	-0.03	0.56
	(4) Net Stock Issues	-0.67	-0.87	0.20	-0.60	-0.97	0.37	0.43	0.30	0.13
	(5) Net Operating Assets	-0.62	-0.79	0.17	-0.55	-1.13	0.58	0.53	0.11	0.42
	(6) Total Accruals	-0.88	-0.56	-0.32	-0.62	-0.61	-0.01	0.46	0.38	0.08
	(7) Ohlson's O	-0.57	-1.10	0.53	-0.59	-0.88	0.29	-0.13	-0.46	0.33
	(8) Return on Assets	-0.75	-1.04	0.29	-0.51	-0.43	-0.07	-0.85	-0.17	-0.68
	(9) Failure Probability	-0.69	-0.27	-0.42	-0.65	-0.84	0.19	-0.52	0.93	-1.45
	(10) Momentum	-0.63	-0.64	0.01	-0.25	0.43	-0.69	-0.95	-1.57	0.62
	(11) Composite Equity Issues	-0.49	-0.72	0.22	-0.52	-0.49	-0.03	-0.20	0.04	-0.24
	(12) Size	-0.14	0.12	-0.26	-0.21	-0.06	-0.15	0.53	0.06	0.47
	(13) Book to Market	0.04	0.21	-0.17	-0.42	0.06	-0.48	1.13	0.25	0.88
	(14) Operating Profitability	-0.22	0.28	-0.50	-0.24	0.06	-0.30	-0.28	-1.51	1.23
	(15) Investments	0.02	0.40	-0.38	-0.32	0.04	-0.37	1.78	0.09	1.69
	(16) Earning to Price	-0.07	0.22	-0.29	-0.38	0.12	-0.50	0.80	-0.12	0.91
	(17) Cash Flows to Price	-0.21	0.23	-0.44	-0.31	0.12	-0.43	-0.04	0.44	-0.49
	(18) Dividend Yield	0.19	0.16	0.03	-0.27	-0.03	-0.24	0.34	0.53	-0.19
	Combination	-0.39	-0.35	-0.03	-0.46	-0.44	-0.01	0.22	0.00	0.22
Kurtosis										
	(1) Asset Growth	2.80	4.14	-1.34	2.87	5.88	-3.00	2.91	3.66	-0.76
	(2) Gross Profitability	2.37	4.68	-2.31	2.63	5.78	-3.15	2.93	2.82	0.10
	(3) Investment to Assets	2.42	4.43	-2.01	3.18	6.89	-3.71	5.16	5.25	-0.10
	(4) Net Stock Issues	3.36	5.09	-1.72	2.88	4.92	-2.04	3.37	3.08	0.29
	(5) Net Operating Assets	2.87	4.94	-2.07	2.76	6.52	-3.76	3.88	2.73	1.15
	(6) Total Accruals	3.88	5.04	-1.16	3.05	4.62	-1.57	4.15	4.06	0.09
	(7) Ohlson's O	2.81	6.05	-3.24	2.91	5.89	-2.98	3.53	3.34	0.19
	(8) Return on Assets	3.33	5.89	-2.56	3.46	4.12	-0.66	4.65	3.41	1.24
	(9) Failure Probability	3.84	4.85	-1.01	2.70	3.47	-0.77	8.51	4.53	3.98
	(10) Momentum	2.77	3.77	-1.00	2.68	5.66	-2.98	5.05	8.60	-3.55
	(11) Composite Equity Issues	2.95	5.29	-2.34	2.84	3.84	-1.00	3.54	2.71	0.83
	(12) Size	2.56	4.41	-1.85	2.48	4.64	-2.16	4.15	2.69	1.46
	(13) Book to Market	2.97	5.28	-2.30	2.59	4.29	-1.70	5.01	2.63	2.39
	(14) Operating Profitability	2.56	5.34	-2.78	2.64	4.22	-1.58	2.88	6.21	-3.33
	(15) Investments	2.88	5.25	-2.36	2.45	4.23	-1.78	9.04	3.84	5.20
	(16) Earning to Price	2.78	5.08	-2.30	2.47	4.45	-1.98	4.27	3.51	0.76
	(17) Cash Flows to Price	2.76	5.59	-2.83	2.46	4.41	-1.95	3.59	3.89	-0.31
	(18) Dividend Yield	3.57	5.22	-1.65	2.47	4.40	-1.93	2.88	3.59	-0.71
	Combination	2.97	5.02	-2.05	2.75	4.90	-2.15	4.42	3.92	0.50
Cornis-Fisher Ratio										
	(1) Asset Growth	0.40	1.49	-1.09	0.40	0.35	0.05	20.17	7.55	12.61
	(2) Gross Profitability	0.91	2.33	-1.42	0.91	1.05	-0.13	11.98	6.46	5.51
	(3) Investment to Assets	-0.48	1.45	-1.92	-0.48	0.17	-0.65	12.46	6.72	5.74
	(4) Net Stock Issues	-0.26	1.73	-1.99	-0.26	0.92	-1.18	16.78	3.99	12.79
	(5) Net Operating Assets	-0.40	2.60	-3.00	-0.40	0.71	-1.11	15.38	9.36	6.02
	(6) Total Accruals	-0.74	1.37	-2.11	-0.74	0.14	-0.88	2.77	4.28	-1.50
	(7) Ohlson's O	-0.61	1.24	-1.86	-0.61	1.89	-2.50	12.60	-0.77	13.37
	(8) Return on Assets	0.93	2.89	-1.95	0.93	-2.41	3.34	13.46	19.95	-6.49
	(9) Failure Probability	1.18	4.34	-3.16	1.18	-2.01	3.18	11.73	18.75	-7.01
	(10) Momentum	16.48	-9.36	25.84	16.48	-9.08	25.56	5.32	-1.31	6.63
	(11) Composite Equity Issues	22.07	-6.29	28.36	22.07	-9.22	31.30	12.03	19.98	-7.95
	(12) Size	25.32	-5.23	30.54	25.32	-3.82	29.13	5.04	-3.96	9.00
	(13) Book to Market	32.41	-5.76	38.17	32.41	-3.90	36.31	25.73	-4.02	29.76
	(14) Operating Profitability	34.78	-4.29	39.08	34.78	-5.24	40.03	11.70	4.32	7.38
	(15) Investments	28.85	-5.17	34.03	28.85	-5.16	34.01	75.42	3.32	72.10
	(16) Earning to Price	33.63	-4.39	38.02	33.63	-3.73	37.36	16.44	-1.71	18.15
	(17) Cash Flows to Price	35.66	-4.14	39.80	35.66	-3.78	39.43	28.62	-1.84	30.46
	(18) Dividend Yield	34.93	-3.80	38.73	34.93	-4.11	39.04	-1.55	3.25	-4.80
	Combination	14.73	-1.61	16.34	14.73	-2.62	17.35	16.45	5.24	11.21

Table 2.37: In this table we present the result of predictive regressions on long-short strategies. The table reports estimates of b in the regression $R_{i,t} = a + bX_{t-T} + u_t$ where $R_{i,t}$ is the excess return in month ton either the long leg, short leg, or the difference, T is the length of the lag and is equal to 1, 3 or 6, while X is one of the following predictors: PLS6, UM, VIX, VRP, FVaR. The values of b are multiplied by 100 in the table.

	Long Leg		Short Leg		SPREAD		Long Leg		Short Leg		SPREAD		Long Leg		Short Leg		SPREAD	
PLS6	t+1 b	t stat	b	t stat	b	t stat	t+3 b	t stat	b	t stat	b	t stat	t+6 b	t stat	b	t stat	b	t stat
(1) Asset Growth	**-0.81**	-3.57	**-1.06**	-4.09	**0.38**	4.65	**-0.71**	-3.11	**-0.96**	-3.69	**0.38**	4.66	-0.41	-1.77	**-0.71**	-2.72	**0.43**	5.24
(2) Gross Profitability	**-0.78**	-3.24	**-0.80**	-3.80	0.15	1.54	**-0.68**	-2.82	**-0.72**	-3.40	**0.17**	1.69	-0.41	-1.69	**-0.51**	-2.40	**0.22**	2.23
(3) Investment to Assets	**-0.79**	-3.44	**-1.02**	-3.96	**0.36**	4.70	**-0.70**	-3.03	**-0.92**	-3.57	**0.35**	4.59	-0.41	-1.76	**-0.66**	-2.53	**0.37**	4.83
(4) Net Stock Issues	**-0.76**	-3.63	**-0.96**	-3.94	**0.33**	4.00	**-0.66**	-3.13	**-0.84**	-3.45	**0.32**	3.81	-0.37	-1.76	**-0.60**	-2.43	**0.35**	4.19
(5) Net Operating Assets	**-0.82**	-3.42	**-0.96**	-3.93	**0.28**	3.83	**-0.72**	-3.02	**-0.87**	-3.54	**0.28**	3.83	**-0.48**	-1.98	**-0.60**	-2.45	**0.25**	3.45
(6) Total Accruals	**-0.61**	-2.34	**-0.96**	-3.40	**0.51**	4.42	-0.47	-1.82	**-0.87**	-3.12	**0.55**	4.94	-0.21	-0.83	**-0.63**	-2.31	**0.56**	5.11
(7) Ohlson's O	**-0.87**	-3.67	**-0.78**	-3.34	0.04	0.43	**-0.80**	-3.37	**-0.68**	-2.89	0.01	0.09	**-0.54**	-2.24	**-0.51**	-2.15	0.09	0.94
(8) Return on Assets	**-0.88**	-3.14	**-0.75**	-2.72	0.04	0.33	**-0.67**	-2.36	-0.53	-1.93	0.03	0.28	-0.25	-0.89	-0.09	-0.33	-0.01	-0.05
(9) Failure Probability	**-0.57**	-1.91	**-0.93**	-3.29	**0.53**	2.76	-0.38	-1.27	**-0.77**	-2.72	**0.56**	2.92	0.06	0.20	-0.40	-1.39	**0.61**	3.18
(10) Momentum	**-0.90**	-3.75	**-0.98**	-3.93	0.21	1.35	**-0.83**	-3.45	**-0.91**	-3.64	0.21	1.34	**-0.70**	-2.89	**-0.74**	-2.93	0.16	1.02
(11) Composite Equity Issues	**-0.71**	-3.63	**-1.05**	-4.34	**0.47**	4.75	**-0.63**	-3.18	**-0.96**	-3.99	**0.47**	4.77	**-0.44**	-2.24	**-0.81**	-3.32	**0.49**	4.94
(12) Size	**-0.97**	-3.69	**-0.65**	-3.29	-0.18	-1.11	**-0.95**	-3.59	**-0.57**	-2.83	-0.25	-1.51	**-0.73**	-2.73	**-0.42**	-2.09	-0.18	-1.09
(13) Book to Market	**-0.75**	-3.17	**-1.00**	-3.67	**0.39**	3.12	**-0.71**	-3.00	**-0.97**	-3.52	**0.39**	3.13	**-0.46**	-1.94	**-0.82**	-2.99	**0.48**	3.91
(14) Operating Profitability	**-0.81**	-3.44	**-1.00**	-3.65	**0.33**	2.80	**-0.70**	-2.99	**-1.00**	-3.63	**0.43**	3.65	**-0.49**	-2.06	**-0.79**	-2.86	**0.43**	3.67
(15) Investments	**-0.89**	-3.37	**-1.01**	-3.78	**0.26**	3.10	**-0.87**	-3.29	**-0.96**	-3.58	**0.22**	2.70	**-0.62**	-2.34	**-0.77**	-2.85	**0.27**	3.30
(16) Earning to Price	**-0.60**	-2.75	**-0.94**	-3.78	**0.47**	4.91	**-0.52**	-2.35	**-0.88**	-3.51	**0.49**	5.12	-0.27	-1.25	**-0.73**	-2.90	**0.58**	6.05
(17) Cash Flows to Price	**-0.66**	-2.91	**-0.93**	-3.81	**0.41**	4.57	**-0.57**	-2.54	**-0.87**	-3.53	**0.42**	4.74	-0.34	-1.50	**-0.71**	-2.87	**0.49**	5.55
(18) Dividend Yield	**-0.42**	-2.45	**-0.75**	-3.38	**0.46**	4.46	-0.33	-1.91	**-0.65**	-2.91	**0.45**	4.34	-0.08	-0.45	**-0.48**	-2.12	**0.52**	5.04
Comination	**-0.49**	-2.52	**-0.70**	-3.42	**0.39**	9.57	-0.35	-1.79	**-0.57**	-2.77	**0.40**	9.68	0.02	0.09	-0.25	-1.19	**0.42**	10.40

UM	t+1 b	t stat	b	t stat	b	t stat	t+3 b	t stat	b	t stat	b	t stat	t+6 b	t stat	b	t stat	b	t stat
(1) Asset Growth	**-2.11**	-0.67	**-2.52**	-0.71	0.70	0.60	0.74	0.24	0.49	0.14	0.46	0.39	3.24	1.03	2.29	0.65	0.98	0.85
(2) Gross Profitability	0.47	0.14	**-3.62**	-1.18	**4.38**	3.29	2.98	0.90	-1.31	-0.42	**4.49**	3.36	4.41	1.34	0.91	0.29	**3.53**	2.62
(3) Investment to Assets	-1.92	-0.61	-1.04	-0.29	-0.59	-0.51	0.99	0.32	2.28	0.64	-1.09	-0.95	3.57	1.14	4.22	1.19	-0.62	-0.54
(4) Net Stock Issues	**-2.31**	-0.87	**-2.82**	-0.81	0.79	0.59	0.54	0.20	-0.06	-0.02	0.81	0.59	2.81	1.05	2.07	0.60	0.76	0.56
(5) Net Operating Assets	-1.43	-0.43	-1.74	-0.52	0.59	0.52	1.05	0.31	1.54	0.46	-0.29	-0.25	2.80	0.83	3.72	1.12	-0.90	-0.79
(6) Total Accruals	0.59	0.18	-0.45	-0.14	1.34	0.89	3.72	1.15	2.37	0.71	1.55	1.04	5.17	1.60	4.35	1.30	0.85	0.57
(7) Ohlson's O	-0.84	-0.26	-0.89	-0.26	0.35	0.24	2.44	0.77	1.41	0.41	1.23	0.84	4.65	1.46	2.58	0.75	**2.10**	1.43
(8) Return on Assets	-0.97	-0.29	**-2.43**	-0.72	1.74	1.17	1.56	0.46	0.55	0.16	1.21	0.81	3.12	0.92	3.21	0.94	-0.06	-0.04
(9) Failure Probability	1.00	0.27	**-2.25**	-0.68	**3.54**	1.51	3.87	1.06	-0.93	-0.28	**5.00**	2.14	5.74	1.58	0.69	0.21	**5.08**	2.17
(10) Momentum	**-7.78**	-2.34	-1.36	-0.39	**-6.13**	-2.79	-3.97	-1.18	3.65	1.04	**-7.41**	-3.38	-1.49	-0.44	6.20	1.77	**-7.66**	-3.48
(11) Composite Equity Issues	**-5.49**	-2.14	**-5.29**	-1.54	0.09	0.05	-1.36	-0.53	-1.30	-0.38	0.15	0.09	1.59	0.61	0.75	0.22	0.86	0.52
(12) Size	-1.30	-0.36	**-5.03**	-1.73	**4.02**	1.79	3.68	1.02	-0.95	-0.33	**4.83**	2.15	6.54	1.82	1.63	0.56	**4.94**	2.18
(13) Book to Market	-2.99	-0.95	-1.02	-0.26	-1.68	-0.93	1.86	0.59	3.30	0.84	-1.24	-0.68	5.81	1.84	4.65	1.18	1.19	0.65
(14) Operating Profitability	-2.08	-0.67	-1.21	-0.31	-0.59	-0.31	3.00	0.96	3.49	0.89	-0.30	-0.15	5.69	1.82	5.99	1.52	-0.27	-0.14
(15) Investments	-1.03	-0.27	-1.80	-0.48	1.06	0.85	4.18	1.11	2.84	0.76	1.54	1.24	**7.65**	2.03	4.74	1.27	**2.94**	2.37
(16) Earning to Price	-2.27	-0.79	-2.65	-0.80	0.68	0.49	2.13	0.74	1.85	0.55	0.48	0.35	5.55	1.92	3.93	1.17	1.64	1.20
(17) Cash Flows to Price	-1.58	-0.52	-2.72	-0.83	1.42	1.13	3.25	1.07	1.67	0.51	1.77	1.41	**6.77**	2.24	3.72	1.13	**3.08**	2.45
(18) Dividend Yield	-3.08	-1.32	-3.60	-1.25	0.81	0.60	0.76	0.33	0.89	0.31	0.07	0.05	**4.76**	2.03	3.65	1.26	1.14	0.85
Comination	-1.95	-0.84	-2.36	-0.94	0.70	1.27	1.75	0.75	1.21	0.48	0.74	1.35	4.35	1.88	3.29	1.31	**1.09**	2.00

VIX	t+1 b	t stat	b	t stat	b	t stat	t+3 b	t stat	b	t stat	b	t stat	t+6 b	t stat	b	t stat	b	t stat
(1) Asset Growth	0.05	1.41	0.06	1.51	-0.01	-0.88	0.04	1.03	0.02	0.57	0.01	0.76	0.03	0.81	0.01	0.30	0.01	0.94
(2) Gross Profitability	0.07	1.77	0.04	1.04	0.03	1.59	0.05	1.25	0.00	0.10	**0.04**	2.47	0.03	0.71	0.01	0.34	0.01	0.62
(3) Investment to Assets	0.05	1.37	0.08	1.88	**-0.03**	-2.13	0.04	0.98	0.04	0.87	0.00	-0.22	0.03	0.77	0.04	0.86	-0.01	-0.83
(4) Net Stock Issues	0.03	0.96	0.06	1.47	**-0.04**	-1.96	0.02	0.58	0.03	0.61	-0.01	-0.64	0.01	0.34	0.02	0.48	-0.01	-0.79
(5) Net Operating Assets	0.07	1.67	0.06	1.48	0.01	0.48	0.04	0.98	0.02	0.41	0.02	1.36	0.01	0.35	0.03	0.62	-0.01	-0.96
(6) Total Accruals	0.07	1.87	0.07	1.75	0.00	0.05	0.08	1.92	0.02	0.45	**0.05**	2.76	0.03	0.74	0.02	0.48	0.01	0.28
(7) Ohlson's O	0.06	1.55	0.08	1.91	-0.02	-1.18	0.05	1.20	0.04	1.00	0.00	0.04	0.03	0.81	0.00	0.10	0.02	1.20
(8) Return on Assets	0.06	1.60	0.07	1.63	-0.01	-0.38	0.04	0.98	0.04	0.92	0.00	-0.17	0.01	0.31	0.05	1.19	**-0.04**	-2.26
(9) Failure Probability	**0.14**	3.08	0.01	0.28	**0.12**	4.12	0.07	1.59	0.01	0.20	0.06	1.95	0.06	1.39	-0.01	-0.14	**0.06**	2.08
(10) Momentum	-0.06	-1.37	0.02	0.49	**-0.08**	-2.75	0.01	0.21	0.08	1.80	**-0.08**	-2.57	0.01	0.35	**0.13**	**2.99**	**-0.12**	-4.26
(11) Composite Equity Issues	-0.03	-0.90	-0.03	-0.62	0.00	-0.13	0.02	0.73	0.03	0.74	-0.01	-0.59	**0.06**	2.03	0.05	1.14	0.01	0.35
(12) Size	0.00	-0.11	0.03	0.82	-0.04	-1.26	**0.11**	2.43	0.05	1.29	**0.06**	2.07	**0.15**	3.28	**0.08**	**2.09**	**0.07**	2.39
(13) Book to Market	-0.03	-0.86	0.05	1.00	**-0.09**	-3.75	0.08	1.88	**0.12**	2.35	-0.04	-1.85	**0.14**	3.50	**0.12**	**2.39**	0.02	0.72
(14) Operating Profitability	0.01	0.23	0.01	0.26	-0.01	-0.26	**0.08**	2.00	**0.12**	2.47	**-0.05**	-2.00	**0.11**	2.99	**0.15**	**3.03**	-0.04	-1.70
(15) Investments	0.01	0.14	0.02	0.39	-0.01	-0.84	**0.13**	2.63	**0.10**	2.11	0.02	1.50	**0.18**	3.85	**0.11**	**2.32**	**0.07**	4.43
(16) Earning to Price	-0.01	-0.36	0.01	0.34	-0.03	-1.80	0.06	1.68	0.07	1.78	-0.01	-0.90	**0.12**	3.29	**0.09**	**2.21**	0.02	1.48
(17) Cash Flows to Price	-0.01	-0.28	0.02	0.45	**-0.03**	-2.07	0.07	1.94	0.07	1.82	0.00	-0.04	**0.13**	3.36	**0.09**	**2.35**	**0.03**	2.03
(18) Dividend Yield	-0.02	-0.58	0.00	-0.03	-0.02	-1.15	0.03	0.91	0.05	1.33	-0.02	-1.42	**0.10**	3.38	**0.08**	**2.28**	0.02	0.96
Comination	0.03	0.90	0.04	1.22	**-0.01**	-2.04	**0.06**	1.97	0.05	1.63	0.00	0.27	**0.07**	2.47	**0.06**	**1.94**	0.01	0.81

VRP	t+1 b	t stat	b	t stat	b	t stat	t+3 b	t stat	b	t stat	b	t stat	t+6 b	t stat	b	t stat	b	t stat
(1) Asset Growth	0.02	1.45	0.02	1.20	0.00	0.53	**0.03**	2.14	0.03	1.65	0.01	0.95	-0.01	-0.83	-0.02	-1.29	0.01	1.78
(2) Gross Profitability	0.02	1.59	0.02	1.08	0.01	1.47	0.03	1.78	**0.03**	2.07	0.00	-0.35	-0.01	-0.57	-0.01	-1.01	0.01	1.13
(3) Investment to Assets	0.02	1.20	0.02	1.49	-0.01	-0.99	**0.03**	2.04	0.03	1.90	0.00	-0.05	-0.01	-0.86	-0.02	-1.12	0.01	1.27
(4) Net Stock Issues	0.01	1.26	0.02	1.33	-0.01	-0.77	**0.03**	2.24	**0.03**	1.99	0.00	-0.70	-0.01	-1.27	-0.02	-1.30	0.01	1.06
(5) Net Operating Assets	0.02	1.44	0.02	1.03	0.01	1.46	0.03	1.81	0.03	1.82	0.00	0.34	-0.02	-1.02	-0.02	-1.66	0.01	1.81
(6) Total Accruals	0.02	1.22	0.01	0.83	0.01	0.94	0.01	0.89	0.01	0.86	0.00	0.20	**-0.03**	-2.25	-0.02	-1.44	-0.01	-1.41
(7) Ohlson's O	0.01	1.00	0.02	1.48	-0.01	-1.02	**0.03**	2.02	0.02	1.26	0.01	1.48	-0.02	-1.22	-0.02	-1.13	0.00	0.17
(8) Return on Assets	0.02	1.49	0.03	1.91	-0.01	-0.88	0.02	1.56	**0.03**	2.26	-0.01	-1.55	-0.02	-1.34	-0.02	-1.01	0.00	-0.41
(9) Failure Probability	0.03	1.59	0.01	0.88	0.01	1.33	**0.04**	2.27	0.02	1.72	0.01	1.22	-0.02	-1.17	-0.01	-0.67	-0.01	-0.75
(10) Momentum	**0.05**	3.44	**0.05**	3.30	0.00	-0.08	**0.05**	3.33	**0.05**	3.03	0.00	0.14	0.00	0.26	-0.04	-2.32	**0.04**	4.06
(11) Composite Equity Issues	**0.04**	3.74	**0.05**	3.20	-0.01	-0.89	**0.05**	4.18	**0.05**	2.92	0.00	0.13	-0.02	-1.47	-0.01	-0.83	0.00	-0.27
(12) Size	**0.05**	3.31	**0.05**	4.18	0.00	0.22	**0.05**	2.82	**0.04**	3.36	0.00	0.40	-0.01	-0.89	-0.02	-1.80	0.01	0.91
(13) Book to Market	**0.05**	3.57	**0.06**	3.47	-0.01	-0.99	**0.05**	3.77	**0.04**	2.34	0.01	1.61	-0.02	-1.26	-0.02	-1.19	0.00	0.45
(14) Operating Profitability	**0.05**	3.72	**0.06**	3.34	-0.01	-0.89	**0.05**	3.93	**0.04**	2.42	0.01	1.08	**-0.03**	-2.15	-0.01	-0.70	-0.02	-1.67
(15) Investments	**0.06**	3.43	**0.06**	3.46	0.00	0.49	**0.05**	3.10	**0.04**	2.51	**0.01**	2.16	-0.01	-0.72	-0.02	-1.46	**0.01**	2.23
(16) Earning to Price	**0.05**	3.87	**0.05**	3.80	0.00	-0.56	**0.05**	4.25	**0.04**	3.02	**0.01**	2.02	**-0.03**	-2.03	-0.03	-1.81	0.00	0.15
(17) Cash Flows to Price	**0.05**	3.81	**0.05**	3.87	0.00	-0.14	**0.05**	3.84	**0.04**	3.16	0.01	1.62	**-0.03**	-2.24	-0.02	-1.71	-0.01	-1.01
(18) Dividend Yield	**0.05**	4.54	**0.04**	3.60	0.00	0.72	**0.05**	4.92	**0.05**	3.79	0.01	0.93	**-0.02**	-2.32	-0.02	-1.81	0.00	-0.17
Comination	**0.03**	3.47	**0.04**	3.33	0.00	-0.03	**0.04**	3.84	**0.04**	3.20	0.00	1.84	-0.02	-1.73	-0.02	-1.83	0.00	1.43

FVaR	t+1 b	t stat	b	t stat	b	t stat	t+3 b	t stat	b	t stat	b	t stat	t+6 b	t stat	b	t stat	b	t stat
(1) Asset Growth	0.02	0.65	0.02	0.64	0.00	-0.41	-0.01	-0.33	-0.02	-0.64	0.01	0.86	0.02	0.71	0.01	0.33	0.01	1.06
(2) Gross Profitability	0.03	1.10	0.01	0.39	0.02	1.60	-0.01	-0.29	-0.02	-0.60	0.01	0.58	0.01	0.36	0.01	0.34	0.00	-0.23
(3) Investment to Assets	0.02	0.74	0.01	0.45	0.01	0.61	0.00	-0.14	-0.02	-0.73	0.02	1.90	0.02	0.58	0.00	0.11	0.01	1.38
(4) Net Stock Issues	0.02	0.79	0.02	0.64	0.00	-0.34	0.00	-0.10	-0.02	-0.52	0.01	1.25	0.02	0.86	0.01	0.40	0.01	0.75
(5) Net Operating Assets	0.02	0.69	0.01	0.41	0.01	0.62	-0.01	-0.43	-0.02	-0.80	0.01	1.10	0.01	0.41	0.00	0.12	0.01	0.75
(6) Total Accruals	0.00	0.03	0.02	0.68	-0.02	-1.44	-0.02	-0.64	-0.03	-1.19	0.01	0.74	-0.01	-0.18	0.00	0.12	-0.01	-0.77
(7) Ohlson's O	0.02	0.52	0.01	0.42	0.00	0.06	-0.02	-0.62	-0.01	-0.43	-0.01	-0.94	0.02	0.61	0.02	0.86	-0.01	-0.85
(8) Return on Assets	0.02	0.71	0.02	0.82	-0.01	-0.60	-0.01	-0.40	-0.01	-0.36	0.00	-0.23	0.01	0.33	0.02	0.59	-0.01	-0.84
(9) Failure Probability	0.00	-0.02	0.03	1.30	**-0.04**	-1.96	-0.01	-0.33	-0.01	-0.30	-0.01	-0.27	0.03	0.86	0.00	-0.04	0.03	1.36
(10) Momentum	0.05	1.61	0.06	1.95	-0.02	-0.94	0.00	-0.03	0.01	0.38	-0.02	-0.78	-0.04	-1.38	-0.01	-0.44	-0.03	-1.34
(11) Composite Equity Issues	**0.06**	2.33	0.06	1.95	0.00	-0.05	0.01	0.29	0.01	0.35	-0.01	-0.64	-0.02	-0.60	-0.02	-0.65	0.00	0.13
(12) Size	**0.06**	2.02	**0.06**	2.37	0.00	-0.18	0.01	0.42	-0.01	-0.25	0.02	1.36	-0.03	-1.06	-0.02	-0.91	-0.01	-0.92
(13) Book to Market	**0.07**	2.26	**0.06**	2.03	0.00	0.30	0.02	0.49	0.00	0.03	0.01	0.98	-0.03	-1.04	-0.03	-1.03	0.00	-0.22
(14) Operating Profitability	**0.06**	2.03	**0.07**	2.09	-0.01	-0.98	0.00	0.08	0.01	0.29	-0.01	-0.96	-0.03	-1.13	-0.03	-0.99	0.00	-0.42
(15) Investments	**0.07**	2.20	0.06	1.91	0.01	1.22	0.01	0.31	0.01	0.18	0.00	0.26	-0.04	-1.20	-0.03	-0.97	-0.01	-1.35
(16) Earning to Price	**0.06**	2.18	0.05	1.93	0.01	0.84	0.01	0.23	0.01	0.24	0.00	-0.34	-0.04	-1.18	-0.03	-1.03	-0.01	-1.05
(17) Cash Flows to Price	**0.07**	2.10	**0.06**	2.00	0.01	0.77	0.00	-0.05	0.01	0.32	-0.01	-1.47	-0.05	-1.56	-0.02	-0.84	**-0.03**	-3.16
(18) Dividend Yield	**0.06**	2.47	**0.06**	1.97	0.00	0.36	0.02	0.74	0.00	0.07	0.01	1.18	-0.02	-0.73	-0.03	-1.13	0.01	0.85
Comination	0.04	1.82	0.04	1.78	0.00	-0.81	0.00	-0.06	-0.01	-0.29	0.00	0.72	-0.01	-0.42	-0.01	-0.39	0.00	-1.01

Table 2.38: This table shows the performance of employing the forecasts coming from the considered indexes in determining the weight of a portfolio optimization problem which has the predicted portfolio and the risk free rate as only possible assets and a weight of the chosen risky asset bounded between -1 and +1.5. We report the out of sample performance generated by such strategies in terms of average return, standard deviation and Sharpe Ratio. Mean returns and standard deviation are reported in percentage. All forecasts are at for month t+1 using the chosen index value at month t. All time series are divided accordingly to the following criteria: 25 % of the data are used for the in sample estimation, 15% are use as hold out period and the remaining is employed for the out of sample performance evaluation of the predictive power of the relevant variables. In this table we report the performance generated for all the 11 anomalies and the 7 factors considered in this paper.

Long Leg	1			2			3			4			5			6			7			8			9		
	Mean	Vol	SR	Mean	Vol	SR	Mean	Vol	SR	Mean	Vol	SR	Mean	Vol	SR	Mean	Vol	SR	Mean	Vol	SR	Mean	Vol	SR	Mean	Vol	SR
Sentiment																											
PC 6	-0.18	0.15	-1.19	-0.10	0.13	-0.77	-0.18	0.01	-12.89	-0.12	0.02	-6.35	-0.01	0.02	-0.41	-0.17	0.01	-15.64	-0.15	0.02	-8.59	0.14	0.03	5.14	-0.28	0.02	-11.73
PLS 6	0.00	0.14	-0.03	0.15	0.22	0.72	-0.02	0.01	-1.53	-0.06	0.01	-5.87	0.22	0.02	9.31	0.04	0.01	2.65	-0.03	0.02	-2.15	0.44	0.04	12.57	-0.07	0.02	-3.73
Uncertainty																											
DEVST	-0.13	0.17	-0.80	-0.11	0.16	-0.66	-0.11	0.01	-8.30	0.00	0.02	0.28	-0.08	0.02	-3.45	-0.13	0.01	-9.25	-0.08	0.02	-5.12	0.12	0.03	3.69	-0.12	0.02	-7.52
UF	0.09	0.33	0.28	0.13	0.32	0.39	0.16	0.04	4.67	0.23	0.03	6.87	0.14	0.03	4.11	0.10	0.03	2.96	0.14	0.04	3.82	0.26	0.04	6.53	0.03	0.04	0.87
UM	0.07	0.31	0.24	-0.01	0.28	-0.04	0.09	0.03	2.89	0.24	0.03	7.74	0.08	0.03	2.52	-0.05	0.03	-1.80	-0.02	0.03	-0.59	0.02	0.03	0.64	-0.11	0.03	-3.23
Investors views																											
MEAN	-0.01	0.15	-0.10	0.09	0.16	0.55	0.01	0.01	1.28	0.09	0.01	6.34	0.08	0.02	4.78	0.03	0.01	2.43	0.04	0.02	2.23	0.38	0.03	12.68	0.05	0.02	2.79
UP	-0.07	0.14	-0.50	0.00	0.14	0.01	-0.04	0.01	-3.68	0.04	0.01	3.23	0.02	0.02	1.47	-0.03	0.01	-3.61	-0.03	0.02	-1.76	0.27	0.03	9.40	-0.06	0.01	-4.11
LOW	0.05	0.19	0.29	0.20	0.20	0.99	0.07	0.02	4.84	0.14	0.02	8.57	0.14	0.02	7.20	0.10	0.02	6.49	0.14	0.02	7.12	0.51	0.03	16.63	0.22	0.02	9.02
Fear																											
Bull-Bear	0.23	0.28	0.82	-0.11	0.22	-0.48	0.20	0.03	7.03	0.19	0.03	6.94	0.07	0.03	2.66	0.05	0.02	2.13	0.19	0.03	5.71	-0.15	0.03	-5.08	0.03	0.02	1.38
BTX	-0.27	0.23	-1.19	-0.31	0.28	-1.09	-0.24	0.02	-10.75	-0.15	0.02	-6.94	-0.26	0.02	-10.44	-0.30	0.02	-14.59	-0.17	0.02	-7.09	-0.26	0.04	-7.19	-0.38	0.03	-13.40
MACRO	-0.05	0.26	-0.19	0.05	0.27	0.18	-0.02	0.03	-0.87	-0.13	0.03	-5.25	0.04	0.03	1.28	0.14	0.03	4.04	0.04	0.03	1.45	0.01	0.04	0.17	0.04	0.04	1.22
VIX	-0.09	0.20	-0.45	-0.15	0.21	-0.72	-0.07	0.02	-2.99	-0.03	0.02	-1.38	-0.12	0.02	-6.42	-0.11	0.02	-5.83	0.01	0.02	0.58	-0.04	0.03	-1.73	-0.33	0.03	-10.57
ANX	-0.24	0.23	-1.05	-0.38	0.30	-1.25	-0.20	0.02	-9.45	-0.31	0.03	-11.73	-0.20	0.02	-11.37	-0.24	0.02	-11.63	-0.38	0.03	-13.04	-0.25	0.03	-9.57	-0.38	0.03	-10.89
VRP	0.28	0.25	1.14	0.48	0.29	1.66	0.29	0.02	11.68	0.19	0.02	8.20	0.39	0.03	14.78	0.37	0.02	15.42	0.27	0.02	12.14	0.43	0.04	12.21	0.49	0.03	14.20
KJ	-0.13	0.12	-1.02	-0.01	0.18	-0.04	-0.11	0.01	-11.85	0.02	0.02	1.03	-0.03	0.02	-1.47	-0.07	0.01	-5.91	0.12	0.03	4.10	0.50	0.04	11.04	-0.11	0.01	-11.39
CATFIN	0.05	0.31	0.17	0.02	0.27	0.06	0.11	0.03	3.40	0.24	0.03	7.36	0.03	0.03	0.88	0.03	0.03	1.24	0.20	0.04	5.31	0.37	0.04	8.43	-0.05	0.03	-1.67
TAIL	1.38	0.46	2.99	1.29	0.50	2.59	1.43	0.05	30.48	1.18	0.04	28.58	1.32	0.05	26.87	1.36	0.05	28.45	1.23	0.05	25.99	1.14	0.04	26.90	1.01	0.05	19.83
FVaR	0.27	0.32	0.82	0.50	0.33	1.54	0.31	0.03	9.27	0.43	0.03	14.20	0.41	0.03	13.71	-0.03	0.03	-1.19	0.10	0.03	3.13	0.54	0.03	17.47	0.66	0.04	18.25

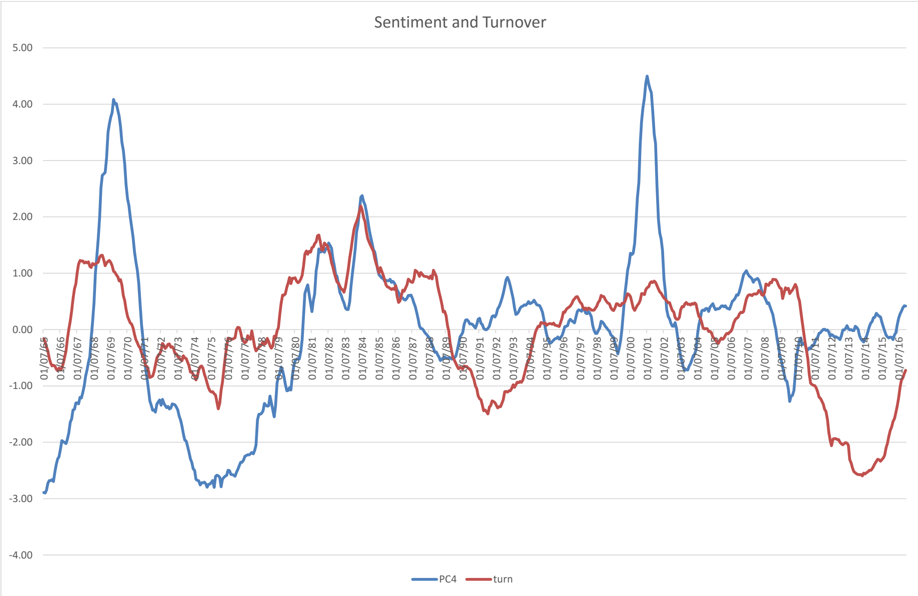
Short Leg	1			2			3			4			5			6			7			8			9		
	Mean	Vol	SR	Mean	Vol	SR	Mean	Vol	SR	Mean	Vol	SR	Mean	Vol	SR	Mean	Vol	SR	Mean	Vol	SR	Mean	Vol	SR	Mean	Vol	SR
Sentiment																											
PC 6	0.22	0.31	0.71	0.32	0.28	1.13	0.09	0.03	3.17	0.11	0.02	4.59	0.04	0.03	1.29	0.17	0.03	5.10	0.12	0.03	4.03	0.39	0.04	10.12	0.78	0.05	16.28
PLS 6	0.50	0.38	1.33	0.59	0.36	1.65	0.35	0.04	9.72	0.39	0.03	11.73	0.23	0.03	7.21	0.41	0.04	10.95	0.40	0.03	11.53	0.60	0.04	14.97	0.84	0.05	17.27
Uncertainty																											
DEVST	0.28	0.41	0.68	0.20	0.39	0.52	0.16	0.03	4.79	0.14	0.03	4.25	0.24	0.04	6.40	0.25	0.04	6.06	0.08	0.03	2.27	0.35	0.04	8.26	0.61	0.05	13.17
UF	0.43	0.44	0.99	0.40	0.42	0.97	0.32	0.04	7.53	0.30	0.04	7.52	0.37	0.04	8.62	0.38	0.04	8.65	0.20	0.04	5.30	0.61	0.05	12.33	0.79	0.05	15.69
UM	0.31	0.39	0.78	0.32	0.39	0.82	0.09	0.04	2.55	0.19	0.04	5.41	0.21	0.04	5.24	0.20	0.04	5.21	0.18	0.04	5.21	0.62	0.05	12.91	0.69	0.05	14.31
Investors views																											
MEAN	0.44	0.33	1.34	0.29	0.26	1.11	0.32	0.03	10.82	0.27	0.02	10.80	0.37	0.03	11.31	0.51	0.04	13.61	0.29	0.02	12.72	0.50	0.04	14.25	0.76	0.05	16.53
UP	0.37	0.32	1.15	0.25	0.27	0.93	0.25	0.03	8.48	0.21	0.02	8.51	0.31	0.03	9.48	0.44	0.04	11.56	0.22	0.02	9.60	0.46	0.04	12.40	0.71	0.05	15.32
LOW	0.48	0.32	1.52	0.32	0.27	1.21	0.40	0.03	13.36	0.31	0.02	12.60	0.42	0.03	13.10	0.57	0.04	15.52	0.36	0.02	15.23	0.54	0.03	16.12	0.78	0.04	18.05
Fear																											
Bull-Bear	0.16	0.36	0.44	0.19	0.34	0.57	0.16	0.04	4.24	0.19	0.04	5.31	0.16	0.04	4.14	0.09	0.04	2.48	0.04	0.03	1.43	0.51	0.05	11.27	0.62	0.05	12.52
BTX	0.05	0.40	0.12	-0.13	0.35	-0.38	-0.01	0.04	-0.26	-0.08	0.04	-2.32	0.01	0.04	0.34	-0.08	0.04	-2.23	-0.01	0.03	-0.22	0.06	0.05	1.31	0.16	0.05	3.27
MACRO	0.13	0.40	0.33	-0.13	0.37	-0.36	0.19	0.04	4.42	0.07	0.04	1.88	0.08	0.04	1.92	-0.04	0.04	-1.17	0.13	0.04	3.59	0.31	0.04	7.43	0.33	0.05	6.84
VIX	0.15	0.29	0.50	0.14	0.30	0.48	0.10	0.03	3.22	0.03	0.03	1.37	0.15	0.04	4.01	0.14	0.03	4.06	-0.03	0.02	-1.42	0.45	0.04	11.20	0.62	0.05	13.51
ANX	-0.14	0.25	-0.55	0.09	0.25	0.34	-0.17	0.03	-6.32	-0.19	0.02	-8.35	-0.17	0.03	-6.23	-0.16	0.03	-5.53	-0.11	0.02	-5.91	0.41	0.04	11.00	0.59	0.05	12.99
VRP	0.55	0.36	1.51	0.38	0.29	1.32	0.49	0.03	14.15	0.50	0.04	14.24	0.25	0.03	8.86	0.42	0.04	11.17	0.61	0.04	17.36	0.67	0.04	16.45	0.72	0.04	16.20
KJ	0.41	0.38	1.08	0.26	0.36	0.72	0.44	0.04	11.09	0.32	0.04	8.85	0.49	0.04	11.46	0.64	0.05	13.91	0.23	0.03	6.92	0.64	0.05	13.14	1.40	0.05	25.73
CATFIN	0.32	0.41	0.79	0.23	0.38	0.62	0.40	0.05	8.89	0.32	0.04	7.79	0.42	0.05	9.19	0.49	0.04	10.94	0.21	0.04	5.60	0.63	0.05	12.51	1.40	0.05	25.46
TAIL	1.24	0.47	2.63	1.16	0.43	2.69	1.18	0.05	24.56	1.25	0.05	26.96	1.18	0.05	25.69	1.21	0.04	28.08	1.02	0.04	23.23	1.28	0.05	27.49	1.64	0.05	33.10
FVaR	0.22	0.31	0.70	0.34	0.33	1.03	0.23	0.03	7.70	0.20	0.03	6.22	0.21	0.03	6.74	0.08	0.03	2.74	0.28	0.03	9.20	0.04	0.03	1.07	-0.20	0.03	-6.31

Table 2.39: Continues from above

Long Leg	10			11			12			13			14			15			16			17			18		
	Mean	Vol	SR	Mean	Vol	SR	Mean	Vol	SR	Mean	Vol	SR	Mean	Vol	SR	Mean	Vol	SR	Mean	Vol	SR	Mean	Vol	SR	Mean	Vol	SR
Sentiment																											
PC 6	0.01	0.15	0.04	-0.05	0.20	-0.27	-0.20	0.03	-6.23	0.13	0.04	3.09	0.03	0.03	1.03	0.06	0.04	1.43	0.21	0.04	5.25	0.14	0.04	3.47	0.17	0.03	5.35
PLS 6	0.20	0.21	0.96	-0.07	0.20	-0.34	-0.01	0.03	-0.37	0.30	0.04	6.90	0.11	0.03	4.02	0.31	0.04	7.23	0.23	0.04	5.42	0.16	0.04	4.00	0.12	0.04	3.19
Uncertainty																											
DEVST	0.00	0.25	0.01	-0.09	0.16	-0.58	-0.09	0.03	-3.26	0.12	0.04	3.39	0.04	0.03	1.68	0.15	0.04	3.52	0.19	0.04	4.91	0.16	0.04	4.25	0.33	0.04	8.87
UF	0.41	0.40	1.00	0.29	0.36	0.80	0.02	0.04	0.63	0.36	0.04	8.55	0.38	0.04	9.71	0.13	0.04	3.40	0.41	0.04	9.64	0.42	0.04	9.64	0.41	0.04	10.88
UM	0.35	0.35	1.00	0.24	0.33	0.74	-0.04	0.04	-1.00	0.27	0.04	6.28	0.15	0.04	4.21	0.16	0.04	3.92	0.24	0.04	5.83	0.19	0.04	4.52	0.32	0.04	8.44
Investors views																											
MEAN	-0.02	0.12	-0.19	-0.07	0.12	-0.55	0.00	0.03	-0.17	0.25	0.04	6.25	0.12	0.03	4.04	0.21	0.04	4.94	0.19	0.03	5.38	0.18	0.03	5.14	0.19	0.03	5.98
UP	-0.05	0.13	-0.40	-0.08	0.11	-0.69	-0.07	0.03	-2.84	0.16	0.04	4.10	0.05	0.03	2.02	0.14	0.04	3.37	0.15	0.03	4.59	0.13	0.03	3.87	0.19	0.03	6.28
LOW	-0.01	0.12	-0.06	-0.05	0.15	-0.33	0.16	0.03	4.82	0.38	0.04	8.80	0.25	0.03	7.60	0.39	0.05	8.46	0.28	0.04	7.41	0.31	0.04	7.98	0.21	0.03	6.42
Fear																											
Bull-Bear	1.27	0.45	2.83	1.61	0.40	4.01	1.93	0.06	34.22	2.21	0.06	39.44	1.83	0.05	38.20	2.21	0.06	35.36	1.99	0.05	41.52	1.95	0.05	39.68	1.41	0.04	34.92
BTX	0.30	0.45	0.65	0.14	0.47	0.29	0.07	0.04	1.65	0.62	0.05	11.91	0.47	0.05	10.12	0.28	0.05	6.10	0.73	0.05	14.37	0.78	0.05	14.99	0.56	0.05	12.39
MACRO	0.27	0.34	0.80	-0.27	0.39	-0.69	0.11	0.04	2.58	0.15	0.05	2.76	0.18	0.04	4.14	0.28	0.05	5.57	0.10	0.05	1.91	0.19	0.06	3.45	0.16	0.05	3.11
VIX	1.59	0.48	3.34	1.23	0.44	2.83	1.34	0.05	27.58	1.67	0.05	32.77	1.59	0.05	32.45	1.35	0.05	27.25	1.59	0.05	32.38	1.71	0.05	32.49	1.21	0.04	28.95
ANX	-0.14	0.19	-0.70	-0.15	0.29	-0.51	-0.22	0.04	-6.21	0.14	0.05	2.82	-0.09	0.04	-2.12	-0.11	0.04	-2.62	0.19	0.05	4.11	0.12	0.05	2.56	0.37	0.04	8.38
VRP	-0.45	0.42	-1.07	0.00	0.41	0.01	0.05	0.05	1.04	0.54	0.06	9.58	0.49	0.05	10.04	0.21	0.05	3.85	0.57	0.05	11.20	0.58	0.05	10.62	0.51	0.04	12.77
KJ	0.40	0.37	1.08	0.18	0.28	0.63	-0.10	0.03	-3.00	0.25	0.04	5.89	0.12	0.02	7.09	0.21	0.05	4.43	0.30	0.03	10.45	0.26	0.03	8.68	0.28	0.02	11.38
CATFIN	1.87	0.54	3.44	1.65	0.42	3.94	2.53	0.06	43.15	2.79	0.06	50.28	2.07	0.05	40.48	2.74	0.06	44.65	2.28	0.05	45.41	2.38	0.05	44.86	1.67	0.04	41.55
TAIL	1.05	0.42	2.52	0.89	0.35	2.52	0.79	0.04	18.63	1.14	0.05	23.89	1.09	0.04	25.14	0.87	0.05	18.74	1.21	0.05	25.89	1.20	0.05	25.11	0.86	0.04	22.43
FVaR	-0.06	0.29	-0.19	-0.11	0.30	-0.37	0.59	0.04	14.43	0.56	0.04	14.40	0.69	0.04	19.17	0.66	0.04	15.96	0.72	0.04	20.30	0.93	0.04	25.74	0.53	0.03	15.72

Short Leg	10			11			12			13			14			15			16			17			18		
	Mean	Vol	SR	Mean	Vol	SR	Mean	Vol	SR	Mean	Vol	SR	Mean	Vol	SR	Mean	Vol	SR	Mean	Vol	SR	Mean	Vol	SR	Mean	Vol	SR
Sentiment																											
PC 6	0.15	0.35	0.42	0.55	0.39	1.43	0.14	0.03	4.71	0.06	0.03	1.88	-0.05	0.03	-1.40	-0.09	0.03	-2.96	-0.14	0.02	-5.91	-0.15	0.02	-6.40	0.13	0.03	4.53
PLS 6	0.35	0.36	0.96	0.68	0.41	1.67	0.55	0.03	17.67	0.26	0.04	7.37	0.14	0.04	3.91	0.21	0.03	6.15	0.12	0.02	5.23	0.12	0.02	5.16	0.16	0.03	6.01
Uncertainty																											
DEVST	0.19	0.40	0.46	0.45	0.46	0.99	-0.06	0.03	-2.28	-0.12	0.03	-4.34	-0.10	0.03	-2.98	-0.14	0.03	-5.25	-0.05	0.02	-2.83	-0.07	0.02	-3.71	0.05	0.02	2.27
UF	0.44	0.50	0.88	0.72	0.51	1.40	0.37	0.03	11.17	0.01	0.03	0.33	0.02	0.03	0.49	0.10	0.04	2.59	0.19	0.03	5.51	0.18	0.03	5.46	0.42	0.04	11.86
UM	0.31	0.48	0.64	0.54	0.47	1.16	0.27	0.03	7.85	-0.09	0.03	-2.71	-0.03	0.04	-0.86	-0.01	0.04	-0.35	0.07	0.03	2.07	0.07	0.03	2.11	0.22	0.03	6.61
Investors views																											
MEAN	0.26	0.29	0.88	0.44	0.34	1.30	0.12	0.03	4.31	0.02	0.02	0.82	0.02	0.03	0.80	0.01	0.02	0.41	0.08	0.02	3.82	0.07	0.02	3.35	0.12	0.02	5.33
UP	0.21	0.30	0.71	0.42	0.35	1.18	0.03	0.03	1.22	-0.05	0.02	-2.53	-0.05	0.03	-1.62	-0.07	0.02	-3.14	0.01	0.02	0.42	0.00	0.02	-0.22	0.08	0.02	3.41
LOW	0.33	0.29	1.13	0.45	0.31	1.47	0.22	0.03	7.30	0.18	0.03	6.75	0.20	0.03	5.78	0.15	0.03	5.78	0.23	0.03	8.77	0.20	0.02	8.32	0.20	0.03	7.57
Fear																											
Bull-Bear	1.64	0.53	3.08	1.41	0.48	2.97	1.38	0.04	30.71	1.57	0.05	29.20	1.83	0.06	30.99	1.50	0.05	28.68	1.73	0.05	35.53	1.81	0.05	36.69	1.82	0.04	40.52
BTX	-0.24	0.45	-0.53	0.15	0.44	0.34	-0.09	0.04	-2.44	-0.09	0.04	-2.35	-0.03	0.04	-0.78	-0.18	0.04	-4.36	0.11	0.04	2.68	0.07	0.04	1.63	0.43	0.05	9.28
MACRO	0.32	0.46	0.71	0.25	0.41	0.61	0.35	0.04	9.33	0.30	0.04	7.93	0.24	0.04	6.62	0.29	0.04	7.55	0.24	0.03	7.43	0.18	0.03	5.78	0.12	0.04	3.26
VIX	1.13	0.56	2.00	1.43	0.51	2.82	1.50	0.04	33.58	1.22	0.05	25.45	1.26	0.05	26.04	1.40	0.05	26.75	1.49	0.05	31.61	1.43	0.05	31.05	1.61	0.05	34.17
ANX	0.09	0.32	0.28	0.22	0.29	0.77	-0.14	0.03	-4.92	-0.34	0.03	-11.90	-0.27	0.03	-8.59	-0.37	0.03	-13.05	-0.19	0.03	-5.76	-0.21	0.03	-6.29	0.00	0.04	-0.04
VRP	-0.04	0.50	-0.08	-0.18	0.48	-0.37	0.27	0.04	6.30	-0.14	0.04	-3.48	-0.08	0.05	-1.86	-0.15	0.04	-3.47	0.26	0.04	5.92	0.27	0.04	6.19	0.41	0.05	8.94
KJ	0.44	0.44	0.99	0.73	0.49	1.49	0.15	0.03	5.26	-0.14	0.01	-10.44	-0.09	0.04	-2.63	-0.11	0.01	-11.17	-0.13	0.01	-13.21	-0.12	0.01	-15.37	0.24	0.02	11.87
CATFIN	2.03	0.56	3.65	2.10	0.55	3.82	1.55	0.05	32.75	1.96	0.06	34.55	2.38	0.06	40.52	2.21	0.06	38.63	2.10	0.05	39.18	2.08	0.05	39.60	1.86	0.05	38.90
TAIL	1.07	0.48	2.22	1.24	0.47	2.62	0.95	0.04	24.60	0.77	0.04	18.50	0.72	0.04	16.89	0.94	0.04	21.79	0.95	0.04	23.13	0.93	0.04	23.33	1.14	0.04	27.34
FVaR	-0.19	0.37	-0.53	-0.15	0.33	-0.46	0.39	0.03	13.17	0.41	0.04	11.57	0.48	0.04	11.80	0.42	0.04	11.18	0.69	0.03	19.72	0.53	0.03	15.18	0.44	0.03	12.77

Figure 2.3: This figure shows the Sentiment Index proposed Baker-Wurgler's employing the 4 of the 6 variables originally proposed (PC4) and the two variables excluded: precisely the turnover (turn) and the number of ipos (nipo) The monthly series include the period 07-1965/12-2016.



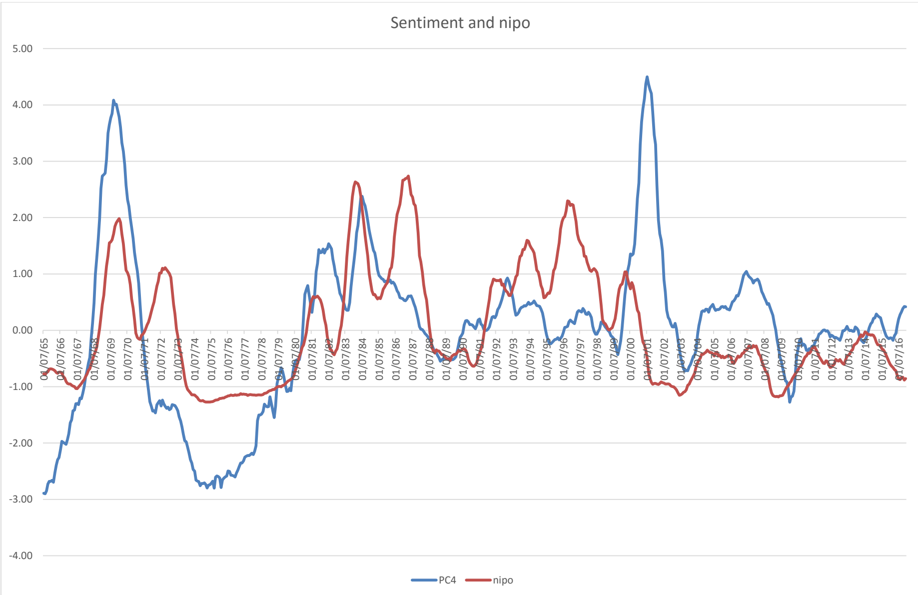
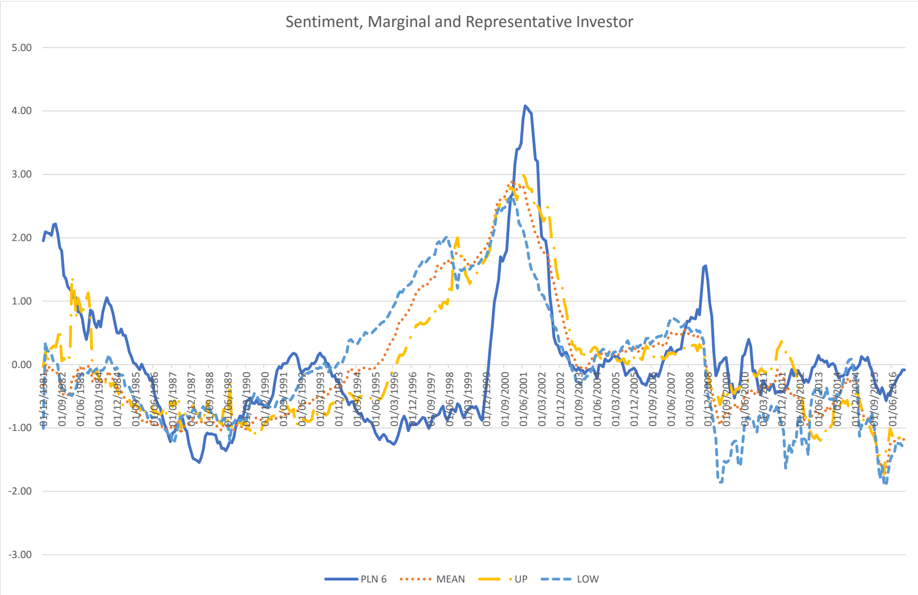
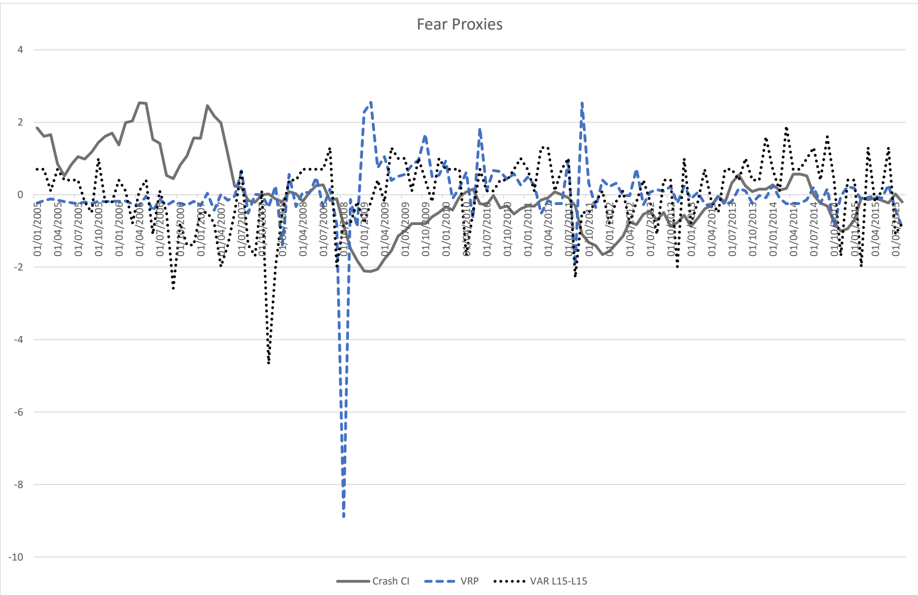


Figure 2.4: The upper figure shows the PLS 6 sentiment proxy proposed by Huang et al. with the upper (UP), lower (LOW) and number of views weighted mean forecast (MEAN) of the EPS long term growth for the period 07-1965/12-2016. All series are monthly and standardized.
The lower figure presents three fear proxies: the Crash Confidence Index (Crash CI), the Variance Risk Premium (VRP) of Hao and the FVaR proxy. All series are monthly and standardized and span the period from 01/2005 to 08/2015.





Chapter 3

The Keys of Predictability

3.1 Introduction

The equity premium predictability literature typically introduces a new model or a new predictor and shows how it can rise the out-of-sample R^2 or Delta Utility. Differently from the typical studies on the field, we acknowledge how stocks' pricing and predictability are intimately related[1]: being able to predict the market out-of-sample enrich our understanding of what ultimately the market prices. Consequently, we write this paper with the joint goal to provide both a comprehensive study of the out-of-sample predictability in equity markets and to trigger a fruitful discussion on the asset pricing implications of our findings. To gain a full understanding of the issues and potentials involved by a deeper understanding of financial market predictability we decompose the topic into three parts: predictive models, predictors and the functions of market uncertainty we aim at forecasting. Each one provides new insight into our understanding of asset pricing and poses a variety of questions which aim at triggering a fruitful debate.
At first, we focus on predictive modeling. We re-examine the challenge posed by Welch and Goyal [2008] by employing the same predictors but combining model selection and machine learning predictive models. We observe how employing more and more powerful techniques our capability to accurately forecast out-of-sample increases steadily. Indeed, when model selection techniques are preventively adopted to alleviate multicollinearity, the results coming from the subsequent forecasts of machine learning techniques improve dramatically reaching R^2_{OS} values above 5% for ensembles of Neural Networks. The remarkable results in terms of precision have substantial economic value for investors: delta Utility (concerning the traditional average mean return benchmark) rises by 2.5% with an even higher value of 4.5% during periods of recession when economic gains

[1] A relevant exception comes from Campbell [1991] who first introduces this relation

are more valuable. Our findings suggest that prices reflect inputs in a non-linear fashion. Consequently, the current research on the mathematical foundations of neural networks has a huge potential to widen our understanding of asset pricing[2]. Indeed, we stress the need for the identification of regime-dependent nonlinear pricing factors. Our results are also a direct challenge to the Efficient Market Hypothesis (Fama [1970]). This widely held assumption states that econometricians cannot systematically outperform the market using widely available information. In sharp contrast with this theory, it is becoming more and more evident how artificial intelligence is consistently able to achieve risk-returns performances well above market. Even more surprisingly, with the progressing of technology, we observe steady and, apparently, unbounded improvements. At this stage, a question naturally arises: how predictability originates? Indeed, it becomes apparent how some components of the pricing kernel are not fully reflected into prices, and this gives rise to the predictability phenomenon reported in our results. The identification of these predictable components and their dynamics is a major point in the financial literature agenda of the future. While the debate on the amount and the rationale of financial markets predictability is still in its infancy, on some points the consensus is broad:

- Equity premium predictability to some extent exists[3];
- It is linked to the the business cycle[4];
- It is linked to sentiment and liquidity[5].
- It is stronger in bear markets[6]
- It is time-varying and affected by financial research[7].
- it can be enhanced by imposing economically motivated constraints[8]

[2]See, e.g., Shrikumar et al. [2016], Wei Koh and Liang [2017], Montavon et al. [2017], Montavon et al. [2018]

[3]See, e.g., Dangl and Halling [2012], Rapach et al. [2010], Golez and Koudijs [2018]

[4]See, e.g., the seminal work of Fama and French [1989] and the recent works coming from Rapach et al. [2010] and Zhu [2015]

[5]Chen et al. [2018] show how to isolate a powerful liquidity predictor while Huang et al. [2015] propose a powerful sentiment one.

[6]Cujen and Hasler [2017] explain this phenomenon through the existence of a risk premium for uncertainty.

[7]Lo [2004] formulates a fascinating adaptive market hypothesis while Mclean and Pontiff [2015] proving how academic research reduce predictability implicitly confirm the hypothesis.

[8]Campbell and Thompson [2008] impose constraints on the regression coefficients and on the predicted returns (when the predicted returns are negative, they are replaced with zero) while Pettenuzzo et al. [2014] successfully introduces a constraint on the conditional Sharpe ratio.

Our paper is also related to the data-science, and the machine learning approaches previously employed in the field of financial market predictability. Among the most remarkable machine learning approaches, we report the Kalman filter approach of Van Binsberg and Koijen [2010], the Markov Switching approach of Guidolin and Timmermann [2008], and the Bayesian system approach of Johannes et al. [2013]. This last paper gave rise to a whole line of research which leverages the Bayesian statistic to make accurate financial forecasts. Among the most successful implementations in this area of study, we report the Bayesian latent threshold approach of Nakajima and West [2013], the dynamic dependent sparse factor model of Zhou et al. [2014], the dynamic dependence networks methodology of Yi et al. [2016], the simultaneous graphical dynamic linear proposal of Gruber and West [2016], and the Bayesian predictive synthesis of Johnson and West [2018]. Finally, the papers most closely related to our one come from Gu et al. [2018] and Feng et al. [2018] who employ neural networks and machine learning techniques in the same framework. Differently from their works, we combine model selection and machine learning techniques boosting the final predictive performance. After that, we focus even on predictors and on a rich number of functions of market uncertainty in the second and third section of the paper. Finally, in the ever-growing list of significant works on machine learning applied to financial forecasting we remark the stochastic neural network combination approach of Sermpinis et al. [2012], the adaptive evolutionary neural networks methodology of Georgios et al. [2015], the evolutionary support vector machines model of Karathanasopoulos et al. [2015], and the genetic programming approach of Karatahansopoulos et al. [2014][9].
The second part of this paper focuses on predictors. At first, we consider as predictors for the $S\&P500$ the 12 different industries indexes. Accordingly, we perform an out-of-sample analysis of the study originally performed in-sample by Hong et al. [2007]. We document big and rising monthly Delta Utility gains which, for the most recent 2001-2017 period, are well above the 4% for the Money sector index and 3% Chemical sector one. After that, we employ as predictors the returns coming from the long-short portfolio strategies commonly named in the literature factors (Fama and French [2015]) or anomalies (Stambaugh and Yuan [2017]). Here, for the 2001-2017 period, we document a record-high monthly R^2_{OS} of 28.6% for the Net Stock Issue matched by a 28% increase in terms of utility gains. Other return spreads sorting on the base of the Investment to Asset (Titman et al. [2003]), and (Ohlson [1980]) O-score metric provide extremely powerful out-of-sample forecasts too.
Our results are related to the literature which proposes new predictors. Among them we report the Sentiment Index of Huang et al. [2015], the Trend Factor of Han

[9] A comprehensive review of the existing literature on machine learning financial forecasting can be found in the works of Dunis et al. [2016] and de Prado [2018]

et al. [2016], the short interest measure of Rapach et al. [2016], the Gold-Platinum ratio Huang and Kilic [2019] and the aggregate Asset Growth indicator of Wen [2019]. The studies more closely related to our one come from Huang and Kilic [2019] who employ industries and Greenwood and Hanson [2012] who employ the net issuance spread. For both cases, we extend their findings in an out-of-sample framework. More recently, even technical[10] and economic[11] indicators have been added to the list of powerful market predictors. Finally, powerful signals have been extrapolated from options. Bakshi et al. [2011] build an option positioning that allows inferring forward variances from option portfolios, Bollerslev and Todorov [2011] build a fear measure from the left tail of the risk-neutral distribution, and Christoffersen and Pan [2017] show how oil option-implied information allows predicting stock market returns.

After having studied the predictive power of the listed predictors, we propose to employ an out-of-sample approach to identify the relevant pricing factors both for the S&P500 and for the French double-sorted portfolios. The identification of the most relevant predictors can shed new light on the drivers of the factorial profitability[12]. We observe how the predictive power of the different predictors is largely complementary in the spectrum of cross-sectional returns and while some stock are highly predictable by sentiment others are largely unaffected by it. This suggests that, contrary to the commonly held assumptions, a one-fits-all approach to the identification of the market pricing kernel could be misleading. Our simple approach is complementary to the blossoming literature on model selection in the asset pricing environment which, differently from our methodology, is entirely in-sample based. This line of literature has the goal to identify the relevant factors at the cross-sectional level. Among the newest approaches, we report the three pass method of Feng et al. [2017], the (Adaptive) Lasso methodology proposed by Messmer and Audrino [2017], the Tree-Based Conditional Portfolio Sorts of Moritz and Zimmermann [2016] and the deep learning methodology introduced by Feng et al. [2019]. Other remarkable approaches to select a parsimonious amount of factors have been recently proposed by Fama and French [2018], Kozak et al. [2017b], and Stambaugh and Yuan [2017].

In the third part of the paper, we extend our analysis to include a broad sample of US stocks. We start by employing the French double-sorted portfolios: on the base of size and momentum, or size and the book-market ratio. We prove how

[10]Among the research on the value of technical analysis we report the seminal study of Lo et al. [2002] followed by the works of Neely et al. [2013] and Lin [2018]

[11]See, e.g.,Hong et al. [2007],Li and Tsiakas [2017] and Luo and Zhang [2017]

[12]This line of research stems from the seminal work of Fama and French [1993]. Subsequently, a rich literature introduces a huge list of other anomalies Campbell et al. [2016]. Among the most notorious we list Frazzini and Pedersen [2014], Chan et al. [1996], Sloan [1996], and Novy-Marx [2013]

predictability is not confined to small illiquid stocks only, but it is present even for the stocks of firms with big market capitalization. After that, we employ all the stocks available in the CRSP dataset to build 30 portfolios on the basis of a list of 10 characteristics. For each portfolio we employ the predictors coming from Baker and Wurgler, the anomalies spread returns and the methodologies which combine the predictors applied in the first part of the paper. We show how overall the Clark and West [2007] p-value for the R^2 out-of-sample statistics are less then 0.1 for the 20% of the cases considered and it is less then 0.05 for the 12% of the cases considered. In terms of economic value, the total average out-of-sample delta Utility is 4.84% with an average maximum delta utility for each portfolio of 9.96%. These results suggest that predictability is not only an attribute of the S&P500, but it is a generalized phenomenon in the US stock market.
The fourth and last topic regards the functions of the market we aim at forecasting. In an influential paper Bakshi and Madan [2000] prove how it is possible to replicate any function of stock uncertainty through the dynamic use of options. After that, Bakshi et al. [2003] show an application of this approach in the rebuilding of the first four moments of the risk-neutral distribution. More recently, Schneider and Trojani [2015] show how it is possible to trade these functions in real markets through a class of swap trading strategies. These recent advances allow us to prove how some functions of market uncertainty are easier to predict than common market returns. These findings open a new pattern of research in the field of market predictability and provide practitioners a new understanding of the potential of this line of research.
The third and last topic regards the functions of the market we aim at forecasting. At first, we focus on forecasting the returns generated by the long-short portfolios considered by Stambaugh et al. [2015]: predictability appears almost ubiquitous. After that, we focus on volatility, downside-volatility and correlation swaps (Buss et al. [2018]). Again we observe positive and statistically significant R^2_{OS} values. Finally, we generalize our intuition leveraging on the influential paper of Bakshi and Madan [2000]. The authors prove how, given a set of conditions, it is possible to replicate any function of stock uncertainty through the dynamic employment of options. After that, Bakshi et al. [2003] show an application of this approach in the rebuilding of the first four moments of the risk-neutral distribution extrapolated from option pricing. While this approach has been widely employed in the asset pricing literature, its out-of-sample potential is largely unexplored. We start studying the predictability of the first four moments contracts of Bakshi et al. [2003] and we report remarkable values of the R^2_{OS} metric matched by positive Delta Sharpe ratios. In conclusion, in this final section, we prove how the possibility to synthesize and trade new securities (spread returns, swaps, and securities built accordingly to Bakshi and Madan [2000]) allows us to build securities with

returns that can be consistently forecasted. These findings open a new pattern of research in the field of market predictability and provide practitioners with a new understanding of the potential of this line of research.
The remaining of this paper is structured in the following way. Part ii) present the data employed. Part iii) introduces the predictive modeling approaches employed and comments on the related empirical results inside the Welch and Goyal [2008] framework. Part iv) employs different sets of predictors and document their predictive performance. Part v) shows how predictability is a generalized feature of the US equity market. Part vi) illustrates the results coming from the study of different functions of market uncertainty. Part vii) concludes.

3.2 Data

In this section, we list all the data employed in our empirical analysis. We start from the Welch and Goyal predictors. Subsequently, we list data about industries and cross-sectional returns (anomalies and factors). Finally, we introduce data on options and swaps.

3.2.1 Welch and Goyal Predictors

The study of Welch and Goyal [2008] (W-G) is a benchmark and a challenge for the existing literature on market predictability. Consequently, we start with the fourteen predictors used in this provocative work[13]. The updated database is coming directly from the website of Goyal[14]. In more detail the predictors are:

- log Dividend-price ratio (DP): the difference between the log of dividends paid on the S&P 500 index and the log of prices, where dividends are measured using a twelve-month moving sum.

- log Dividend yield (DY): the difference between the log of dividends and the log of lagged prices.

- log Earnings-price ratio (EP): the difference between the log of earnings on the S&P 500 index and the log of prices, where earnings are measured using a twelve-month moving sum.

- log Dividend payout ratio (DE): the difference between the log of dividends and the log of earnings.

[13] Table 3.13 in the online appendix reports the correlation among the W-G predictors and the results for the autoregressive analysis of these predictors

[14] http://www.hec.unil.ch/agoyal/

- Stock variance (SVAR): the sum of squared daily returns on the S&P 500 index.
- Book to market (BM): the ratio of book value to market value for the Dow Jones Industrial Average.
- Net equity expansion (NTIS): the ratio of twelve-month moving sums of net issues by NYSE-listed stocks to the total end-of-year market capitalization of NYSE stocks.
- T-bill rate (TBL): the interest rate on a 3-month Treasury bill (secondary market).
- Long-term yield (LTY): long-term government bond yield.
- Long-term return (LTR): return on long-term government bonds.
- Term spread (TMS): the difference between the long-term yield and the T-bill rate.
- Default yield spread (DFY): the difference between BAA- and AAA-rated corporate bond yields.
- Default return spread (DFR): the difference between long-term corporate bond and long-term government bond returns.
- Inflation (INF lag): calculated from the CPI (all urban consumers); since inflation rate data are released in the next month, we use $x_{i,t-1}$.

In addition we employ the Sentiment Index of Huang et al. [2015]. Data come directly from Zhou website[15].

3.2.2 Anomalies and Industries

In this section, we detail the factors and anomalies employed in this study. An anomaly is a statistically significant difference in cross-sectional average returns that persist after the adjustment for exposures to the Fama and French [1993] three factors model. Our empirical analysis makes use of i) the eleven anomalies proposed by Stambaugh et al. [2015], ii) the four factors of the extended Fama and French [2015] model iii) Momentum, Long and Short term reversal. All data are monthly and span the period from 01-1965 to 12-2016 except the net operating assets, the accruals, the return on assets, and the distress anomaly for which

[15] http://apps.olin.wustl.edu/faculty/zhou/

data are available respectively only from 8-1965, 1-1970, 5-1976, and 1-1977. The considered factors-anomalies are:

- Financial distress. Campbell et al. [2008] show that firms with high failure probability have lower, not higher, subsequent returns (Distress). Another closely related measure of distress is the Ohlson [1980] O-score (O).

- Net stock issues and composite equity issues. Loughran and Ritter [1995] show that, in post-issue years, equity issuers under-perform non-issuers with similar characteristics (Net Stock Issues). Daniel and Titman [2006] propose an alternative measure, composite equity issuance (Comp eq Issue), defined as the amount of equity issued (or retired by a firm) in exchange for cash or services.

- Total accruals. Sloan [1996] demonstrates that firms with high accruals earn abnormal lower returns on average than firms with low accruals (Accruals).

- Net operating assets. Hirshleifer et al. [2004] find that net operating assets, computed as the difference on the balance sheet between all operating assets and all operating liabilities divided by total assets is a negative predictor of long-run stock returns (NOA).

- Momentum. The momentum effect, proposed by Jegadeesh and Titman [1993] is one of the most widespread anomalies in asset pricing literature (Mom).

- Gross profitability premium. Novy-Marx [2013] shows that sorting on gross-profit-to-assets creates abnormal benchmark-adjusted returns, with more profitable firms having higher returns than less profitable ones (Gross Prof).

- Asset growth. Cooper et al. [2008] show how companies that grow their total assets more earn lower subsequent returns (Asset Growth).

- Return on assets. Chen et al. [2011] show that firms with higher past return on assets gain higher subsequent returns (ROA).

- Investment-to-assets. Titman et al. [2003] show that higher past investment predicts abnormally lower future returns (Inv to Assets).

- The four factors proposed by the extended model of Fama and French [2015]: Small Minus Big (SMB), High Minus Low (HML), Robust Minus Weak (RMW), and Conservative Minus Aggressive (CMA).

- The Short and Long Term Reversal factors (ST, LT): as presented in the website of Professor Kenneth R. French.

Data for the four factors chosen by Fama and French [2015], the Momentum, and the two Short-Long Reversal Factors comes from the website of Professor Kenneth R. French[16] while anomalies are build matching CRSP and Compustat data following the approach detailed in Stambaugh and Yuan [2017]. After that, we consider monthly data on the 12 industries indexes coming from the website of Professor Kenneth R. French. The time series span the period from January 1927 to December 2017. In detail, the indexes are: Consumer NonDurables, Consumer Durables, Manufacturing, Energy, Chemicals, Business Equipment, Telecommunications, Utilities, Shops, Healthcare, Finance and Others (Mines, constructions, Hotels, Entertainment, Business Services, Transportation).

3.2.3 Options and Swaps

We use European options on the S&P500 Index (symbol: SPX) to build the Bakshi et al. [2003] four moment contracts. All option data comes from OptionMetric. The market for these options is one of the most active in the world. The options are European and have no wild card features. SPX options can be hedged using the active market on the S&P500 futures. Consequently, these options have been object of many empirical investigations, including Aït-Sahalia and Lo [1998], Heston and Nandi [2015] and Barone-Adesi et al. [2008].
To be consistent with the original paper of Bakshi et al. [2003], the data were screened to eliminate (i) bid-ask option pairs with missing quotes, or zero bids, and (ii) option prices violating arbitrage restrictions that $C(t, \tau, K) < S(t)$ or $C(t, \tau, K) > S(t) - PVD[D] - PVD[K]$, for present value function $PVD[.]$ and dividends D. As longer- (and very short-) maturity stock option quotes may not be active, options with less than 9 days and more than 120 days to expiration were also discarded. Finally, we only keep OTM calls and puts. Consequently, puts have moneyness corresponding to $\frac{K}{S(t)}|\frac{K}{S(t)} < 1$ and calls have moneyness corresponding to $\frac{K}{S(t)}|\frac{K}{S(t)} > 1$. We consider prices for each last day of the month from January 1996 to December 2017. At each point in time, we consider options with 20 or 40 business days to maturity. When needed, data are obtained interpolating the two contracts whose maturities straddle the needed one.
Using the term structure of zero-coupon default-free interest rate, the riskless interest rate for each given maturity τ is obtained by linearly interpolating the two interest rates whose maturities straddle τ. This procedure is repeated for each contract, and each day in the sample[17].

[16] $http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html$

[17] The summary statistics for the options analyzed are reported in Table 3.14 of the online appendix. There we report mean and standard deviations of the available options clustered for Maturity and Moneyness. The variables detailed are: Price in dollars, % Black-Sholes implied volatility, Bid-Ask spread, Volumes, Open Interest, Delta in % and number of observations.

After that, we employ implied correlation (Buss et al. [2018]), model-free implied volatility, model-free downside implied volatility (Jackwerth and Vilkov [2018]), Realized Correlation and the Variance Risk premium. All these data come from Professor Vilkov website[18]. Monthly data span the period from April 1996 to December 2017.

3.3 Predictive Models

In this section, we first list the predictive models employed and subsequently we detail the methodology for each one of them. After that, we present the performance metrics employed in our analysis. Finally, we report our empirical results, and we discuss them in light of the existing literature.

3.3.1 Econometric and Machine Learning Methodologies

To study the informative content which is possible to extrapolate from the predictors of Welch and Goyal [2008] we employ a wide list of models coming from the empirical financial literature and the Machine Learning one. While the list is far from being exhaustive, it is one of the first efforts to compare the predictive power of traditional econometric techniques with advanced machine learning ones in the field of empirical finance. Our approach combines model selection with machine learning and statistical approaches.
In this subsection, we list the methodologies considered while full details are reported in the following pages. Our list of models includes:

1. Univariate OLS regressions for each predictor.
2. A predictive OLS multivariate regression model (kitchen-sink) that incorporates all predictors jointly ("OLS" in the Tables).
3. A median combination forecasts approach which employ the median forecast among the ones generated by the univariate OLS regressions ("Pooled forecast: median", in the Tables).
4. The pooled DMSPE forecasts method proposed by Stock and Watson [2004] and successfully employed by Rapach et al. [2010] ("Pooled forecast: MDSFE" in the Tables).
5. Sum-of-the-parts forecast model of Ferreira and Santa-Clara [2011] (Sum-of-the-parts).

[18] http://www.vilkov.net/codedata.html

6. The Multivariate Adaptive Regression Splines approach Friedman [1991] for variable selection and a multivariate Support Vector Machine regression model (Boser et al. [1992] and Drucker et al. [1997]) to make out-of-sample forecasts ("MARS", in the Tables).

7. The SIC (Schwartz Information Criterion) for the variable selection and a multivariate Support Vector Machine regression model (Boser et al. [1992] and Drucker et al. [1997]) to make out-of-sample forecasts ("SVM SIC", in the Tables)

8. The Lasso for the variable selection and a multivariate Support Vector Machine regression model (Boser et al. [1992] and Drucker et al. [1997]) to make out-of-sample forecasts ("Lasso SVM" in the Tables).

9. The Regression Forest approach of Breiman [2001, 1996] built using regression trees (CART) Breiman and Friedman [1985] ("Random Forest", in the Tables).

10. The diffusion index approach employed by Ludvigson and Ng [2007] to filter the information and the univariate Support Vector Machine regression model (Boser et al. [1992] and Drucker et al. [1997]) to make out-of-sample forecasts ("Diffusion Index", in the Tables).

11. The Partial Least Squares approach of Kelly and Pruitt [2013] to filter the information and the univariate Support Vector Machine regression model (Boser et al. [1992] and Drucker et al. [1997]) to make out-of-sample forecasts ("PLS" in the Tables).

12. Variable selection made on the base of the MSFE performance of univariate OLS regressions. Out-of-sample forecasts generated though the Trimmed-Mean or Median of an ensemble of multi layer Neural Networks (Minsky and Papert [1969], Miller et al. [1995]) ("Neural Networks T-Mean" and "Neural Networks Median" in the Tables).

3.3.2 Basic linear models

The Kitchen Sink Regression is a simple OLS multivariate regression which includes all the predictors at once. The estimation is performed employing all predictors up to time t-1 (the last available information) to perform the parameter estimation. After that, we use the estimated parameters to make inference for time t+1 employing regressors values at time t. In formulas this can be summarized in a two step procedure:

$$R_t = \alpha + \beta X_{t-1} + \epsilon_t \tag{3.1}$$

where R is the t*1 vector of the S&P500 returns and X is the t*N matrix of the N predictors considered in the analysis.

$$\hat{r}_{t+1} = \hat{\alpha}_t + \hat{\beta}_t X_t \tag{3.2}$$

where $\hat{r}_{t+1}$ is the univariate forecast produced by the model, $\hat{\alpha}_t$, $\hat{\beta}_t$ are the coefficient estimated in the previous step employing data up to time t-1, and X_t is the 1*N vector of predictors at time t. For univariate model N (the number of predictors) is equal to 1.

3.3.3 Combination Forecasts

Combination forecasts are common methodologies employed in the literature (Rapach et al. [2010], Aiolfi and Timmermann [2006], Strauss and Detzel [2017]). The DMSPE approach is based on a three-stages estimation.

1. At first for each date t, we run a separate univariate regression for each regressor, x_{t-1}, on the equity premium at time t using all data available up to that date.
$$R_t = \alpha + \beta x_{i,t-1} + \epsilon_t \tag{3.3}$$
2. After that, each univariate OLS model previously estimated is employed with predictors available at time x_t to make inference on the equity premium for the subsequent period, $\hat{R}_{t+1}$
$$\hat{R}_{t+1} = \hat{\alpha}_t + \hat{\beta}_t x_t \tag{3.4}$$
3. Finally, we combine the forecasts generated by univariate regressions via combination forecasts methods.
$$\hat{R}_{t+1,Comb} = \sum_{i=1}^{N} w_{i,t} \hat{R}_{t+1} \tag{3.5}$$

In the Pooled-DMSPE approach we computes the weights for the third step in the following way:

$$w_{i,t} = \frac{\phi_{i,t}^{-1}}{\sum_{k=1}^{K} \phi_{k,t}^{-1}} \tag{3.6}$$

where

$$\phi_{i,t} = \sum_{s=m}^{t-1} \theta^{t-1-s} (r_{s+1} - \hat{r}_{i,s+1}) \tag{3.7}$$

θ is a discount factor (equal to 0.5 in this study), m+1 is the start of the holdout period and K is the number of past periods considered to compute the weights

(K=13 in this paper). The DMSPE method thus assigns greater weight to individual forecasts that had better forecasting performance in terms of lower mean-squared prediction errors.
The Pooled-Median, instead of using equation (5), simply employs the median of the univariate regression forecasts from equation (4).

3.3.4 Sum-of-the-Parts Method

The Sum-of-the-Parts Method has been proposed by Ferreira and Santa-Clara [2011]. The authors start decomposing returns in the following manner:

$$R_{t+1} = \frac{P_{t+1} + D_{t+1}}{P_t} = CG_{t+1} + DY_{t+1} \tag{3.8}$$

where P_t is the stock price, D_t is the dividend, $CG_{t+1} = \frac{P_{t+1}}{P_t}$ is the gross capital gain, and $DY_{t+1} = \frac{D_{t+1}}{P_t}$ is the dividend yield. After that, the gross capital gain can be expressed as

$$CG_{t+1} = \frac{\frac{P_{t+1}}{E_{t+1}}}{\frac{P_t}{E_t}} \frac{E_{t+1}}{E_t} = \frac{M_{t+1}}{M_t} \frac{E_{t+1}}{E_t} = GM_{t+1} GE_{t+1} \tag{3.9}$$

where E_t denotes earnings, $M_t = \frac{P_t}{E_t}$ is the price-earnings multiple, $GM_{t+1} = \frac{M_{t+1}}{M_t}$, is the gross growth rate of the price-earnings multiple (earnings), and $GE_{t+1} = \frac{E_{t+1}}{E_t}$. Now the dividend yield can be written as

$$DY_{t+1} = \frac{D_{t+1}}{P_{t+1}} \frac{P_{t+1}}{P_t} = DP_{t+1} GM_{t+1} GE_{t+1} \tag{3.10}$$

where $\frac{D_t}{P_t}$ is the dividend-price ratio. Based on these results the gross return becomes

$$R_{t+1} = GM_{t+1} GE_{t+1} (1 + DP_{t+1}) \tag{3.11}$$

which for the log return can be expressed as

$$log(R_{t+1}) = gm_{t+1} + ge_{t+1} + dp_{t+1} \tag{3.12}$$

The authors argue that, since price-earnings multiples and dividend-price ratios are highly persistent and nearly random walks, reasonable forecasts for gm_{t+1} and dp_{t+1} based on information available at time t are zero and dp_t. Finally, a 20-year moving average of log earnings growth through t ge_t^{20}, is employed as a forecast of ge_{t+1}. The sum-of-the-parts equity premium forecast is then given by

$$\hat{r}_{t+1}^{SOP} = \bar{ge}_t^{20} + dp_t - r_{f,t+1} \tag{3.13}$$

where $r_{f,t+1}$ is the log risk-free rate for time t+1, which is known at the end of time t.

3.3.5 Multivariate Adaptive Regression Splines and Support Vector Machines for Regression

Given a set of predictors the MARS model (Friedman [1991]) selects and breaks a predictor into two groups and models linear relationships between the predictor and the outcome in each group. To determine the cut point each data point for each predictor is evaluated as a candidate cut-point by creating a linear regression model with the candidate features, and the corresponding model error is calculated. The predictor/cut point combination that achieves the smallest error is then used for the model. After the initial model is created with the first two features, the model conducts another exhaustive search to find the next set of features that, given the initial set, yield the best model fit. This process continues until a stopping point is reached. Once the full set of features has been created, the algorithm sequentially removes individual features that do not contribute significantly to the model equation. This "pruning" procedure assesses each predictor variable and estimates how much the error rate was decreased by including it in the model. MARS builds models of the form:

$$\hat{f}(x) = \sum_{i=1}^{m} c_i B_i(x) \tag{3.14}$$

where c_i is a fix coefficient and B_i can be equal to 1 or to a hinge function (a hinge function has the form max(0, x-const) or max(0, const-x)) or a product of hinge functions.

Our implementation of the algorithm builds the model in two phases: forward selection and backward deletion. In the forward phase, the algorithm starts with a model consisting of just the intercept term and iteratively adds reflected pairs of basis functions giving the largest reduction of training error (Mean Squared Error). We set the maximum number of basis functions to min(200, max(20,2d))+1, where d is the number of input variables. We do not allow for self-interaction. We impose no penalty for adding a new variable to a model in the forward phase, and we employ hinge functions only. The forward phase is executed until adding a new basis function changes R^2 by less than 1e-4.

At the end of the forward phase we have a large model which over-fits the data, and so a backward deletion phase is engaged. In the backward phase, the model is simplified by deleting one least important basis function (i.e., deletion of which reduces training error the least) at a time until the model has only the intercept term. At the end of the backward phase, from those "best" models of each size, the one with the lowest Generalized Cross-Validation (GCV) is selected and outputted as the final one. GCV, as an estimator for Prediction Mean Squared Error, for a

MARS model is calculated as follows:

$$CVG = \frac{MSE_{train}}{(1 - \frac{enp}{n})^2} \tag{3.15}$$

where MSE_{train} is the Mean Squared Error of the model in the training data, n is the number of observations in the training data, and *enp* is the effective number of parameters:

$$enp = k + c * (k + 1)/2 \tag{3.16}$$

where k is the number of basis functions in the model (including the intercept term), and c=3 is the Generalized Cross-Validation (GCV) penalty. We impose no further constraints on the Maximum number of basis functions (including the intercept term) in the final pruned model[19].
Once the model is built we perform variable importance assessment. The criterion counts the number of model subsets that include the variable. Where by "subsets" we mean the subsets of terms generated by the pruning pass. There is one subset for each model size (from 1 to the size of the selected model) and the subset is the best set of terms for that model size. Obviously, only subsets that are smaller than or equal in size to the final model are used for estimating variable importance. We select only variables with a score bigger than 12. After that, we use the selected variables to estimate a machine vector regression model.
The intuition of SVM for regression is to modify the traditional simple linear regression regularized error function

$$\frac{1}{2}\sum_{n=1}^{N}(y_n - t_n)^2 + \frac{\lambda}{2}||w||^2 \tag{3.17}$$

by introducing an ϵ insensitive error function.

$$E_\epsilon(y(x) - t) = \begin{cases} 0 & if \quad |y(x) - t| < \epsilon \\ |y(x) - t| - \epsilon & otherwise \end{cases} \tag{3.18}$$

This implies that we minimize a regularized error function given by

$$C\sum_{n=1}^{N} E_\epsilon(y(x_n) - t_n) + \frac{1}{2}||w||^2 \tag{3.19}$$

where C is a regularization parameter.
Now for each data point x_n, we now need two slack variables $\xi_n \geq 0$ and $\hat{\xi}_n > 0$,

[19] To boost computational performance, and following Friedman [1991], we employ piecewise-cubic modelling for the final model only after both the forward and the backward phases.

where $\xi_n > 0$ corresponds to a point for which $t_n > y(x_n)+\epsilon$ and $\hat{\xi}_n < 0$ correspond to a point for which $t_n < y(x_n) + \epsilon$. Consequently, a target point lies inside the ϵ tube whether $y_n - \epsilon \leq t_n \leq y_n + \epsilon$ where $y_n = y(x_n)$. The introduction of the two slack variables allows points to lie outside the tube provided the slack variables are different from zero:

$$t_n \leq y(x_n) + \epsilon + \xi_n \quad \textit{and} \quad t_n \geq y(x_n) - \epsilon - \hat{\xi}_n \tag{3.20}$$

This implies that the error function for support vector regression can then be written as

$$C\sum_{n=1}^{N}(\xi_n + \hat{\xi}_n) + \frac{1}{2}||w||^2 \tag{3.21}$$

which should be minimized subject to the constraints $\xi_n \geq 0$ and $\hat{\xi}_n \geq 0$ plus the conditions $t_n \leq y(x_n) + \epsilon + \xi_n$ and $t_n \geq y(x_n) - \epsilon - \hat{\xi}_n$. Consequently, the problem can be solved optimizing the Lagrangian with multipliers $a_n \geq 0$, $\hat{a}_n \geq 0$, $\mu_n \geq 0$ and $\hat{\mu}_n \geq 0$

$$\begin{aligned} L = C\sum_{n=1}^{N}(\xi_n + \hat{\xi}_n) + \frac{1}{2}||w||^2 - \sum_{n=1}^{N}(\mu_n\xi_n + \hat{\mu}_n\hat{\xi}_n) \\ - \sum_{n=1}^{N} a_n(\epsilon + \xi_n + y_n - t_n) - \sum_{n=1}^{N}\hat{a}_n(\epsilon + \hat{\xi}_n - y_n + t_n) \end{aligned} \tag{3.22}$$

Computing the partial derivatives and replacing gives

$$\tilde{L}(a,\hat{a}) = -\frac{1}{2}\sum_{n=1}^{N}\sum_{m=1}^{N}(a_n - \hat{a}_n)(a_m - \hat{a}_m)k(x_n, x_m) - \epsilon\sum_{n=1}^{N}(a_n + \hat{a}_n) + \sum_{n=1}^{N}(a_n - \hat{a}_n) * t_n \tag{3.23}$$

where $k(x, x') = \phi(x)^T\phi(x')$ is the kernel.
Replacing $w = \sum_{n=1}^{N}(a_n - \hat{a}_n)\phi(x_n)$ in the general case $y(x) = w^T\phi(x) + b$ where $\phi(x)$ denotes a fixed feature-space transformation, $\phi(x) * \phi(x) = k(x, x_n)$, and b is the bias parameter, we see that predictions can be made using

$$y(x) = \sum_{n=1}^{N}(a_n - \hat{a}_n)k(x, x_n) + b \tag{3.24}$$

We implement the regularized support vector machines regression presented above in the following manner. The half width of the epsilon-insensitive band is set equal to the ratio of the interquartile range of the independent variable distribution and the scalar value 1.349. The regularization Lambda is set equal to one divided the training sample size. The objective function minimization technique chosen is SpaRSA (sparse reconstruction by separable approximation optimization, Wright et al. [2009]). Initial estimates of regression coefficients are all set to zero except the bias one which is initially fixed to the weighted median of the dependent variable in the training set. The criteria for convergence during the optimization process are[20]:

- Relative tolerance on linear coefficients and bias term: 1e-4
- Absolute gradient tolerance: 1e-6
- Size of history buffer for Hessian approximation: 15
- Maximal number of optimization iterations: 1000

For each date t, the model is estimated with predictors data up to t-1. Then the values of the regressors at time t are employed to make inference for date t+1.

3.3.6 Diffusion Indices and Partial Least Squares

The diffusion index approach assumes a latent factor model structure for the potential predictors:

$$x_{i,t} = \lambda_i' f_t + e_{i,t} \tag{3.25}$$

with (i=1,..., K) and f_t is a q-vector of latent factors, λ_i is a q-vector of factor loadings, and $e_{i,t}$ is a zero-mean disturbance term. Co-movements in the predictors are primarily governed by movements in the small number of factors (the number of factors is much smaller than the number of predictors). The latent factors can be consistently estimated by principal components. To implement this approach we started standardizing all the predictors (standard deviation of 1 and zero mean). After that for each date t, we compute the first principal component employing all data available up to t-1. The first principal component is then employed as a regressor to estimate a support vector machine regression. Finally, the support vector machine regression previously estimated with data up to t-1 and the value f_t of the first principal component are used to make inference for time t+1. The approach employed for the estimation of the support vector machine regression is the same explained in the previous subsection: Multivariate Adaptive Regression Splines and Support Vector Machines for Regression.

[20]Further details on the optimization procedure can be found looking at the details of the Matlab function "fitrlinear"

The approach followed for the PLS is similar. At first, the PLS predictor is estimated following the approach of Kelly and Pruitt [2015] and Kelly and Pruitt [2013]:

$$Y^{PLS} = XJ_NX'J_TR(R'J_TXJ_NX'J_TR)^{-1}R'J_TR \tag{3.26}$$

where X denotes the T x N matrix of predictors, $X = (x_1', x_2', ..., x_T')$, and R denotes the T x 1 vector of excess stock returns as $R = (R_2, ..., R_{T+1})'$. The matrices J_T and J_N, $J_T = I_T - \frac{1}{T}i_Ti_T'$ and $J_N = I_N - \frac{1}{T}i_Ni_N'$ enter the formula because each regression is run with a constant. I_T is a T-dimensional identity matrix, and i_T is a T-vector of ones. The PLS predictor is then employed to estimate a univariate support vector machine regression. Finally, the support vector machine regression previously estimated with data up to t-1 and the value Y_t^{PLS} of the PLS predictor are used to make inference for time t+1. The approach employed for the estimation of the support vector machine regression is the same explained in the previous subsection: Multivariate Adaptive Regression Splines and Support Vector Machines for Regression.

3.3.7 Regression Trees and Regression Forest

Classification and regression trees or CART models (Breiman and Friedman [1985]), also called decision trees are defined by recursively partitioning the input space, and defining a local model in each resulting region of the input space.

$$f(x) = E[y|x] = \sum_{m=1}^{M} w_m I(x \in R_m) = \sum_{m=1}^{M} w_m \phi(x, v_m) \tag{3.27}$$

where R_m is the mth region, w_m is the mean response in this region, and v_m encodes the choice of the variables to split on, and the threshold values, on the path from the root to the mth leaf. Consequently, a CART is just an adaptive basis-function model, where the basic functions define the regions, and the weights specify the response value in each region. The split function chooses the best feature (j), and the best value for that feature (t), as follows:

$$(j^*, t^*) = arg \min_{j \in (1,...,D)} \min_{t \in T_j} cost(x_i, y_i : x_{i,j} \leq t) + cost(x_i, y_i : x_{i,j} > t) \tag{3.28}$$

Tree regressions extend the idea of CART but terminal nodes instead of providing the simple average employ a linear model to predict the outcome. Finally, Regression Forest follows an extension of the tree regression based on bootstrapping. The approach of the random forest consists of forecasting through the average (mean) of regression trees generated by bootstrapping the original data. At first, a number (m) of wanted regression trees is fixed. For each m a bootstrap sample of

the original data is generated, and with them, trees regressions are trained. This approach introduces a change in the building of each tree: for each split, the model randomly selects k (less than P) of the total original predictors (P) and partitions the data selecting the best predictor among the k predictors.
To calibrate this model we follow the suggestions of Kuhn and Johnson [2013]. First, all trees are decision trees with binary splits for regression. Second, only 2% of data are employed (with replacement) for building each tree. After that, the number of predictor or feature variables to select at random for each decision split is set to three. We grow the tree using MSE (mean squared error) as the splitting criterion. The stopping criteria for the building of the tree are:

- The maximal number of decision splits (or branch nodes) per tree is equal to the number of observations-1
- Each leaf must have at least five observations
- Each splitting node in the tree must have at least ten observations.

No pruning is performed after the creation of the trees, and no cost function is imposed on errors. Finally, the forecasts generated by each tree are the result of the forecasts coming from leaves only, not from a weighted average of leaves and nodes. This procedure is employed to create 1000 different trees. Once every tree is grown we compute the average prediction from all individual trees and this mean is our forecast of market return at month t+1.
We repeat this procedure for each date t: the model is estimated with predictors up to t-1, then the values of the predictors at time t and the previously estimated parameters are employed to make inference for t+1.

3.3.8 SIC - Lasso Support Vector Machine

The joint employment of all the available predictors is likely to give rise to severe multicollinearity and poor out-of-sample performance. Consequently, employing variable selection is likely to boost the performance of the predictive model. Following this intuition, we consider two separate model selection approaches, and subsequently, we make use of the selected variables into a Support Vector Machine regression model. The first model selection approach considered is the Schwartz Information Criterion (SIC)(Schwarz [1978]).
We employ the SIC, imposing a maximum of 2 predictors for the model selection. For each date t, we use all data available up to that moment, we consider all individual regressors and all possible combinations among two regressors, and we compute the related SIC values

$$log(SIC) = log\left(\frac{SSR}{T}\right) + k * \frac{log(T)}{T} \tag{3.29}$$

where T is the number of observations, k is the number of predictors and SSR is the sum of squared residuals. After that, for each date t, we pick the model with the lowest SIC. Subsequently, we use the predictors of the chosen model to estimate a support vector machine regression model. Finally, we employ it to make inference using the values of predictors at time t to forecast the S&P500 returns at time t+1.
The alternative approach which we employ for model selection is Lasso. At each time t, we run a 10-fold Cross-validated Lasso.

$$\min_{\beta} RSS + \lambda \sum_{j=1}^{N} |\beta_j| \tag{3.30}$$

where N is the number of regressors, λ is the Lagrange multiplier, RSS is the sum of squared residuals. The value of lambda selected is the 95^{th} higher from a default geometric sequence of 100 values, with only the largest able to produce a model which exclude all predictors.
After that, the predictors selected by Lasso are employed to estimate the Linear Support Vector Machine. Finally, we employ it to make inference using the values of predictors at time t to forecast the S&P500 returns at time t+1.

3.3.9 Ensemble of Neural Networks

Feed-forward Network functions are extensions of classical models for regression and classification, which are based on linear combinations of fixed nonlinear basis functions $\phi(x)$ and take the form

$$y(x, w) = f(\sum_{j=1}^{M} w_j \phi_j(x)) \tag{3.31}$$

here f(.) is a nonlinear activation function in the case of classification and is the identity in the event of regression. Neural networks use basis functions that follow the same form so that each basis function is itself a nonlinear function of a linear combination of the inputs, where the coefficients in the linear combination are adaptive parameters. Consequently, the basic neural network model can be described as a series of functional transformations. At first we construct M linear combinations of the input variables $x_1, x_2, \ldots, x_D$ in the form

$$a_j = \sum_{i=1}^{D} w_{ji}^{(1)} x_i + w_{j,0}^{(1)} \tag{3.32}$$

where j=1,..., M and the superscript (1) indicates that the corresponding parameters are in the first 'layer' of the network. The quantities a_j are known as activations. Each of them is then transformed using a differentiable, nonlinear activation function h(.) to give

$$z_j = h(a_j) \tag{3.33}$$

These quantities correspond to the outputs of the basis function y(x,w) above that in the context of neural networks are called hidden units. In our approach, the non-linear functions h(.) are sigmoid. Finally, these values are again linearly combined to give output unit activations.

$$a_k = \sum_{j=1}^{M} w_{kj}^{(2)} z_j + w_{k0}^{(2)} \tag{3.34}$$

where k=1,...,K, and K is the total number of outputs. We can combine these various stages to give the overall network function that takes the form

$$y_k(x, k) = \sum_{j=1}^{M} w_{kj}^{(2)} h(\sum_{i=1}^{D} w_{ji}^{(1)} x_i + w_{j,0}^{(1)}) + w_{k0}^{(2)} \tag{3.35}$$

Thus, the neural network model is simply a nonlinear function from a set of input variables x_i to a set of output variables y_k controlled by a vector w of adjustable parameters.
Our approach involves a preliminary variable selection step. Consequently, only the 4 variables which up to time t have the highest cumulated R^2_{OS} value in univariate predictive regressions are subsequently employed for the estimation of the neural networks. Our neural networks have a structure composed of six layers in which each higher layer has half the number of neurons of the subsequent one, and the first layer has 32 neurons.

Insert Figure 3.8

Inputs are connected to all the neurons of the first and fourth layer. All neurons of one layer are fully connected with the neurons of the subsequent layer. To train the network, we minimize the Mean Absolute Error changing the weights of the network. Training is performed through the Resilient backpropagation algorithm. To avoid overfitting issues we adopt the following procedures:

- We estimate an ensemble of 100 networks with different initialization points.
- We employ the Early Stopping approach.
- We adopt regularization.
- We include a network in the ensemble only whether it generates an R^2 above 20% in the training sample and 25% for the validation one.

- Before the training of each network we randomly divide the data available into three parts: training sample (60%), validation sample (30%) and test sample (10%).

After the estimation of the ensemble, we use the most updated predictors available at time t to forecast the equity premium at time t+1. Finally, we employ the median, and 40^{th} percentile forecasts generated by the ensemble (Neural Networks Median and Neural Networks 40^{th} in the Tables).

3.3.10 Performance Metrics

To asses the out-of-sample predictive performance of the models and predictors considered in this study we follow the literature[21] and employ the R^2_{os}, Delta Utility and Delta Sharpe ratios metrics:

- The R^2_{os} statistic:

$$R^2_{os} = 1 - \frac{\sum_{t=1}^{T}(r_t - \hat{r}_t)^2}{\sum_{t=1}^{T}(r_t - \bar{r}_t)^2} \tag{3.36}$$

  R^2_{os} measures the percent reduction in mean squared forecast error (MSFE) between the forecasts generated by the chosen predictive model, $\hat{r}$, and the historical average benchmark forecast, $\bar{r}$. To assess the statistical significance of R^2_{os} we employ the p-values coming from the Clark and West [2007] MSFE-adjusted statistic. This indicator tests the null hypothesis that the historical average MSFE is less than or equal to the forecasting method MSFE against the alternative that the historical average MSFE is greater than the forecasting method MSFE (corresponding to $H_0 : R^2_{os} <= 0$ against $H_1 : R^2_{os} > 0$).

- The Delta Utility measure. Following the literature (Campbell and Thompson [2008], Rapach et al. [2010]), we estimate the expected variance ($\hat{\sigma}^2_{t+1}$) using a ten-year rolling window of monthly returns. We consider a mean-variance investor who forecasts the equity premium using the historical averages. She will decide at the end of period t to allocate the following share of her portfolio to equity in the subsequent period t+1:

$$w_{0,t} = \frac{1}{\gamma}\frac{\bar{r}_{t+1}}{\hat{\sigma}_{t+1}} \tag{3.37}$$

[21] Both these measures are introduced in the seminal work of Campbell and Thompson [2008] and subsequently employed in a number of studies among which Rapach et al. [2010], Strauss and Detzel [2017] and Rapach et al. [2016]

where $\hat{\sigma}_{t+1}$ is the rolling-window estimate of the variance of stock returns. Over the out-of-sample period, she will obtain an average utility of:

$$\hat{v}_0 = \hat{\mu}_0 - \frac{1}{2}\gamma\hat{\sigma}_0^2 \tag{3.38}$$

where $\hat{\mu}_0$ and $\hat{\sigma}_0^2$ are the sample mean and variance, over the out-of-sample period for the return on the benchmark portfolio formed using forecasts of the equity premium based on the historical average. Then we compute the average utility for the same investor when she forecasts the equity premium using one of the predictive approaches proposed in this paper. In this case, the investor will choose an equity share of:

$$w_{j,t} = \frac{1}{\gamma}\frac{\hat{r}_{t+1}}{\hat{\sigma}_{t+1}} \tag{3.39}$$

and she will realize an average utility level of:

$$\hat{v}_j = \hat{\mu}_j - \frac{1}{2}\gamma\hat{\sigma}_j^2 \tag{3.40}$$

where $\hat{\mu}_j$ and $\hat{\sigma}_j$ are the sample mean and variance, over the out-of-sample period for the return on the portfolio formed using forecasts of the equity premium based on one of the methodologies proposed. In this paper, we measure the utility gain as the difference between $\hat{v}_j$ and $\hat{v}_0$, and we multiply this difference by 100 to express it in average annualized percentage return. In our analysis, following the existing literature,[22] we report results for $\gamma = 3$ and constraint the final weight for the risky asset in the range between -0.5 and 1.5.

3.3.11 Empirical Results and Discussion

Now we turn to the detailed results for the out-of-sample analysis, which are presented in Table 3.1 and Table 3.2. These tables report R^2_{OS} statistics and average utility gains for each of the individual predictive regression models and machine learning models relative to the historical average benchmark model. For the R^2_{OS} statistics statistical significance is assessed with the Clark and West [2007] MSPE-adjusted statistic, as discussed in section 3.10. For brevity, the two tables included in the main text are the ones which report results for the longest out-of-sample period 1986:1-2017:12. For univariate OLS models, the restrictions imposed follows the approach of Campbell and Thompson [2008] while for all the machine

[22] Among the most cited works on the subject Campbell and Thompson [2008] and Rapach et al. [2010] impose the same level of risk aversion

learning approaches the only restriction is that if the forecasted return is negative, it is replaced with zero. The upper part of Table 3.1 based on the out-of-sample predictive performance of univariate linear regression largely confirms the results of Welch and Goyal [2008]: out of 14 predictors, only 2 have a positive R^2_{OS}, and no one of them has a p-value under 0.1. Imposing the constraint of Campbell and Thompson [2008] results improve but again no positive R^2_{OS} statistics exhibit a p-value under 0.1. Our results diverge from the one originally presented by Campbell and Thompson [2008] confirming how the R^2_{OS} metric fluctuates dramatically changing the out-of-sample period. The average utility gains stemming from the same predictors confirms the previous conclusions: only the Earning Price ratio produces an increment of more than 1%, and this result is entirely due to its performance in Recession periods.

For predictive models, results are striking. While, as expected the R^2_{OS} value for the multivariate OLS model is negative, even the well-known Pooled forecast approach of Rapach et al. [2010] and the Sum-of-the parts methodology of Ferreira and Santa-Clara [2011] do not obtain statistically significant R^2_{OS} values. These results hold even for the restricted version of the previous predictive models. When yearly utility gains are considered only the Sum-of-the-Parts approach generates increments around 1% but again this performance arises almost entirely in recession periods. Our newly introduced methodologies, which combine model selection (MARS, SIC, and Lasso) with support vector machines all produce positive R^2_{OS} values which are significant at the 10% level. The related utility gains are relatively small ranging from 0.86% for the SIC Support Vector Machine approach to 2.29% for the MARS Support vector machine approach. These predictive approaches perform, as before, especially well during recession periods, but now the gains are positive even during expansions. After that, diffusion indexes produces a R^2_{OS} of 0.73 which with a related p-value of 0.05 but fail to produce positive utility gains. Finally, our approach which employs neural networks is the winner of the horse race: R^2_{OS} values are above $3-4\%$ and are statistically significant at the 10% level while the delta utility gains are around 1.5 %, and for the 40^{th} percentile approach the performance is stable both in expansion and recession periods. In Figure 3.2 we compare the cumulated returns arising by a buy and hold strategy on the S&P500 and the returns generated by the median restricted forecast of our ensemble of neural networks. It is immediately apparent how the strategy is superior in terms of returns per unit of risk.

Insert Table 3.1

Insert Table 3.2

Insert Figure 3.2

To test the robustness of our findings, we repeat the analysis performed in Tables 3.1 and 3.2 using other out-of-sample periods: 2001:1-2017-12 and 2011:1-2017:12. Results for these robustness checks are reported in the online appendix in Tables 3.15-3.17 and confirm our main results. Indeed the R^2_{OS} statistics generated by our Neural Network approach are above 5% for the 2001-2017 window and remain above 3% for the shorter 2011-2017 period. The related Delta Utility gains are equally important and amount to an average yearly 2.7% for the 2001-2017 window and 2.3% for the 20011-2017 one. Interestingly, the performances of the constrained versions of the Neural Networks are weaker than the performance of their unconstrained counterparts suggesting how these models are successful in the timing of market declines. In these more recent periods, remarkably positive performances are generated even by MARS and Random Forest predictive approaches. For these algorithms, the R^2_{OS} statistics are above 1% with a p-value close or lower to 0.1 The related delta utility gains are approximately 2% for the MARS approach while they reach a recession dependent average 5% for the Random Forest approach.
The findings just recorded implies that some of the most influential papers published in the literature are sample dependent and unable to account for markets structural breaks[23] while our Neural Networks approach appears to remain mostly unaffected by them. These considerations are relevant in light of the highly competitive and fast-changing environment which characterizes stock markets nowadays. Indeed, some studied include in their out-of-sample window even remote periods when the understanding of financial markets was more limited (and market were less efficient) and consequently returns of that time are highly predictable with our state-of-the-art technology. Consequently, the results reported in those studies are biased and unlikely to hold in the current financial market environments.
The results just detailed confirm and augment the finding of Gu et al. [2018]. Overall, these results pose a significant challenge to the Efficient Market Hypothesis, which states that prices incorporate all the information efficiently, and return in excess to the risk-free rate must be matched by higher risks. Now, it is becoming apparent how relatively simple machine learning techniques can consistently beat the market without incurring in higher risks. While neural networks are black boxes and the precise genesis of rationale underpinning predictability remains largely unexplained is getting apparent how more and more powerful machine learning models continuously improve our capability to forecast returns out-of-sample. This poses two fundamental challenges:

[23] Lettau and Van Nieuwerburgh [2007] identifies structural breaks in the dynamics of US stock markets in the early nineties. We prove the robustness of our result by choosing a hard out-of-sample window (1986:1-2017:12) which starts soon before the structural breaks.

1) Understand the genesis of the predictability: which are the factors (linear and non-linear) which the market is unable to reflect promptly and which ultimately generate the predictability detected by our models?
2) Does exist an upper bound to our capability to precisely time the market? Or the only limits are technological and informative? Whether this hypothesis holds financial markets are not efficient but adaptive (Lo [2004]).

3.4 Predictors

The identification of powerful stock predictors is the second pillar of market predictability. While well known, the predictors of Welch and Goyal [2008] are not necessarily the best predictors for the S&P500 index. We start by re-examining the results of Hong et al. [2007] who employs industry indexes as predictors. The authors perform extensive in-sample analysis and conclude that the returns of industry portfolios can predict the movements of the aggregate market. We reexamine their findings adopting an out-of-sample approach. The predictive models employed in our analysis are the same ones adopted in the previous part and include both univariate OLS regressions and machine learning methodologies. To make our results consistent with the ones of the previous literature we consider two windows of monthly returns: a long one spanning the period 1986:1-2017:12 and a shorter one considering the period 2001:1-2017:12. The most striking evidence is that predictability appears to be higher when we consider only the last seventeen years of monthly data. These results are against the hypothesis that the effect captured by Hong et al. [2007] is due to mispricing and consequently it is destinated to disappear. The R^2_{OS} metrics for the predictions of univariate regressions are positive and statistically significant at the 10% level only for three industries: Health care (1.27%), Money (1.97%) and Others (1.90%). Interestingly, the yearly delta utility percentage gains are positive for all the individual predictors in both the out-of-sample windows considered. These gains appear remarkable and, in the period 2001:1-2017:12, pick to 4.3% and 3.74% for the Money and the Chemical index respectively.
Overall, our results confirm and augment the seminal findings of Hong et al. [2007]: industries lead the stock market. After that, we focus on the performance generated by combining the predictors through our machine learning techniques. Here the results are surprisingly disappointing: R^2_{OS} metrics are usually negative, and their p-value is never below the 0.05 threshold. The related yearly percentage of delta utility increments are consistently positive only for Pooled forecasts and for Random Forests, but these values are below the ones generated by the forecasts of the most performing univariate regressions employed before. In conclusion, when industry indexes are employed as predictors for the S&P500 there is no evidence

that by combining predictors we obtain improvements relatively to employing individual predictors only. Our results imply that the results of Rapach et al. [2010] are linked to a specific set of predictors (the Welch and Goyal [2008] ones) and can not be generalized to all typologies of predictors.

Insert Table 3.3

The second alternative set of predictors which we employ to forecast the S&P500 is composed by the 17 spread returns of the factors-anomalies listed in section 2.2. These returns are the results of the difference between long and short factors-anomalies portfolios returns. As before, two out of sample windows are considered 1986:1-2016:12 and 2001:1-2016:12 and forecasts are performed both through univariate OLS regressions and machine learning techniques which consider all this set of predictors. The results which emerge from the univariate OLS out-of-sample forecasts are impressive. Out of 17 predictors, 3 generate high R^2_{OS} results with a p-value close to zero in both the out-of-sample evaluation windows. More precisely for the 1986:1-2016:12 window the R^2_{OS} resulting from the Asset Growth spread, the Net Stock Issue spread and of the Ohlson spread are respectively equal to 13.2%, 23,5%, and 6.4%. Remarkably the 23,5% R^2_{OS} value stemming from the Net Stock Issue spread is record-high in the financial literature on out-of-sample forecasting. The related yearly delta utility spreads are equally impressive: for the 1986:1-2016:12 period the percentage gains generated by the Asset Growth return spread, the Investment to Asset return spread, the Net Stock Issue return spread and the Ohlson spread are respectively of 11.47%, 10.30%, 23.7%, and 4.53%. These results are confirmed by the 2001:1-2016:12 window. These results while novel and impressive are not entirely unexpected: a relatively unknown study, Greenwood and Hanson [2012], shows how the difference between the attributes of stock issuers and repurchasers can forecast characteristic factor returns.
While seminal and elegant, the analysis performed by the authors remains confined into the in-sample domain. We borrow and extend this intuition to forecast the S&P500 with a variety of spread returns coming from different firms' characteristics. After that, the results of the employment of the spread return predictors in our machine learning approaches provide equally satisfactory results. Neural networks achieve an especially positive performance reaching a R^2_{OS} of 17.15% for the 1986:1-2016:12 out-of-sample period and of an 8.8% (delta utility of 17.15%) for the 2001:01-2016:12 one (delta utility of 15.85%). Remarkably, even OLS, Pooled MDSFE forecasts, and the Diffusion index approach are performing extremely well: for the 1986:1-2016:12 approach in terms of R^2_{OS} the performances are 17.69%, 12.36%, and 13.54%. While for the same out-of-sample window the yearly percentage Utility Gains of the three approaches are respectively 12.39%, 10.56%, and 7.11%. These results prove the economic value of our methodologies which is well beyond the ones commonly reported in the current academic

literature.

Insert Table 3.4

Now we study a new, often ignored, feature of predictors. They are relevant not only because they allow to achieve better forecasts but even because they indirectly provide novel information on what ultimately the market prices. Indeed, as stressed by Campbell [1991] the field of asset pricing and predictability are intimately connected and represent two sides of the same issue. While, these ideas are largely accepted, nowadays persists a visible shortage of studies address this aspect of the problem[24]. We address it by showing how the study of the predictive power of the different predictors allows us to gain a deeper understanding of the drivers of stock prices and of spread returns. Our approach is closely linked to the vibrant literature which is currently employing powerful model selection techniques[25] to identify the key factors among the "factor zoo" denounced by Cochrane [2011] but our model selection technique is applied to identify the best predictors out-of-sample and only indirectly to measure their impact on the cross-section of stock returns.

Indeed, while predictors are pivotal components in any predictive approach, they can also be employed to gain a better understanding of equity markets both at the aggregate level (S&P500) and at the cross-sectional one (portfolios built on the base of sorting on size, financial ratios or firms characteristics). It is reasonable to believe that the predictors which are better able to forecast out-of-sample an index are somehow informative of the index or portfolio which they can consistently predict. Following this intuition, we propose an extremely simple, yet effective out-of-sample model selection approach, which can be complementary to the commonly employed in sample ones. For the S&P500, six portfolios sorted on the base of size and Momentum, and for six portfolios sorted on the base of size and the Book to Market ratio we identify the four predictors which in univariate regressions achieve the highest R^2_{OS} (Best Individuals in Table 3.5) AND the combination of four predictors which jointly provides the highest R^2_{OS} in a multivariate linear regression (Combination in Table 3.5). Our results are based on the monthly out-of-sample period 1998:1-2016:12.

Insert Table 3.5

Our results imply that the most relevant predictors for the S&P500 are Sentiment and Variance followed by measures extracted from the fix income market: the t-bill

[24]A recent exception comes from Cujen and Hasler [2017] who explain the higher predictability detected during recessions through the existence of an uncertainty risk premium.

[25]There is a vast blossoming literature on model selection both in therm of the identification of the relevant pricing kernel factors Feng et al. [2017] and on the cross-sectional ones **?**,Fama and French [2018] Feng et al. [2017], Kelly et al. [2018], Barillas and Shanken [2018], Hwang and Rubesam [2018],Messmer and Audrino [2017], Kozak et al. [2017a]

rate, the Long-Term yield, and the Long term return. After that, the most effective spread returns predictors for the S&P500 are the Net-Stock-Issue and the Ohlson ones followed by the Asset Growth and the Small minus Big Spread. Overall it appears how the most influential predictors for the S&P500 index can be clustered into two main categories: sentiment based and default risk-based. The first set of predictors do not include only the Sentiment index itself but even measures which are closely linked like Asset Growth and Net-stock-issue. The second set of predictors is linked to the default risk and include the Ohlson spread the Small minus Big spread, the long term yield, and the Long term return. In conclusion, our results agree with the broadly accepted view that risks and risks pricing are the driving forces of financial markets[26]. In conclusion, an effective predictor needs to be able to predict one of these two key features[27].
Looking at double-sorted portfolios, we report many novel findings. As before the upper panel employs the Welch and Goyal [2008] predictors while the lower panel employs the spread returns coming from factor-anomalies. First, we observe how, coherently with the results of Baker and Wurgler, sentiment is especially powerful in predicting stocks with a low book to market ratio: it is the most powerful predictors when individual regressions are considered and is one of the predictors included in the combination of the four most powerful predictors. Second, stocks with a high book to market value appear to be driven mostly by fundamentally driven predictors, like inflation and volatility. After that, default yield and long term bond returns are especially successful in forecasting the returns of the portfolios of stocks which experienced negative returns (low prior) while stocks which reported positive performances in the recent past (high prior) are better predicted by volatility, sentiment and long term yield. The lower panel (anomalies) reinforce the previous findings. The stocks which have a high book to market value are forecasted by the Net stock issue spread (a variable linked to the Baker-Wurgle Sentiment index formulation) while the Distress spread strongly predicts stocks which have a low book to market value. Now firms with relatively poor past stock returns are forecasted by the Distress spread while Net stock issue spread predicts stocks which experienced high past returns. Finally, the low-high Book/Market spread is strongly forecasted by the Asset Growth spread, and by the Net Operating Asset spread suggesting how profitability is linked to the relative performance

[26] The first seminal studies which address this topic comes from Campbell and Shiller [1988] and Campbell [1991] who introduce the key conceptual framework at the base of our understanding of financial markets. More recently Fuss et al. [2016] and Campbell et al. [2013] applied this framework to the study of the 2008 financial crisis. Remarkable studies on behavioural asset pricing include Shefrin [2008] and Shefrin and Statman [1994] for stocks and Barone-Adesi et al. [2016] for options.

[27] A first promising way to study the genesis of the out-of-sample predictability comes from Rapach et al. [2016] and Wen [2019]

of Book to Market sorted stocks. On the other hand, the High minus Low prior spread is better forecasted by the Ohlson, Distress, and Return on Asset spreads suggesting that default risk is the dominant issue here.
The results of this section while far from being conclusive aim at triggering fruitful discussions:

1. Market efficiency is challenged not only by more and more powerful models but even by more and more powerful predictors. This implies that we can address the challenge posed by Goyal even by using a simple univariate regression whether the predictor employed is powerful enough.

2. We suggest how commonly employed model selection techniques which perform well in-sample should be backed by complementary out-of-sample ones.

3. More broadly, out-of-sample analyses are as informative as in-sample ones to gain a better understanding of financial market dynamics.

3.5 Predictability as a generalized phenomenon

In the previous sections, we proved how using more powerful predictive models or more powerful predictors it is possible to forecast out-of-sample the returns of the S&P500. These results are interesting because of the high efficiency of the U.S. stock market and suggest that in less efficient markets predictability should be even higher. In this section, we address this issue while remaining focused on the US equity stock market. Whether efficiency is directly linked to predictability, less efficient markets should be more predictable than more efficient ones. In the universe of US equities, small stocks are a natural candidate to test this hypothesis. Indeed, small caps are intrinsically less liquid, it is not always possible to short them and when it is possible this procedure is more expensive. After that, to reduce transaction costs, passive funds try to minimize their investments in them while they receive less attention from analysts and media. Even more importantly due to their illiquidity risk and high transaction costs some categories of institutional investors (like high-frequency trading funds and hedge funds) are less prone to invest in them. On the other hand, big capitalization stocks are the natural counterpart of small stocks to verify our hypothesis. Finally, our analysis allows us to test whether the predictability is driven by small stocks only.
To perform our empirical investigation, for each variable out-of-sample evaluation is based on the most recent 30% of the available monthly time series. To be consistent with our previous analyses we report the R^2_{OS} metric and the Δ Utility one. To anchor our result to the existing literature on the field we make use of the double sorted portfolio returns coming from the French data library: the six

double-sorted portfolios formed on the base of size and the Book to market ratio and the six double-sorted portfolios formed on the base of size and the previous returns performance (Momentum). For each portfolio, we report the average R^2_{OS} generated by the univariate OLS forecasts and all the machine learning methodologies detailed in section 2. We repeated these analyses twice: at first by making use of the Welch and Goyal [2008] predictors and subsequently by employing the 17 spread returns predictors introduced in section 2.2[28].

Insert Table 3.6

In the upper panel of the table, we present averages of R^2_{OS} for individual portfolios with the related subtotals R^2_{OS}. After that, we perform a difference between means hypothesis test between portfolios which diverge on size only (e.i. both have a low Book-Market ratio but have a different size). The null hypothesis is that the two means are equal against the general alternative hypothesis. The p-values generated by our analysis are reported in the lower panel of Table 3.6. Our results confirm that small stocks are more predictable than Big ones confirming that efficiency and predictability are closely linked. Indeed, the bottom line of the SMALL-BIG columns shows that the difference in mean is statistically significant at the 0.01 level for the Delta Utility and at the 0.05/0.1 level for the R^2_{OS} metrics while the summary Delta Utility and R^2_{OS} metrics are always higher for Small than for Big caps. After that, the table shows how while Small stocks are more predictable, predictability is a broad phenomenon which includes even big caps: we observe how using return spreads predictors (Anomalies in the Table) it is possible to achieve utility gains for each portfolio of big stocks considered. These results are confirmed by the average R^2_{OS} values achieved using return spreads predictors: 0.68% and 1.16% for portfolios built on Book to market and Momentum sorting. Finally, some predictability patterns emerge: stocks with low Book-to-Market ratio are more predictable than stocks with a high Book-to-Market ratio while stocks with lower previous market returns are more predictable than stock with higher previous market returns. While a study on the genesis of this predictability is beyond the scope of this paper, our out-of-sample analysis in the previous section could provide some preliminary hints.
Having studied the dynamics of predictability inside the French double sorted portfolio framework, now we want to address the issue in a more general framework employing a broader set of stocks. Consequently, we studied the predictability for the returns of thirty equally weighted portfolios and ten related returns spreads[29]

[28]The detailed results for both the R^2_{OS} and Δ Utility metrics are reported, for brevity, in the online appendix: Tables 3.18-3.25

[29]A return spread for a given anomaly implies taking a long position on the portfolio which has the highest expected return and short on the portfolio which has the lowest expected return.

built following the method proposed by Stambaugh and Yuan [2017] who consider a set of eleven anomalies (we do not include Momentum because we have already analyzed it in Table 3.6). We consider the monthly out-of-sample period 1:1986-12:2017 to perform our out-of-sample analyses. Forecasts are based on the Welch and Goyal [2008] predictors: we consider both univariate regressions and all the machine learning techniques detailed in the second part of this paper. For each portfolio and spread we report the average, median, maximum, and minimum value for the R^2_{OS} metric, for the related Clark and West [2007] p-value (Table 3.7) and, for the yearly percentage Delta Utility (Table 3.8). In Table 3.7 for each portfolio, we report even the percentage of forecasts which have a R^2_{OS} p-value lower than 0.1 and 0.05. Finally, in the lower panels of table 3.7 and 3.8, we report summary statistics from the panels above.

Insert Table 3.7

Insert Table 3.8

Our results document the existence of an extensive degree of predictability in financial markets: the 20% of the R^2_{OS} values is positive with a p-value under 0.1 while the average Maximum R^2_{OS} documented for each portfolio is 1.9%. Even more remarkable are the results in terms of utility gains where the comprehensive average value for all the portfolios and spreads is 4.8%, and the average maximum delta utility is close to 10%. These results imply that on average it is possible to add value through predictive models. Even more importantly these results are not confined to the S&P500, to small stocks or a specific subset of the US equity market, but they are generalizable to the average U.S. equity stock. We want to stress how our results are conservative because they relay on the Welch and Goyal [2008] predictors which are less powerful than the spread return ones. The results of these last two table confirm and augment the ones coming from Gu et al. [2018] and Rasekhschaffe and Jones [2019] who used a broad set of machine learning predictors to identify the stocks which are more likely to perform relatively better or worse than the others. Differently, from them, we focused on portfolios built under a variety of criteria reaching similar conclusions: machine learning techniques can consistently time the market.

3.6 Predictable Functions

The existing literature is focused on predicting future stocks returns while it neglects the opportunity coming from forecasting and trading other function of the future market uncertainty. With this section, we aim at fulfilling this gap.

The first and most obvious case which we consider concerns return spreads. These returns arise from going long on a security (or portfolio of securities) and going short on another security (or portfolio of securities). The literature on this topic is large and fast-growing, and it includes both studies on so-called factor-anomalies and statistical arbitrage trading strategies.[30]. For brevity, we focus on factor-anomalies only leaving the study of the predictability of statistical arbitrage strategies to a subsequent study. The factor-anomalies spread returns considered in this section are the same ones considered in the previous one: we zoom into the results succinctly summarised in the previous section by focusing on spread returns only. To make our results comparable with the ones of the previous sections we always employ the R^2_{OS} metric and related Clark and West [2007] p-value. In Table 3.9 we report results arising by employing the Welch and Goyal [2008] predictors while in Table 3.10 we repeat the same analyses using as predictors lagged (t-1) spread portfolio returns. In both cases to make the forecasts we employ both univariate regressions and the machine learning approaches detailed in section 3.1. Coherently with the analyses of the previous sections, when anomalies are employed as predictors, the out-of-sample monthly window spans the period 1986:1-2016:12. Finally, for the forecasts based on the Welch and Goyal [2008] predictors the monthly out-of-sample period considered is the most recent 30% for each predicted variable.

Insert Table 3.9

Insert Table 3.10

The results which come from the tables are striking we observe R^2_{OS} values well above the levels typically recorded for the S&P500: we observe a lot of values above 10% with peaks above 50%. After that, it is apparent how the spread-anomalies returns predictors are much more powerful than the Welch and Goyal ones. The key pattern to notice is that Welch and Goyal [2008] predictors are effective in forecasting the Investment to Asset, the NOA, the Accruals, and the Distress spread. On the other hand, returns spread predictors are more successful in forecasting the SMB, HML, RMW, CMA, LT, ST, Momentum and Composite equity Issue spreads. Overall, out of 17 return spreads 12 exhibits high, statistically significant R^2_{OS} values[31]. Our results raise new challenging questions for future research:
1) Which are the connections among spread returns which give rise to the predictability detected by our models?

[30] The first branch of this literature includes the so-called "factor zoo" (Cochrane [2011]) Interested readers can find a valid summary study in Campbell et al. [2016]. On the other hand, the literature on statistical arbitrages is less known but includes above 90 studies. An updated review of the literature comes from Krauss [2015]

[31] In the online appendix, Tables 3.26 and 3.27 we report our complementary results in terms of yearly percentage utility gains. The empirical evidence which emerges suggests that the capability to forecast return spreads has remarkable economic potential.

2) Which are the links between the spread predictability and the real economy? While spread returns portfolios exhibit a promising degree of predictability, now we extend our analysis to consider others directly or indirectly tradable variables. We consider Implied correlations (IC), model-free implied variance (IV), variance risk premium (VRP), down semivariance (IVD) and realized correlation (RC). For seek of coherence, all these measures are based on the S&P500 index and its components. IC comes from OptionMetrics Surface File using Simple Variance Swaps estimated following the methodology introduced by Martin and Wagner [2019], IV is computed through Simple Variance Swaps, VRP is computed as IV minus realized variance from high-frequency and overnight S&P returns, IVD is computed as corridor variance from OTM puts following the approach of Andersen and Bondarenko [2007], RC is computed as equicorrelation from daily stock returns (same formula as for IC). We focus on standard maturities of 30 and 91 days. As before we employ monthly returns, but now available time series span only the shorter period 1996:1-2016:12. Consequently, we employ the briefer out-of-sample window 2005:1-2016:12 and the 17 spread-portfolio returns as predictors for the returns of the variables just introduced (IC, IV, VRP, IVD, and RC). As before we make use of the R^2_{OS} metric and the related Clark and West [2007] p-values[32].

Insert Table 3.11

The results which emerge show how the Net Stock Issue is extremely effective even in the forecasting of implied volatility, implied downside volatility and implied correlation for all the considered horizons. The related R^2_{OS} values are 8.8% and 14.11% for the 30 and 91 days ahead implied correlations, 10.59% and 15.82% for the implied volatility and 10.96% and 16.18% for the downside implied volatility. All these results are statistically significant and robust through subperiods. After that, the Composite Equity issue, the HML, and the RMW factors are effective in forecasting the VRP at the 91 days horizon (R^2_{OS} values are respectively 2.17%, 2.52%, and 1.56%). The results coming from the machine learning methodologies introduced in section 2 show how the Neural Networks achieve highly significant R^2_{OS} values for all the variables forecasted but the 30 days Realized Correlation (RC 30). Finally, we report how both the pooled MDSFE forecast and the OLS ones produce positive R^2_{OS} values for 91 days ahead Implied correlations, implied volatility and implied downside volatility. In conclusion, we proved how predictability is an attribute of a broader set of financial variables than previously believed. The predictability documented stems both from the employment of powerful predictors (Net Stock Issue and Asset Growth spread returns) and by the adoption of

[32]The complementary out-of-sample Δ Utility performance is reported in Table 3.28, online appendix. We document machine learning approaches can generate remarkable utility gains for all the variables studied out-of-sample.

powerful machine learning methodologies like Neural Networks.
We conclude this paper generalizing our results on predictability: we aim to show how it is possible to synthesize arbitrary functions which own highly predictable returns. To achieve this goal we build on the influential paper of Bakshi and Madan [2000]. The authors show how from the characteristic function of the state-price density, we could price options on almost any arbitrary transformation of the underlying uncertainty. Crucially, the authors show how by differentiating the characteristic function, limitless spanning and pricing opportunities can be designed. In a subsequent application of this first intuition Bakshi et al. [2003] show how it is possible to analytically recover from the market prices of out-of-the-money European calls and puts contracts which approximate the risk-neutral volatility, skewness, and kurtosis. These recent advances make the study of the predictability of risk-neutral implied measures of stringent interest for both academics and practitioners. While in the current study we focus only on better known risk-neutral central moments contracts, the same logic can be easily extended to contracts which approximate other more complex functions like differential multi-assets moments and whole families of trading signals.
In Bakshi et al. [2003] the authors prove how a position in bonds, stocks, and out-of-the-money options can span any twice differentiable payoff function allowing to replicate risk-neutral moments. Importantly, these moments making use of options data only are intrinsically forward-looking, and by definition rely only on options and stocks prices to be estimated. More in detail, let q denote the probability distribution function under the risk-neutral measure. Now we define the "M2", "M3" and "M4" contracts as having a payoff function equal to the squared return, cubed return, and quadratic return respectively, for a given horizon τ. The fair value of these contracts are:

$$M2 = e^{-r\tau} E^Q[R^2] \tag{3.41}$$
$$M3 = e^{-r\tau} E^Q[R^3] \tag{3.42}$$
$$M4 = e^{-r\tau} E^Q[R^4] \tag{3.43}$$

Crucially, Bakshi et al. [2003] show that under any martingale pricing measure, the Var, Cubic and Quad contract prices can be recovered from the market prices on portfolios of out-of-the-money European calls $C(\tau, K)$ and puts $P(\tau, K)$, where K is the strike price and τ denotes the time to maturity.

The price of the Var, Cubic and Quad contract are:

$$M2 = \int_S^\infty \frac{2(1 - ln[\frac{K}{S}])}{K^2} C(\tau, K)dK - \int_0^S \frac{2(1 - ln[\frac{S}{K}])}{K^2} P(\tau, K)dK \quad (3.44)$$

$$M3 = \int_S^\infty \frac{6ln[\frac{K}{S}] - 3ln[\frac{K}{S}]^2}{K^2} C(\tau, K)dK - \int_0^S \frac{6ln[\frac{S}{K}] + 3ln[\frac{S}{K}]^2}{K^2} P(\tau, K)dK \quad (3.45)$$

$$M4 = \int_S^\infty \frac{12(ln[\frac{K}{S}])^2 - 4(ln[\frac{K}{S}])^3}{K^2} C(\tau, K)dK - \int_0^S \frac{12(ln[\frac{S}{K}])^2 + 4(ln[\frac{S}{K}])^3}{K^2} P(\tau, K)dK \quad (3.46)$$

where S is the price of the underlying security and using a fourth order approximation the risk-neutral mean can be approximated by:

$$E^Q[R] = e^{r\tau} - 1 - \frac{e^{r\tau}}{2} M2 - \frac{e^{r\tau}}{6} M3 - \frac{e^{r\tau}}{24} M4 \quad (3.47)$$

allowing us to recover the "M1" contract having a payoff function equal to the return for a given horizon τ

$$M1 = e^{-r\tau} E^Q[R] \quad (3.48)$$

To make our results comparable with the others coming from the previous sections of the paper, we test the out-of-sample performance with the R^2_{OS} metric and the related Clark and West [2007] p-values[33]. The out-of-sample monthly window spans the period 1:2005-12:2017. The variable forecasted are the returns of the first four 20 and 40 days ahead moments contracts. We employ as predictors both the Welch and Goyal [2008] variables (W-G), and the portfolio spread returns (Anomalies). For brevity, we report only the results generated by the machine learning methodologies detailed in section 3.1 of this paper.

Insert Table 3.12

The results which emerge exhibit high and statistically significant values for the R^2_{OS} statistic for the majority of the considered contracts. These values are very heterogeneous: they are especially high for the M3-40 contract (with picks above 50%) while they are low for the M2 20 contract (the few positive values are not significant at the 10% level). Overall R^2_{OS} values are higher for forecasts made with the spread return predictors than with the Welch and Goyal [2008] ones providing

[33] In Table 3.29 of the online appendix we test the out-of-sample Delta Sharpe ratio. We decided to employ this measure instead of the traditional Delta Utility one because, in this special context, the sensitivity of Delta Utility to small changes in the risk aversion parameters is excessive.

further confirmation that the former predictors are more powerful than the latter. We further document how out of the eight contracts considered four exhibit R^2_{OS} above 4% suggesting how the returns of these contracts are predictable.
In conclusion, the results documented in this section show how different functions of market uncertainty are highly predictable. Even more importantly, the capability to synthesize and trade contracts with arbitrary payoff opens the way to a new research pattern: instead of searching for more powerful predictive models and predictors we can aim at identifying functions of the market uncertainty which are highly predictable. This new approach has both an economic and academic, largely unexplored, potential and provides a new further challenge to the efficient market hypothesis and more broadly to our understanding of asset pricing.

3.7 Conclusions

In this paper we examine the three key aspects of financial market predictability: predictive modeling, predictors and the functions of market uncertainty we aim at forecasting.
At first, we focus on predictive models employing as inputs the well known Baker-Wurgler predictors. We show how combining machine learning and model selection techniques the capability to forecast out-of-sample the S&P500 rises dramatically. Remarkably, when model selection techniques are combined with Ensembles of multilayer Neural Networks the monthly R^2_{OS} riches a statistically significant 4.4% for the period 1986-2017 and 6.14% for the shorter 2001-2017 period. The related annualized utility gains are of an equally relevant magnitude picking at 3% for the 2001-2017 interval. The implications of these findings for the theory of finance are twofold. From one side our results pose a significant challenge to the efficient market hypothesis proving how machine learning experts can build algorithms capable of consistently outperforming the market, on the other side they suggest how new asset pricing models should include nonlinear interdependencies in the formulation of the pricing kernel.
In the second section of the paper, we consider a variety of different predictors. We show how the returns generated from the long-short strategies (often addressed as anomalies in the literature) have a surprisingly strong out-of-sample predictive power for the S&P500. The most successful predictors are the spread returns based on Asset Growth, Net Stock Issue, Olshon and Investment to Asset characteristics which, for the 1986-2016 out-of-sample period reach a record high R^2_{OS} level of 13%, 23.5%, 6.4% and 11.1%. The Delta Utility gains generated by these predictors confirm their profitability. After that, we study the predictability of the double-sorted portfolios of Fama and French, and we find that while small stocks are on average more predictable then big ones, predictability is a generalized feature

of financial markets when machine learning techniques are employed. Finally, in this section, we propose to employ an out-of-sample approach as a complement to the traditional in sample techniques to identify which characteristics are ultimately reflected into stock prices. Our simple method opens the ground to a much-needed study on the relationship between predictability and pricing.

In the third part of our analysis, we propose a new approach to address the issue of financial market predictability, by conceptually reversing the issue. Instead of focusing on powerful predictive models or powerful predictors we propose to study highly predictable functions of market uncertainty. We focus on the well known Bakshi-Madan contracts for the first four moments of the risk-neutral distribution and volatility and correlation swaps. We detect surprisingly high predictability for the contracts analyzed out-of-sample both regarding R^2_{OS} and Delta Utility-Sharpe ratios. While remarkable in their own, the results showed are only examples of a much general approach which has unexplored potential.

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3.8 Tables and Figures

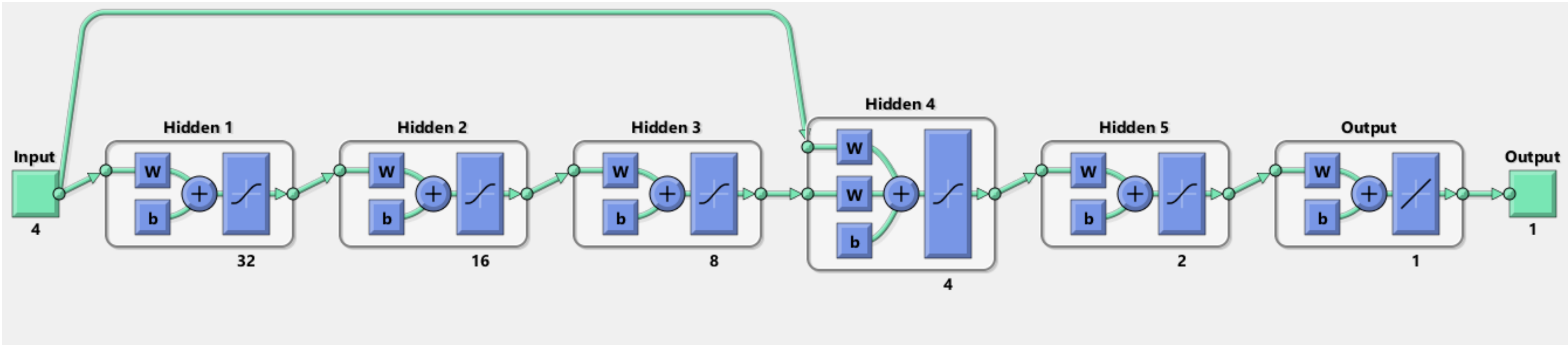

Figure 3.1: **Neural Network Structure**: 6 layers, 4 inputs and 1 output (the equity premium forecast). Activation all activation functions are sigmoids with the exception of the last one which is linear. Inputs are connected with the first and the fourth layer only. The number of neurons for each layer are 32,16,8,4,2 and 1. Training occurs through Resilient Backpropagation.

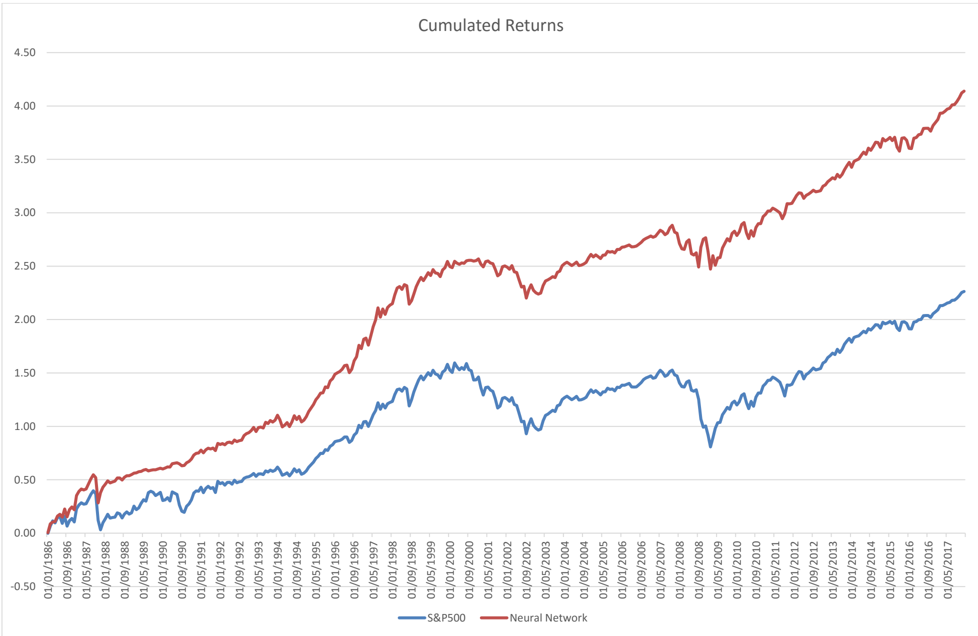

Figure 3.2: **Cumulated monthly returns for the 1986:1-2017:12 period**. The Blue line tracks cumulated returns for the S&P500 index (Blue) and for the strategy which employs the median (Restricted) forcast arising from an ensamble of Neural Networks to proxy for expected returns in the optimization process (Red).

Table 3.1: **Monthly equity premium out-of-sample forecasting results for individual forecasts, and machine learning methods**. The R^2_{OS} is the Campbell Thompson (2008) out-of-sample R^2 statistic. Statistical significance for the R^2_{OS} statistic is based on the p-value for the Clark and West (2007) out-of-sample MPSE-adjusted statistic; the statistic corresponds to a one-sided test of the null hypothesis that the competing forecasting model has equal expected square prediction error relative to the historical average benchmark forecasting model against the alternative hypothesis that the competing forecasting model has a lower expected square prediction error than the historical average benchmark forecasting model. The results refer to monthly forecasts for the out-of-sample period 1986-2017. For predictions based on univariate forecasts the restrictions are the ones suggested by Campbell and Thompson (2008) while for the machine learning methods when equity premium forecasts are negative they are replaced with zero. *,** and *** indicate significance level at the 10%, 5% and 1%. Bold indicates a pvalue for the R^2_{OS} statistic less than 0.1. .

Standard	**1986-2017**		**Restricted**	**1986-2017**	
Predictor	$R^2_{OS}(\%)$	**pval**	**Predictor**	$R^2_{OS}(\%)$	**pval**
DP	-1.34	0.52	DP	-1.00	0.50
DY	-1.99	0.48	DY	-1.17	0.52
EP	-1.41	0.32	EP	0.07	0.20
DE	-0.54	0.54	DE	-0.03	0.31
SVAR	0.39	0.16	SVAR	0.32	0.13
BM	-2.28	0.57	BM	-1.29	0.56
NTIS	-1.77	0.65	NTIS	-1.77	0.65
TBL	-0.21	0.47	TBL	-0.20	0.46
LTY	-0.06	0.44	LTY	-0.06	0.44
LTR	-0.31	0.40	LTR	-0.36	0.44
TMS	-0.83	0.64	TMS	-0.83	0.64
DFY	-0.20	0.92	DFY	-0.20	0.92
DFR	0.18	0.29	DFR	-0.19	0.43
INFL lag	-0.35	0.84	INFL lag	-0.35	0.84

Model	$R^2_{OS}(\%)$	**pval**	**Model**	$R^2_{OS}(\%)$	**pval**
OLS	-5.83	0.36	OLS	-1.83	0.24
Pooled forecast: median	0.08	0.32	Pooled forecast: median	0.08	0.32
Pooled forecast: DMSFE	-0.01	0.42	Pooled forecast: DMSFE	-0.01	0.42
Sum-of-the-parts	0.24	0.21	Sum-of-the-parts	0.47	0.12
MARS	**0.89****	**0.02**	MARS	**0.95*****	**0.01**
SVM SIC	**0.49***	**0.06**	SVM SIC	**0.71****	**0.02**
Lasso SVM	**0.37***	**0.10**	Lasso SVM	**0.58****	**0.05**
Random Forest	**0.52***	**0.10**	Random Forest	**0.59***	**0.08**
Diffusion index	**0.73****	**0.05**	Diffusion index	**0.73****	**0.05**
PLS	0.02	0.15	PLS	**0.31***	**0.09**
Neural Networks Median	**3.22***	**0.09**	Neural Networks Median	**0.03***	**0.06**
Neural Networks 40^{th}	**4.38***	**0.10**	Neural Networks 40^{th}	**0.85****	**0.03**

Table 3.2: **Monthly equity premium out-of-sample forecasting results for individual forecasts, and machine learning methods**. Utility gain (Δ Utility) is the portfolio management fee (in annualized percentage return) that an investor with mean-variance preferences and risk aversion coefficient of three would be willing to pay to have access to the forecasting model considered relative to the historical average benchmark forecasting model; the weight on stocks in the investor's portfolio is restricted to lie between -0.5 and 1.5 (inclusive). The restriction imposed for the restricted case are the same of Table 1. The results refer to monthly forecasts for the out-of-sample period 1986-2017. The division between Recession and Expansion months comes from the NBER database. *,** and *** indicate a Δ Utility % increase above 1%, 5% and 10%. **Bold** indicates a Δ Utility above 1.00%.

Δ Utility	**1986-2017**			**Δ Utility**	**1986-2017**		
Standard	**Total**	**Expansion**	**Recession**	**Restricted**	**Total**	**Expansion**	**Recession**
DP	-2.59	-5.29	**23.72*****	DP	-1.23	-3.78	**23.62*****
DY	-2.66	-6.10	**31.22*****	DY	-1.16	-4.44	**31.14*****
EP	**1.83***	-1.50	**34.59*****	EP	**2.01***	-1.17	**33.32*****
DE	-0.26	-0.21	-0.43	DE	-0.05	-0.06	0.00
SVAR	-0.58	-0.42	-2.07	SVAR	0.05	0.03	0.35
BM	-2.67	-6.40	**34.25*****	BM	-1.03	-4.56	33.86
NTIS	-0.66	-0.10	-6.53	NTIS	-0.66	-0.10	-6.53
TBL	0.00	0.45	-4.49	TBL	0.00	0.45	-4.49
LTY	0.06	0.23	-1.63	LTY	0.06	0.23	-1.63
LTR	-0.18	-0.63	**3.73***	LTR	-0.26	-0.60	**2.65***
TMS	-1.08	-0.73	-4.61	TMS	-1.08	-0.73	-4.61
DFY	-0.90	-0.58	-4.68	DFY	-0.90	-0.58	-4.68
DFR	0.96	0.26	**7.81****	DFR	0.87	0.21	**7.46****
INFL lag	-0.74	0.08	-8.41	INFL lag	-0.74	0.08	-8.41

Standard	**Total**	**Expansion**	**Recession**	**Restricted**	**Total**	**Expansion**	**Recession**
OLS	-1.23	-4.76	**33.46*****	OLS	0.72	-2.22	**29.42*****
Pooled forecast: median	0.07	0.28	-1.89	Pooled forecast: median	0.07	0.28	-1.89
Pooled forecast: DMSFE	-0.05	-0.24	**1.90*****	Pooled forecast: DMSFE	-0.05	-0.24	**1.90*****
Sum-of-the-Parts	0.60	-0.44	**10.77*****	Sum-of-the-Parts	0.91	-0.31	**12.79*****
MARS	**2.29***	**1.45***	**10.48*****	MARS	**2.37***	**1.47***	**11.13*****
SVM SIC	0.86	0.28	**6.86****	SVM SIC	**1.20***	0.28	**10.33*****
Lasso SVM	**1.17***	0.47	**8.14****	Lasso SVM	**1.35***	0.47	**10.05*****
Random Forest	**1.54***	-0.08	**17.39*****	Random Forest	**1.54***	-0.08	**17.39*****
Diffusion Index	-0.24	0.12	-4.32	Diffusion Index	-0.24	0.12	-4.32
PLS	0.22	0.60	-3.64	PLS	0.27	0.66	-3.64
Neural Networks Median	**1.38***	**1.80***	-1.34	Neural Networks Median	**1.18***	**1.52***	**2.10***
Neural Networks 40^{th}	**1.71***	**1.71***	**1.71***	Neural Networks 40^{th}	**1.64***	**1.62***	**1.92***

Table 3.3: **Industry predictors**: monthly equity premium out-of-sample forecasting results for individual forecasts, and machine learning methods. We consider two monthly out-of-sample windows: 1986:1-2017:12 and 2001:1-2017:12. For the R^2_{OS} statistic *,** and *** indicate significance level at the 10%, 5% and 1%. For ΔUtility % * indicates an yearly increase above 1%. Bold indicates a ΔUtility above 1.00% or a R^2_{OS} with a p-value lower than 0.1.

	1986-2017		**2001-2017**	
Predictor	R^2_{OS}	**pval**	R^2_{OS}	**pval**
NoDur	-0.60	0.41	0.00	0.34
Durbl	-0.37	0.29	0.94	0.14
Manuf	-0.31	0.33	0.99	0.18
Enrgy	-0.42	0.67	0.08	0.36
Chems	-0.24	0.30	1.12	0.15
BusEq	-0.38	0.18	1.45	0.11
Telcm	-0.28	0.47	0.79	0.17
Utils	0.30	0.21	0.98	0.17
Shops	0.32	0.18	0.73	0.17
Hlth	-0.11	0.27	**1.27***	**0.09**
Money	0.07	0.17	**1.97***	**0.08**
Other	0.50	0.14	**1.90***	**0.09**
	1986-2017		**2001-2017**	
Model	R^2_{OS}	**pval**	R^2_{OS}	**pval**
OLS	-2.79	0.12	-1.20	0.14
Pooled forecast:median	0.21	0.23	1.07	0.13
Pooled forecast:MDSFE	0.18	0.24	1.29	0.12
MARS	-3.00	0.97	-3.00	0.89
SVM SIC	-0.60	0.38	-1.52	0.64
Lasso SVM	-0.64	0.39	-1.59	0.66
Radom Forest	0.06	0.30	**0.90***	**0.09**
Diffusion index	-0.35	0.26	-1.00	0.49
PLS	-1.29	0.56	-2.08	0.65
Neural Networks Median	-0.01	0.22	-1.21	0.52

	1986-2017	**2001-2017**
Predictor	**Δ Utility**	**Δ Utility**
NoDur	0.46	**1.94***
Durbl	0.53	**2.45***
Manuf	0.40	**2.80***
Enrgy	0.81	**1.85***
Chems	**1.08***	**3.74***
BusEq	0.31	**3.21***
Telcm	0.13	**2.61***
Utils	**2.03***	**3.44***
Shops	**1.35***	**2.50***
Hlth	0.60	**2.91***
Money	**1.27***	**4.37***
Other	**1.75***	**3.90***
	1986-2017	**2001-2017**
Model	**Δ Utility**	**Δ Utility**
OLS	0.09	**3.17***
Pooled forecast:median	**1.37***	**3.21***
Pooled forecast:MDSFE	**1.49***	**3.57***
MARS	-3.47	-1.61
SVM SIC	-0.93	-0.94
Lasso SVM	-0.94	-0.96
Radom Forest	**1.37***	**2.61***
Diffusion index	-0.41	-0.49
PLS	-0.96	-1.01
Neural Networks Median	0.02	-0.94

Table 3.4: **Factors-Anomalies spread return predictors**: monthly equity premium out-of-sample forecasting results for individual forecasts, and machine learning methods. We consider two monthly out-of-sample windows: 1986:1-2016:12 and 2001:1-2016:12. For the R^2_{OS} statistic *,** and *** indicate significance level at the 10%, 5% and 1%. For ΔUtility % *,** and *** indicate an increase above 1%, 5% and 10%. Bold indicates a ΔUtility above 1.00% or a R^2_{OS} with a p-value lower than 0.05.

	1986-2016		**2001-2016**	
Predictor	R^2_{OS}	**pval**	R^2_{OS}	**pval**
SMB	-0.45	0.29	-0.98	0.49
HML	-0.22	0.35	0.07	0.33
RMW	-0.40	0.43	-0.41	0.41
CMA	0.19	0.07	0.55	0.17
LT	-0.42	0.39	-0.87	0.54
ST	-0.76	0.82	-2.15	0.97
Mom	-0.78	0.90	-1.12	0.89
Asset Growth	**13.20*** **	**0.00**	**3.55*** **	**0.00**
Gross Prof	-0.15	0.00	-11.67	0.83
Inv to Assets	**11.13*** **	**0.00**	-1.17	0.01
Net Stock Issues	**23.54*** **	**0.00**	**28.67*** **	**0.00**
NOA	-2.95	0.36	-4.18	0.80
Accruals	-1.72	0.01	-10.18	0.56
O	**6.43*** **	**0.00**	**6.69** **	**0.01**
ROA	-3.64	0.04	-12.88	0.95
Distress	0.71	0.08	0.14	0.25
Comp Eq Issue	-0.38	0.49	-0.19	0.32
	1986-2016		**2001-2016**	
Model	R^2_{OS}	**pval**	R^2_{OS}	**pval**
OLS	**15.71*** **	**0.00**	**17.69*** **	**0.00**
Pooled Forecast median	**2.37*** **	**0.00**	**3.50* **	**0.00**
Pooled Forecast MDSFE	**10.89*** **	**0.00**	**12.36*** **	**0.00**
MARS	**11.82** **	**0.00**	**4.90* **	**0.00**
SVM SIC	-20.13	0.34	-12.36	0.18
Lasso svm	-12.46	0.24	-9.03	0.18
Random Forest	-0.01	0.40	0.12	0.18
Diffusion Index	**4.16*** **	**0.01**	**13.54*** **	**0.00**
PLS	-30.75	0.92	-32.40	0.97
Neural Networks Median	**16.06*** **	**0.00**	**8.72** **	**0.00**

	1986-2016	**2001-2016**
Predictor	**Δ Utility**	**Δ Utility**
SMB	-0.58	-1.44
HML	0.11	**1.23* **
RMW	0.39	**1.20* **
CMA	0.99	**1.51* **
LT	0.45	0.46
ST	-0.68	-2.20
Mom	-0.61	-0.66
Asset Growth	**11.47*** **	**6.96** **
Gross Prof	**1.06* **	-6.68
Inv to Assets	**10.30*** **	**6.29** **
Net Stock Issues	**23.56*** **	**28.53*** **
NOA	-2.31	-3.64
Accruals	**2.39* **	-1.85
O	**4.53** **	**5.43** **
ROA	0.05	-5.50
Distress	**2.36* **	**2.59* **
Comp Eq Issue	-0.10	0.77
	1986-2016	**2001-2016**
Model	**Δ Utility**	**Δ Utility**
OLS	**14.13*** **	**12.39*** **
Pooled Forecast median	**5.05** **	**3.38* **
Pooled Forecast MDSFE	**12.76*** **	**10.56*** **
MARS	**5.11** **	**13.10*** **
SVM SIC	0.24	0.16
Lasso svm	0.00	0.86
Random Forest	0.08	0.47
Diffusion Index	**10.97*** **	**7.11** **
PLS	-9.67	-4.99
Neural Networks Median	**7.96** **	**15.64*** **

Table 3.5: **Out-of-sample model selection approach.** This table considers the S&P500 index, six portfolios built sorting on the base of size and the Book/Market ratio, six portfolios built sorting on the base of size and Momentum, and four portfolios spreads. The out-of-sample monthly evaluation period is 1998:1-2016:12. The upper panel of the table shows the results by employing the Welch and Goyal [2008] variables plus the Sentiment index of Huang et al. [2015] (W-G in the Table) while the lower panel considers the 16 spreads of factors-anomalies considered in this paper plus the sentiment index of Huang et al. [2015] (Anomalies in the Table). For each variable considered the table ranks the 4 predictors which individually exhibit the highest R^2_{OS} in univariate regression forecasting (Best Individual in the Table) and the four variables which jointly have the highest R^2_{OS} in multivariate OLS forecasting (Combination). Data are monthly and the R^2_{OS} metrics are based on the out-of-sample period from 1998 to 2016. Where for the W-G panel the numbers mean: DP(1), DY(2), EP(3), DE(4), SVAR(5), BM(6), NITIS(7), TBL(8), LTY(9), LTR(10), TMS(11), DFY(12), DFR(13), INFlag(14), SENT(15). While for the Anomalies panel the numbers means: SMB(1), HML(2), RMW(3), CMA(4), LT(5), ST(6), MOM(7), Asset Growth(8), Gross Profitability(9), Investment to Assets(10), Net Stock Issues(11), NOA(12), Accruals(13), Ohlson(14), ROA(15), Distress(16), Composite Equity Issue(17).

Combination					**Best individual**				
W-G					**W-G**	**(1)**	**(2)**	**(3)**	**(4)**
S&P 500	5	10	14	15	S&P 500	15	5	9	8
SMALL LoBM	5	9	10	15	SMALL LoBM	15	5	10	9
ME1 BM2	5	10	11	12	ME1 BM2	5	9	15	8
SMALL HiBM	5	10	11	14	SMALL HiBM	5	9	15	11
BIG LoBM	5	10	14	15	BIG LoBM	15	5	9	10
ME2 BM2	5	10	14	15	ME2 BM2	5	15	14	9
BIG HiBM	5	10	14	15	BIG HiBM	5	14	15	9
SMALL LoPRIOR	1	2	10	12	SMALL LoPRIOR	15	10	12	9
ME1 PRIOR2	5	10	11	12	ME1 PRIOR2	5	10	9	15
SMALL HiPRIOR	5	8	9	10	SMALL HiPRIOR	5	9	15	10
BIG LoPRIOR	10	12	14	15	BIG LoPRIOR	15	10	14	6
ME2 PRIOR2	5	10	14	15	ME2 PRIOR2	15	5	8	14
BIG HiPRIOR	5	9	10	15	BIG HiPRIOR	5	15	9	13
SMALL LoBM-SMALL HiBM	7	11	12	15	SMALL LoBM-SMALL HiBM	15	5	12	14
BIG LoBM-BIG HiBM	5	10	14	15	BIG LoBM-BIG HiBM	14	5	11	15
SMALL HiPRIOR- SMALL LoPRIOR	1	2	3	9	SMALL HiPRIOR- SMALL LoPRIOR	4	3	12	9
BIG HiPRIOR-BIGLoPRIOR	6	10	12	14	BIG HiPRIOR-BIGLoPRIOR	12	10	5	4

Anomalies					**Anomalies**	**(1)**	**(2)**	**(3)**	**(4)**
S&P 500	1	11	12	14	S&P 500	11	14	8	10
SMALL LoBM	5	6	7	11	SMALL LoBM	11	8	10	14
ME1 BM2	6	11	14	16	ME1 BM2	11	16	7	10
SMALL HiBM	6	11	14	16	SMALL HiBM	11	16	7	6
BIG LoBM	1	5	11	14	BIG LoBM	11	14	8	10
ME2 BM2	6	11	12	14	ME2 BM2	11	16	14	10
BIG HiBM	9	11	12	15	BIG HiBM	11	16	10	14
SMALL LoPRIOR	5	6	11	16	SMALL LoPRIOR	11	16	10	8
ME1 PRIOR2	6	7	11	16	ME1 PRIOR2	11	16	10	7
SMALL HiPRIOR	1	6	11	14	SMALL HiPRIOR	11	7	5	3
BIG LoPRIOR	11	12	14	16	BIG LoPRIOR	16	11	10	8
ME2 PRIOR2	11	12	14	16	ME2 PRIOR2	11	14	16	8
BIG HiPRIOR	1	5	6	11	BIG HiPRIOR	11	14	3	17
SMALL LoBM-SMALL HiBM	8	11	12	16	SMALL LoBM-SMALL HiBM	11	8	14	10
BIG LoBM-BIG HiBM	6	8	12	15	BIG LoBM-BIG HiBM	14	15	8	12
SMALL HiPRIOR- SMALL LoPRIOR	12	14	15	16	SMALL HiPRIOR- SMALL LoPRIOR	16	15	10	12
BIG HiPRIOR-BIGLoPRIOR	12	14	15	16	BIG HiPRIOR-BIGLoPRIOR	16	15	14	12

Table 3.6: **Out-of-sample predictability of big vs small stocks.** In this table we compare the out-of-sample predictability of a set of 12 portfolios: six double sorted on the base of size and the Book to Market ratio and six sorted on the base of size and the previous performance (Momentum). In the first eight rows we report the average performance for each portfolios in terms of R^2_{OS} using the Welch and Goyal [2008] predictors (W-G) and the 17 factors-anomalies spread returns (Anomalies). In both cases we employ univariate regressions and all the machine learning methodologies previously detailed. The monthly out-of-sample period considered is 1:1986-12:2016. Total Average rows and SMALL and BIG columns (in bold in the table) compute the sub-total averages. In rows form 9 to 16 we repeat the same exercise with the Delta Utility metric.
In the last eight rows of the table we report the p-values for the difference in mean between portfolios which diverge only because of size. The Null Hypothesis is that there is no difference in means. ***,**, and * indicates a pvalue under 0.01, 0.05 and 0.1.

R^2_{OS}	SMALL LoBM	ME1 BM2	SMALL HiBM	SMALL	BIG LoBM	ME2 BM2	BIG HiBM	BIG
W-G	-0.65	-1.41	-2.08	**-1.38**	-0.73	-1.48	-1.70	**-1.30**
Anomalies	3.78	1.37	1.36	**2.17**	1.57	-0.20	0.67	**0.68**
Total Average	**1.56**	**-0.02**	**-0.36**	**0.39**	**0.42**	**-0.84**	**-0.51**	**-0.31**
R^2_{OS}	SMALL LoPRIOR	ME1 PRIOR2	SMALL HiPRIOR	SMALL	BIG LoPRIOR	ME2 PRIOR2	BIG HiPRIOR	BIG
W-G	-0.88	-1.59	-0.88	**-1.12**	-1.49	-1.12	-0.60	**-1.07**
Anomalies	5.43	2.01	1.49	**2.98**	3.46	0.33	-0.31	**1.16**
Total Average	**2.27**	**0.21**	**0.31**	**0.93**	**0.99**	**-0.40**	**-0.45**	**0.05**
Δ Utility	SMALL LoBM	ME1 BM2	SMALL HiBM	SMALL	BIG LoBM	ME2 BM2	BIG HiBM	BIG
W-G	-0.27	-0.50	-1.30	**-0.69**	0.53	0.25	-1.84	**-0.35**
Anomalies	7.22	4.56	3.88	**5.22**	3.85	2.64	2.93	**3.14**
Total Average	**3.48**	**2.03**	**1.29**	**2.26**	**2.19**	**1.45**	**0.55**	**1.40**
Δ Utility	SMALL LoPRIOR	ME1 PRIOR2	SMALL HiPRIOR	SMALL	BIG LoPRIOR	ME2 PRIOR2	BIG HiPRIOR	BIG
W-G	-1.66	-0.48	0.13	**-0.67**	-2.29	-0.02	0.92	**-0.47**
Anomalies	4.46	4.95	6.33	**5.24**	3.71	3.12	4.23	**3.68**
Total Average	**1.40**	**2.23**	**3.23**	**2.29**	**0.71**	**1.55**	**2.57**	**1.61**

p-values

R^2_{OS}	LoBM	ME1 BM2	HiBM	SMALL-BIG	LoPRIOR	PRIOR2	HiPRIOR	SMALL-BIG
W-G	0.58	0.67	**0.10***	0.45	**0.00*****	**0.06***	0.33	0.74
Anomalies	0.23	0.21	0.41	**0.05****	**0.10***	0.12	0.15	**0.01*****
Total Average	0.21	0.19	0.69	**0.07***	**0.04****	0.25	0.22	**0.01*****
Δ Utility	LoBM	ME1 BM2	HiBM	SMALL-BIG	LoPRIOR	PRIOR2	HiPRIOR	SMALL-BIG
W-G	**0.04****	**0.00*****	**0.02****	**0.06***	**0.10***	0.32	**0.02****	0.37
Anomalies	**0.01***	**0.01***	**0.08***	**0.00*****	0.27	**0.00*****	**0.01*****	**0.00*****
Total Average	**0.07***	0.12	**0.01*****	**0.00*****	**0.08***	**0.08***	0.13	**0.00*****

Table 3.7: **Out-of-sample predictability of anomalies portfolios: R^2_{OS}.** In the Upper Panel we report the Average, Median, Maximum and Minimum R^2_{OS} values for 30 portfolios based on characteristics sorting and 10 spread portfolios returns. The monthly out-of-sample period considered is the most recent 30% for each variable. Forecasts are based on Welch and Goyal [2008] predictors: we consider both univariate regression and all the machine learning techniques detailed in the second part of this paper. Subsequently, we reported the related Clark and West [2007] p-values. Finally, for each portfolio and spread we report the % of p-values under 0.1 and under 0.05. In the Lower Panel we briefly summarize the results coming from the upper panel. We use bold to remark Maximum R^2_{OS} values above 1% and Minimum p-values under 0.1.

	R^2_{OS}	**Average**	**Median**	**Max**	**Min**	**% Pval<0.1**	**% Pval<0.05**
Asset Growth	Low	0.09	0.42	**2.42**	-5.98		
	pval	0.27	0.14	0.88	**0.01**	0.38	0.27
	Medium	-0.48	0.15	**1.81**	-8.37		
	pval	0.30	0.17	0.86	**0.03**	0.35	0.15
	High	-1.41	-0.52	**1.42**	-12.24		
	pval	0.45	0.48	0.83	**0.02**	0.08	0.08
	Spread	-4.40	-4.49	**2.55**	-17.88		
	pval	0.43	0.35	0.97	**0.01**	0.19	0.12
Gross Prof	Low	-0.39	-0.20	**1.82**	-6.95		
	pval	0.38	0.32	0.94	**0.03**	0.27	0.15
	Medium	-1.07	-0.41	**1.31**	-8.64		
	pval	0.40	0.33	0.86	**0.01**	0.08	0.04
	High	-0.91	0.08	**1.65**	-11.87		
	pval	0.28	0.21	0.90	**0.00**	0.27	0.15
	Spread	-2.80	-1.93	**0.94**	-21.68		
	pval	0.58	0.65	0.84	**0.06**	0.08	0.00
Inv to Assets	Low	0.26	0.73	**2.35**	-6.21		
	pval	0.25	0.09	0.87	**0.02**	0.50	0.31
	Medium	-0.66	0.03	**1.74**	-8.01		
	pval	0.33	0.31	0.87	**0.01**	0.19	0.15
	High	-1.56	-0.60	**0.85**	-11.51		
	pval	0.53	0.61	0.98	**0.02**	0.08	0.04
	Spread	-0.73	0.34	**3.59**	-10.89		
	pval	0.30	0.09	1.00	**0.00**	0.50	0.46
Net Stock Issues	Low	-0.70	0.07	**2.82**	-11.69		
	pval	0.29	0.18	0.89	**0.01**	0.35	0.12
	Medium	-0.39	0.31	**2.16**	-7.79		
	pval	0.30	0.22	0.82	**0.01**	0.31	0.12
	High	-0.64	0.00	**1.45**	-7.76		
	pval	0.35	0.30	0.80	**0.02**	0.19	0.15
	Spread	-1.55	-1.77	**0.25**	-4.07		
	pval	0.60	0.59	0.98	**0.13**	0.00	0.00
NOA	Low	0.42	0.17	**3.58**	-2.05		
	pval	0.26	0.15	0.89	**0.00**	0.31	0.19
	Medium	-0.10	-0.07	**3.20**	-3.20		
	pval	0.31	0.28	0.68	**0.00**	0.19	0.12
	High	-0.99	-0.14	**2.07**	-5.27		
	pval	0.50	0.44	0.99	**0.01**	0.12	0.04
	Spread	2.04	2.69	**5.50**	-2.04		
	pval	0.20	0.00	0.85	**0.00**	0.69	0.65

	R^2_{OS}	**Average**	**Median**	**Max**	**Min**	**% Pval<0.1**	**% Pval<0.05**
Accruals	Low	-0.33	-0.14	0.36	-2.81		
	pval	0.35	0.31	0.73	0.14	0.00	0.00
	Medium	-0.89	-0.44	0.65	-3.42		
	pval	0.46	0.47	0.76	0.11	0.00	0.00
	High	-1.57	-0.47	**1.06**	-7.67		
	pval	0.52	0.50	0.96	**0.04**	0.08	0.04
	Spread	1.22	0.49	**8.51**	-4.78		
	pval	0.38	0.06	1.00	**0.00**	0.54	0.50
O	Low	-0.31	-0.01	**1.30**	-3.67		
	pval	0.37	0.29	0.88	**0.02**	0.12	0.04
	Medium	-0.73	-0.28	**1.74**	-5.32		
	pval	0.34	0.26	0.79	**0.02**	0.04	0.04
	High	-0.63	-0.16	**1.65**	-4.72		
	pval	0.32	0.29	0.78	**0.03**	0.19	0.04
	Spread	-2.02	-1.01	**3.00**	-17.49		
	pval	0.51	0.56	0.99	**0.00**	0.19	0.08
ROA	Low	-0.24	-0.28	**2.00**	-3.04		
	pval	0.45	0.48	0.82	**0.01**	0.08	0.08
	Medium	-0.01	-0.01	**1.90**	-1.95		
	pval	0.37	0.29	0.95	**0.01**	0.19	0.04
	High	-0.34	-0.06	**2.05**	-3.70		
	pval	0.47	0.34	0.98	**0.01**	0.08	0.04
	Spread	-2.45	-1.44	**0.33**	-11.41		
	pval	0.81	0.92	1.00	**0.09**	0.04	0.00
Distress	Low	-0.33	-0.37	**1.67**	-4.00		
	pval	0.41	0.30	1.00	**0.02**	0.31	0.15
	Medium	-0.35	-0.10	0.64	-2.96		
	pval	0.49	0.45	0.96	0.12	0.00	0.00
	High	-0.86	-0.26	0.33	-7.65		
	pval	0.45	0.37	0.88	0.20	0.00	0.00
	Spread	-1.40	0.03	**2.51**	-25.32		
	pval	0.20	0.06	0.99	**0.00**	0.58	0.46
Comp Eq Issue	Low	-1.15	-0.67	**1.67**	-16.04		
	pval	0.30	0.20	0.89	**0.04**	0.27	0.12
	Medium	-1.20	-0.54	**0.93**	-13.32		
	pval	0.34	0.24	0.81	**0.09**	0.15	0.00
	High	-1.20	-0.37	0.37	-12.22		
	pval	0.49	0.40	0.93	0.20	0.00	0.00
	Spread	-6.23	-5.83	**1.14**	-33.87		
	pval	0.59	0.60	0.97	**0.01**	0.04	0.04

Totals	**% Pval<0.1**	0.2	**Average Max** R^2_{OS}	1.93	**% Max** R^2_{OS} **>2**	0.38
	%Pval <0.05	0.12	**% Max** R^2_{OS} **>1**	0.75	**Number of Variables**	40.00

Table 3.8: **Out-of-sample predictability of anomalies portfolios: Δ Utility.** In the Upper Panel we report the Average, Median, Maximum and Minimum yearly percentage Δ Utility values for 30 portfolios based on characteristics sorting and 10 spread portfolios returns. The monthly out-of-sample period considered is the most recent 30% for each variable. Forecasts are based on Welch and Goyal [2008] predictors: we consider both univariate regression and all the machine learning techniques detailed in the second part of this paper which jointly consider all these predictors. In the Lower Panel we briefly summarize the results coming from the upper panel. We use bold to remark yearly Δ Utility gains above 5%.

	Δ Utility	**Average**	**Median**	**Max**	**Min**		**Δ Utility**	**Average**	**Median**	**Max**	**Min**
Asset Growth	Low	**7.63**	**8.43**	**11.44**	1.88	**Accruals**	Low	**13.79**	**13.81**	**15.04**	**12.45**
	Medium	**5.46**	**6.01**	**8.53**	0.59		Medium	**5.47**	**6.20**	**8.26**	0.72
	High	1.87	2.33	4.97	-1.84		High	1.70	2.08	**5.28**	-2.19
	Spread	-0.74	1.47	1.69	-5.23		Spread	0.46	-0.79	**4.36**	-0.89
Gross Prof	Low	**11.56**	**10.57**	**17.87**	4.15	**O**	Low	**9.85**	**6.81**	**18.21**	3.28
	Medium	**10.49**	**10.39**	**15.44**	4.22		Medium	**7.64**	**8.11**	**11.71**	3.22
	High	**7.38**	**7.62**	**11.95**	1.75		High	**10.42**	**10.85**	**14.07**	3.73
	Spread	-0.72	-0.79	2.25	-3.75		Spread	-0.04	0.19	1.75	-1.89
Inv to Assets	Low	**10.63**	**10.85**	**15.44**	4.72	**ROA**	Low	1.94	1.84	**5.44**	-1.29
	Medium	**6.77**	**6.92**	**10.74**	1.94		Medium	2.83	-0.31	**11.77**	-5.61
	High	**7.99**	1.26	**23.03**	-3.29		High	2.62	-0.75	**10.42**	-3.96
	Spread	-0.70	0.59	0.81	-4.54		Spread	-2.42	0.49	2.99	-9.47
Net Stock Issues	Low	4.34	4.97	**7.89**	-0.63	**Distress**	Low	0.37	0.19	3.71	-0.59
	Medium	**8.50**	**8.76**	**13.31**	1.84		Medium	4.27	-0.96	**15.99**	-7.68
	High	**10.51**	**6.44**	**21.70**	1.82		High	4.68	1.81	**14.09**	-5.01
	Spread	-0.90	0.07	0.44	-3.42		Spread	-2.89	-0.85	-0.59	-7.90
NOA	Low	**12.41**	**11.17**	**18.08**	5.94	**Comp Eq Issue**	Low	4.01	4.80	**6.98**	-0.05
	Medium	**7.24**	**7.87**	**11.24**	1.72		Medium	**7.03**	**7.37**	**10.49**	1.42
	High	**7.05**	0.47	**21.27**	-2.39		High	**7.76**	2.03	**20.51**	-3.39
	Spread	-0.29	-0.20	0.17	-2.32		Spread	-2.52	-0.53	-0.20	-8.21

Totals			
Average Total	4.84	**Number Variables**	40
Average Max	9.96		

Table 3.9: **Out-of-sample predictability of spread portfolio returns with Welch and Goyal [2008] predictors: R^2_{OS}.** In this table we compare the out-of-sample predictability of a set 17 spread portfolio returns: SMB (1), HML (2), RMW (3), CMA (4), LT (5), ST (6), Mom (7), Asset Growth (8), Gross Prof (9), Inv to Asset (10), Net Stock Issue (11), NOA (12), Accruals (13), O (14), ROA (15), Distress (16), Comp Eq Issue (17). The monthly out-of-sample period considered is the most recent 30% for each variable. Forecasts are based on Welch and Goyal [2008] predictors: we consider both univariate regression and all the machine learning techniques detailed in the third part of this paper which jointly consider all these predictors. * and ** indicate a p-value for the R^2_{OS} metric under 10%, and 5%. Bold and Blue indicate respectively a Clark and West [2007] p-value for the R^2_{OS} metric under 10% and under 5%.

R^2_{OS}	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
DP	-5.75	-0.38	-2.87	-0.65	-1.99	2.01**	-1.00	-17.88	-4.62	-10.78	-2.07	-2.04	-4.78	-1.15	-0.51	0.53*	-8.29
DY	-10.96	-0.34	-3.10	-0.46	-1.82	1.98**	-1.59	-17.09	-4.62	-10.89	-1.91	-1.84	-4.27	-1.67	-0.56	0.37	-7.71
EP	-2.28	0.21	-1.27	0.44	-1.75	1.54*	-0.36	-9.64	-1.40	-5.93	-1.18	-0.74	-4.49	0.09	-1.40	-0.53	-3.42
DE	0.11	-3.78	-0.20	-0.48	2.57**	-1.17	-0.49	1.95**	0.56	0.67	0.20	-0.34	-0.82	-0.06	-0.08	0.29	-0.59
SVAR	-0.56	-1.53	-0.70	-0.81	-0.14	-0.80	0.52*	-0.43	-4.90	0.36	-0.18	0.38**	0.37	1.85	-1.14	-0.67	-0.05
BM	-3.03	0.50	-0.52	0.26	-0.08	1.10*	-0.03	-4.49	-1.38	-2.57	-0.97	0.56	-2.43	-0.17	-1.47	0.28	-2.70
NTIS	-0.02	0.91	-2.13	-0.01	0.71	0.07	-0.55	2.55**	-0.89	0.53	0.15	0.64*	-0.50	-3.42	-0.58	-0.55	0.78
TBL	-0.08	0.45	-0.39	-1.10	-0.86	-0.23	-0.32	-0.36	-0.61	0.52*	-0.38	3.24**	0.60*	1.47*	-0.31	-0.03	-0.98
LTY	-0.22	0.48	-0.54	0.34	-1.56	-0.33	0.01	-0.67	-0.21	0.29	0.23	2.33***	-2.00	-0.12	-0.12	0.23	-0.25
LTR	-1.51	-0.03	0.43	-0.21	-0.07	-0.97	-0.36	-1.02	-0.32	-1.11	-0.24	-0.18	0.10	0.49	-0.94	0.10	-0.47
TMS	0.11	-0.27	1.23*	-2.07	-1.35	-0.06	-0.32	-0.10	0.37	0.09	0.25	0.85	-0.06	3.00*	-0.07	0.08	1.14**
DFY	-0.49	-1.27	-0.57	0.23	0.04	0.55	-0.21	-0.42	-2.88	-0.69	-0.29	1.05**	-2.80	-0.26	-0.15	1.61**	-0.53
DFR	-0.11	0.66	0.01	-0.53	-0.20	-0.39	-0.08	0.75*	-1.17	0.33	-0.13	-0.11	-0.22	-2.37	-0.41	-0.70	0.27
INFL lag	0.48	-1.02	-0.33	-0.11	-0.67	-0.19	0.08	-0.70	0.94*	-0.57	-0.96	-0.24	-0.49	-1.00	0.33	0.40	-0.09
R^2_{OS}																	
OLS	-19.18	-7.16	-5.46	-1.32	-2.56	-4.26	-4.80	-11.31	-21.68	-0.89	-3.48	3.06**	8.31**	-8.15	-5.78	0.82**	-13.34
Pooled forecast:median	-1.73	-0.76	-2.05	-2.21	-0.40	0.02	-1.17	-5.04	-1.92	0.54**	-2.48	3.90**	2.52**	-1.02	-3.29	-1.41	-6.25
Pooled forecast:MDSFE	-2.02	-0.88	-2.20	-2.38	-0.47	0.22	-1.27	-5.52	-2.10	0.42**	-2.59	4.06**	2.12**	-0.73	-3.41	-1.40	-6.71
MARS	-3.51	-0.65	-1.91	-2.10	0.86	1.78**	1.74**	-5.89	-2.90	-1.15	-2.74	3.85**	8.51**	-1.07	-5.32	-0.69	-8.51
SVM SIC	-1.92	-1.87	-2.02	-1.38	-1.12	0.72	-1.76	-4.49	-2.01	1.23**	-2.07	4.14**	4.76**	-1.69	-2.87	1.43**	-6.02
Lasso SVM	-4.53	-1.73	-2.28	-0.99	-1.03	0.94*	-1.96	-7.41	-3.62	1.11**	-2.19	3.45**	3.11**	-1.21	-4.37	-11.87	-5.82
Radom Forest	-1.98	-0.55	-2.19	-2.01	-0.81	-0.12	-1.21	-5.38	-1.94	0.54**	-2.22	4.37**	3.10**	-1.05	-3.21	-1.60	-6.34
Diffusion index	-3.62	-0.75	-2.03	-1.37	-0.22	0.94*	-2.21	-4.43	-2.75	0.75**	-1.64	3.98**	3.20**	-1.37	-2.32	1.57**	-5.84
PLS	-4.71	-10.55	-4.83	-3.65	-1.24	-2.62	-1.78	-5.16	-7.31	-0.08	-2.76	4.24**	1.69**	1.28*	-11.41	-25.32	-6.05
Neural Networks Median	-0.57	0.45	-4.36	-3.82	1.04**	-0.06	-2.42	-4.96	-1.59	2.44**	-3.92	4.43**	4.02**	-17.49	-5.48	-0.92	-33.87

Table 3.10: **Out-of-sample predictability of spread portfolio returns with lagged spread portfolio returns: R^2_{OS}.** In this table we compare the out-of-sample predictability of a set 17 spread portfolio returns: SMB (1), HML (2), RMW (3), CMA (4), LT (5), ST (6), Mom (7), Asset Growth (8), Gross Prof (9), Inv to Asset (10), Net Stock Issue (11), NOA (12), Accruals (13), O (14), ROA (15), Distress (16), Comp Eq Issue (17). The monthly out-of-sample period considered is 1:1986-12:2016. Forecasts are based on the same lagged (t-1) 17 spread portfolio returns. We consider both univariate regression and all the machine learning techniques detailed in the third part of this paper which jointly consider all these predictors. * and ** indicate a p-value for the R^2_{OS} metric under 10%, and 5%. Bold and Blue indicate respectively a Clark and West [2007] p-value for the R^2_{OS} metric under 10% and under 5%.

R^2_{OS}	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
SMB	-1.98	-0.97	-1.07	-0.73	-0.73	-3.22	-0.50	0.73	-0.53	-0.37	-0.26	-1.17	-0.26	1.23*	-0.90	-1.10	-1.35
HML	-1.29	1.58**	-0.64	0.21	-0.36	0.16	-0.52	-1.00	-0.63	-0.95	-0.38	-0.43	-0.40	-0.99	-0.57	-1.57	-0.01
RMW	-4.76	-2.75	-4.71	-2.93	-3.19	-1.19	-1.72	-1.82	-1.10	-2.08	-2.15	-4.23	-0.45	-1.07	-1.24	-3.46	-1.83
CMA	-0.65	-0.31	-0.84	-0.27	-0.72	1.17	-0.88	-0.62	-0.65	-0.37	-0.51	1.71**	-0.31	-1.32	-0.54	1.26	-0.77
LT	-0.49	1.22**	-1.10	0.99**	2.29**	-0.96	-0.51	-0.61	-0.44	-0.77	-0.36	-0.38	-0.49	-0.56	-0.62	-0.94	0.01
ST	0.59	1.14**	-1.71	0.44	-0.21	-1.57	-1.04	-1.50	-0.69	-0.98	-0.77	-1.71	-0.11	-0.43	-0.84	-1.04	-0.42
Mom	0.89**	-1.49	-1.74	-1.37	-0.09	-1.86	-1.10	-1.28	0.20	-0.64	-1.51	-1.36	-0.61	-0.84	-0.42	-1.94	-2.26
Asset Growth	-1.47	21.14**	-3.95	57.61**	21.54**	2.28	-2.82	0.68	-1.17	-0.31	-0.45	-0.96	-0.52	-0.16	-0.91	-0.88	17.60**
Gross Prof	-1.54	-3.32	7.76**	3.49**	-1.37	0.61	-3.00	-0.72	2.01**	-0.75	0.97**	0.43	0.16	1.70**	-0.09	-1.17	-0.71
Inv to Assets	0.05	8.38**	-2.74	33.42**	13.39**	0.56	2.76**	0.75	-0.57	0.32	-0.72	1.03	0.51**	0.31	-0.47	-0.29	11.09**
Net Stock Issues	14.49**	23.93**	44.48**	23.59**	-4.79	0.24	-0.60	-1.09	-0.63	-0.92	-0.22	-2.03	-0.52	-0.89	-0.51	-1.42	71.67**
NOA	-2.79	3.03**	24.62**	-7.48	-1.18	-1.88	2.55	-0.68	-1.28	-0.70	-1.55	-1.99	-0.33	-0.30	-1.03	-3.53	5.05**
Accruals	-1.36	4.72**	-1.04	7.57**	4.17**	-1.21	-0.78	-0.95	-0.68	-0.68	-0.86	-1.03	-0.88	-1.10	-0.59	-1.02	1.74**
O	2.89**	19.00**	-1.27	23.48**	10.80**	-1.67	1.34**	-0.84	-0.77	-0.92	-1.04	-0.95	-0.61	-2.06	-0.66	-0.95	8.42**
ROA	-0.76	5.56**	11.61**	3.38**	8.54**	-0.12	9.60**	0.77**	-0.86	0.40	-0.27	-0.09	-0.89	-0.31	-0.16	-1.46	-2.80
Distress	-2.66	0.63	-3.55	-0.97	-1.11	31.62**	52.96**	-0.40	-1.21	-0.66	-0.11	-1.00	-0.86	1.06	-0.64	-2.78	-2.05
Comp Eq Issue	-2.91	-1.17	-1.36	-0.45	-1.11	-0.02	-1.03	0.02	-1.32	-0.75	-1.77	-2.16	-0.44	-0.89	-0.72	-2.75	-0.19
R^2_{OS}																	
OLS	30.47**	44.34**	54.29**	59.28**	26.00**	23.20**	53.07**	-17.09	-9.83	-12.48	-10.98	-16.65	-8.51	-12.20	-10.79	-23.26	71.91**
Pooled forecast:median	1.42**	4.83**	1.43**	5.97**	1.82**	0.76	0.71**	0.38	0.15	0.09	0.03	0.59	-0.14	0.14	-0.12	0.03	3.01**
Pooled forecast:MDSFE	4.26**	23.17**	13.75**	29.33**	9.07**	6.18**	16.99**	0.40	0.24	-0.23	-0.16	-0.28	0.08	0.34	-0.21	-0.74	35.01**
MARS	15.81**	15.34**	16.88**	30.58**	6.24**	19.81**	40.59**	-6.05	-1.56	-8.11	-1.31	-6.09	-3.79	-0.15	-0.38	-3.23	38.34**
SVM SIC	-3.08	-26.56	-4.26	-35.60	-7.01	-6.44	-1.86	-1.19	-1.13	0.04	-0.01	0.34	0.39	0.23	0.24	1.02**	-14.71
Lasso SVM	-9.78	-23.78	-4.69	-29.16	-5.07	-23.29	-28.27	-1.34	-1.08	0.30	-0.20	0.33	0.70**	0.28	0.31	0.87**	-18.59
Radom Forest	0.42	0.58	0.37	0.81**	0.44	0.10	0.57**	0.15	-0.15	0.08	-0.06	0.21	-0.03	0.05	0.25	-0.27	0.72**
Diffusion index	-2.57	18.49**	-1.88	44.08**	17.80**	3.06**	-2.15	-1.98	-1.38	0.24	0.35	-0.31	-0.73	0.85	-0.73	1.08**	13.43**
PLS	-34.16	-46.19	-33.26	-50.08	-21.24	-39.87	-58.83	-7.76	-7.52	-2.73	-10.36	-7.47	-3.65	-4.46	-5.26	-3.19	-38.57
Neural Network Median	-6.66	2.70**	0.64*	2.30**	18.66**	-1.35	-5.26	-8.47	-6.39	0.03*	-0.81	-6.15	-0.45	0.12	-10.78	1.98**	-1.78

Table 3.11: **Out-of-sample predictability of volatility-correlations swaps and risk premia: R^2_{OS}.** We document the R^2_{OS} metric and the related Clark and West [2007] p-values. We report the results employing the 17 spread returns portfolios as predictors for the monthly out-of-sample period 1:2005-12:2016. The variable forecasted are: the 30 and 90 days ahead implied correlation (IC 30 and IC 91), the 30 and 90 days ahead implied volatility (IV 30 and IV 90), the implied variance risk premium at 30 and 90 days ahead (VRP 30 and VRP 91) the 30 and 90 days ahead implied downside variance risk premium (IVD 30 and IVD 90) and the 30 days-91 days realized correlation (RC 30 and RC 90). * and ** indicate a p-value for the R^2_{OS} metric under 10%, and 5%. **Bold** and **Blue** indicate respectively a p-value for the R^2_{OS} metric under 10% and under 5%.

R^2_{OS}

Predictors	IC 30	IC 91	IV 30	IV 91	VRP 30	VRP 91	IVD 30	IVD 91	RC 30	RC 91
SMB	-0.84	-0.56	-0.86	-0.78	-7.13	0.55	-0.88	-0.85	-0.44	0.00
HML	-0.32	0.40	-0.33	-0.43	-1.38	2.52*	-0.47	-0.67	-0.21	-0.62
RMW	-0.53	0.09	-0.19	-0.08	0.17	1.56*	-0.17	0.02	-0.13	1.29*
CMA	0.31	0.75	0.44	0.18	-0.60	-0.06	0.50	0.23	-0.10	-1.04
LT	-1.67	-1.04	-0.46	-0.72	-8.73	-1.44	-0.60	-0.84	-1.17	-0.43
ST	-0.47	-0.06	-0.19	-0.24	-0.17	0.32	-0.02	-0.05	-0.41	1.25*
Mom	-0.38	-1.03	1.29	1.78*	-0.81	-0.27	1.23*	1.68*	-1.01	1.87**
Asset Growth	-0.37	-0.13	0.63	1.25*	-0.23	-1.43	1.21*	2.18*	-1.58	1.01**
Gross Prof	-0.88	-1.26	-1.15	-1.72	-1.06	-1.22	-1.29	-2.06	-1.34	-0.69
Inv to Assets	-3.24	-6.17	-2.39	-2.14	-0.62	-2.44	-2.16	-1.48	-1.41	0.29
Net Stock Issues	8.80**	14.11**	10.59**	15.82**	0.34	-0.58	10.96**	16.18**	0.59	10.68**
NOA	1.15*	2.15*	0.61	0.48	-2.42	-0.74	0.46	-0.03	-0.18	-0.02
Accruals	-2.01	-3.04	-1.70	-1.92	-4.82	-0.82	-1.98	-2.33	-0.77	-0.01
O	-3.29	-4.83	-1.02	-1.75	0.11	0.82	-1.04	-1.82	1.05	-0.68
ROA	-0.57	0.75	-1.11	-1.17	-2.62	-0.86	-0.78	-0.58	-0.43	-1.25
Distress	-0.11	-0.11	0.30	1.62*	-5.30	-1.48	0.12	1.38*	0.42	0.03
Comp Eq Issue	-0.04	0.54	0.23	0.14	-0.12	2.17**	0.27	0.20	-0.33	0.55
Model										
OLS	-0.41	3.51**	4.82**	10.70**	-61.23	-7.83	5.51**	10.93**	-4.24	6.79**
Pooled forecast:median	0.01	0.64	0.07	0.10	-0.07	0.07	0.09	0.26	0.04	0.70**
Pooled forecast:MDSFE	0.68*	2.39**	1.21**	2.12**	-0.39	0.07	1.41**	2.48**	-0.06	1.66**
MARS	-0.44	1.93*	-2.10	2.10*	2.05	0.38	-0.84	-0.34	-4.12	-0.25
SVM SIC	-2.72	-2.08	-4.29	-2.78	1.99**	0.50	-5.12	-3.47	-5.82	2.01**
Lasso SVM	-5.59	-7.36	-6.46	-3.49	1.99**	0.69	-7.96	-5.60	-5.47	2.46**
Radom Forest	-0.34	0.54	-0.08	0.12	0.26	0.12	-0.12	0.29	-0.11	-0.27
Diffusion index	-2.93	-1.55	-3.82	-2.28	2.47**	0.88	-4.78	-4.18	-5.21	1.13
PLS	-5.47	-7.48	-8.33	-9.67	1.76**	-0.37	-9.50	-10.45	-4.88	-4.98
Neural Networks Median	5.27**	5.03**	2.48**	4.70**	3.10**	1.52*	3.39**	6.05**	-4.56	9.40**

Table 3.12: **Out-of-sample predictability the moments contracts:** R^2_{OS}. We document the R^2_{OS} metric and the related Clark and West [2007] p-values. We report the results employing as predictors the 17 spread returns portfolios (Anomalies), or the Welch and Goyal [2008] (W-G) variables for the monthly out-of-sample period 1:2005-12:2016. The predictive approaches used are the same detailed in section 3.1. The variables forecasted are the returns of the first four 20 and 40 business days ahead moments contract (M1 20, M1 40, M2 20, M2 40, M3 20, M3 40, M4 20, M4 40) built following Bakshi et al. [2003]. *, ** and *** indicate a p-value for the R^2_{OS} metric under 10%, 5% and 1%. **Bold** indicates a p-value for the R^2_{OS} metric under 5%.

R^2_{OS}																
Anomalies	**M1 20**	**pval**	**M2 20**	**pval**	**M3 20**	**pval**	**M4 20**	**pval**	**M1 40**	**pval**	**M2 40**	**pval**	**M3 40**	**pval**	**M4 40**	**pval**
OLS	-12.82	0.75	-0.44	0.15	-7.56	0.01	-44.45	0.84	-8.58	0.28	-82.04	0.13	-1045.00	0.11	-31.15	0.35
Pooled Forecast median	-0.13	0.96	-0.01	0.51	**5.40*****	**0.00**	-0.23	0.86	0.02	0.42	-0.11	0.73	-17.82	1.00	-0.31	0.99
Pooled Forecast MDSFE	-0.20	0.89	0.15	0.23	**5.67*****	**0.00**	-0.65	0.82	0.03	0.39	-0.14	0.52	-4.81	0.27	-0.47	0.91
MARS	**1.46****	**0.04**	-1.87	0.46	**5.19*****	**0.00**	**4.50*****	**0.00**	**1.78****	**0.02**	**3.70*****	**0.00**	**54.86*****	**0.00**	0.69*	0.08
SVM SIC	**1.46****	**0.04**	-2.05	0.49	**4.20*****	**0.00**	**4.47*****	**0.00**	**1.85*****	**0.01**	**3.47*****	**0.00**	**54.78*****	**0.00**	0.62*	0.10
Lasso SVM	0.99	0.10*	-2.14	0.50	**4.97*****	**0.00**	**4.49*****	**0.00**	**1.71****	**0.04**	**3.29*****	**0.00**	**54.73****	**0.00**	0.62*	0.09
Random Forest	**0.15****	**0.02**	-0.26	0.98	**4.86*****	**0.00**	-0.81	0.85	0.25*	0.09	-0.64	0.70	-0.58	0.24	0.07	0.41
Diffusion Index	0.96*	0.08	-2.01	0.48	**4.92*****	**0.00**	**4.49*****	**0.00**	**1.47****	**0.02**	**3.67*****	**0.00**	**54.75*****	**0.00**	0.66*	0.09
PLS	0.39	0.25	-2.01	0.49	**5.02*****	**0.00**	**4.49*****	**0.00**	0.63	0.11	**3.58*****	**0.00**	**54.73*****	**0.00**	0.53	0.13
Neural Networks Median	0.66*	0.07	-1.97	0.47	**4.80*****	**0.00**	**4.47*****	**0.00**	0.82	0.13	**3.39*****	**0.00**	**54.37*****	**0.00**	0.93*	0.06
W-G	**M1 20**	**pval**	**M2 20**	**pval**	**M3 20**	**pval**	**M4 20**	**pval**	**M1 40**	**pval**	**M2 40**	**pval**	**M3 40**	**pval**	**M4 40**	**pval**
OLS	-42.41	0.56	-19.22	0.22	-22.32	0.00	-116.53	0.84	-45.87	0.50	-152.88	0.84	-943.07	0.00	-49.48	0.81
Pooled Forecast median	-1.34	0.77	0.27	0.21	**5.42*****	**0.00**	**0.71*****	**0.00**	-1.16	0.64	**2.31****	**0.05**	**39.43*****	**0.00**	-0.15	0.94
Pooled Forecast MDSFE	-1.75	0.63	0.52	0.11	**5.24*****	**0.00**	**2.37*****	**0.00**	-0.49	0.46	**2.29****	**0.02**	**51.99*****	**0.00**	-0.50	0.71
MARS	**1.47****	**0.03**	-1.88	0.46	**5.00*****	**0.00**	**4.46*****	**0.00**	-0.22	0.43	**3.50*****	**0.00**	**54.79*****	**0.00**	0.67*	0.09
SVM SIC	**1.26***	**0.08**	-1.85	0.45	**5.02*****	**0.00**	**4.49*****	**0.00**	**1.72*****	**0.01**	**3.92*****	**0.00**	**54.80*****	**0.00**	0.62*	0.10
Lasso SVM	0.02	0.43	-1.85	0.43	**4.98*****	**0.00**	**4.46*****	**0.00**	0.13	0.38	**3.87*****	**0.01**	**54.80*****	**0.00**	0.72*	0.08
Random Forest	0.11	0.18	-0.10	0.71	**5.25*****	**0.00**	-0.96	0.82	0.18*	0.10	0.30	0.27	-2.80	0.50	0.00	0.43
Diffusion Index	-0.86	0.67	-1.91	0.47	**5.10*****	**0.00**	**4.50*****	**0.00**	-2.02	0.92	**4.03*****	**0.01**	**54.80*****	**0.00**	0.57	0.13
PLS	-6.22	0.76	-1.81	0.45	**5.06*****	**0.00**	**4.49*****	**0.00**	-5.96	0.72	**4.03*****	**0.00**	**54.80*****	**0.00**	0.67*	0.10
Neural Networks Median	-3.61	0.68	-1.85	0.40	-0.07	0.00	**2.00****	**0.03**	-7.64	0.70	**4.22*****	**0.01**	-495.95	0.03	0.20	0.22

3.9 Online Appendix

3.9.1 Toolboxes Employed

The making of this paper leveraged on many libraries. We list them both because we want to help the replicability of our results and because we want to express our genuine gratitude for all the people who worked to build and maintain them. The current paper makes use of Matlab only, and consequently, all the libraries which we will list are in this language. In detail the libraries employed are:

- The Statistic and Machine Learning Toolbox and the Deep Learning Toolbox of Matlab.
- The Optimization Toolbox and the Financial toolbox of Matlab.
- The ARESLab Toolbox by Gints Jekabsons.
- The website of by Professor Guofu Zhou
- The website of by Professor Grigory Vilkov
- The website of Attilio Meucci

3.9.2 Additional Performance Metric

Delta Sharpe Ratio. It is computed as the difference between the Sharpe ratio arising from returns coming from a portfolio optimization which employs as proxies for expected returns forecasts coming from a given model and the Sharpe ratio generated from a portfolio optimization which employs the historical average return as a proxy for expected returns. A a ten-year rolling window of monthly returns is used in both optimizations to estimate expected variance. As before optimal weight for the risky asset is constrained between 0 and 1.5 .

$$\Delta\ Sharpe\ Ratio = SR_{Model} - SR_{Mean} \tag{3.49}$$

where SR_{Model} is the average Sharpe Ratio generated using the reference model to proxy expected returns in the portfolio optimization and SR_{Mean} is the average Sharpe Ratio generated using the historical average return to proxy expected returns in the portfolio optimization.

3.9.3 Additional Tables

In the following pages we report the tables, which for brevity have been omitted from the main text, these include:

- Summary statistics for the Welch and Goyal [2008] predictors and the european options employed (A1-A2)
- Robustness checks for the out-of-sample predictability of the S&P500 for different time horizons: 2001:1-2017:12, 2006:1-2017:12, 2011:1-2017:12 (A3-A5)
- The detail of the monthly out-of-sample predictability (1986:1-2016:12) both in term of R^2_{OS} and Δ Utility for:
  1. six double-sorted portfolios of French: on the basis of Size and the Book to Market ratio (A6-A9)
  2. six double-sorted portfolios of French: on the basis of Size and Momentum (A10-A13).
- The out-of-sample Δ Utility and Δ Sharpe ratios for the variables predicted in Section 6 (A14-A17).

Table 3.13: **Welch-Goyal predictors: Summary Statistics**. In the upper panel we report the correlation matrix for the deltas of the W-G predictors. Correlations higher than 0.5 are reported in red while negative ones in blue. In the lower panel for each predictor we estimate the autoregressive coefficients up to the sixth lag and we report the related t-statistic.

Correlation	**DP**	**DY**	**EP**	**DE**	**SVAR**	**BM**	**NTIS**	**TBL**	**LTY**	**LTR**	**TMS**	**DFY**	**DFR**	**INFL lag**
DP	1.00													
DY	0.11	1.00												
EP	0.76	0.00	1.00											
DE	0.10	0.14	-0.57	1.00										
SVAR	0.23	0.01	0.20	-0.01	1.00									
BM	0.81	0.10	0.66	0.01	0.13	1.00								
NTIS	0.05	-0.12	0.05	-0.01	0.06	-0.03	1.00							
TBL	0.07	-0.02	0.11	-0.08	0.04	0.06	0.01	1.00						
LTY	0.10	-0.07	0.14	-0.09	0.00	0.12	0.01	0.34	1.00					
LTR	-0.02	0.12	-0.05	0.04	0.04	-0.05	-0.01	0.02	-0.65	1.00				
TMS	-0.01	-0.03	-0.02	0.02	-0.04	0.02	-0.01	-0.78	0.33	-0.45	1.00			
DFY	0.27	0.40	0.13	0.14	0.07	0.33	-0.14	-0.14	-0.14	0.04	0.05	1.00		
DFR	-0.07	0.02	-0.07	0.01	-0.05	-0.06	0.02	-0.01	0.27	-0.53	0.19	-0.01	1.00	
INFL lag	0.01	-0.05	0.02	-0.01	-0.05	-0.01	0.03	0.04	0.04	0.01	-0.01	-0.07	-0.03	1.00

Coefficients	**DP**	**DY**	**EP**	**DE**	**SVAR**	**BM**	**NTIS**	**TBL**	**LTY**	**LTR**	**TMS**	**DFY**	**DFR**	**INFL lag**
AR1	0.10	0.11	0.25	0.69	-0.46	0.19	0.13	0.38	0.07	-0.80	0.10	0.21	-0.98	-0.59
AR2	0.00	-0.01	0.08	0.10	-0.44	-0.10	0.02	-0.19	-0.08	-0.72	-0.10	-0.07	-0.88	-0.47
AR3	-0.09	-0.09	0.00	0.10	-0.33	-0.17	-0.04	0.03	-0.07	-0.58	0.01	-0.15	-0.69	-0.37
AR4	0.05	0.04	0.05	-0.15	-0.24	0.04	0.07	-0.07	0.02	-0.38	-0.05	-0.06	-0.48	-0.20
AR5	0.08	0.08	0.05	0.00	-0.20	0.09	0.11	0.11	0.02	-0.25	0.00	0.02	-0.26	-0.20
AR6	-0.05	-0.06	-0.07	-0.03	-0.09	-0.10	0.02	-0.22	0.02	-0.09	-0.09	0.00	-0.08	-0.15
t-stat	**DP**	**DY**	**EP**	**DE**	**SVAR**	**BM**	**NTIS**	**TBL**	**LTY**	**LTR**	**TMS**	**DFY**	**DFR**	**INFL lag**
AR1	5.54	5.79	14.45	64.42	-55.03	19.23	6.63	39.57	4.02	-37.68	7.81	15.12	-53.13	-28.19
AR2	-0.09	-0.30	4.03	5.89	-22.77	-7.34	0.88	-13.62	-4.46	-29.20	-4.46	-3.73	-30.60	-19.83
AR3	-4.40	-4.41	-0.13	11.05	-18.74	-13.69	-1.98	1.79	-4.32	-18.69	0.38	-10.48	-23.85	-14.37
AR4	2.38	1.65	1.95	-10.46	-13.45	2.45	3.66	-4.74	0.91	-11.31	-2.52	-6.25	-15.48	-7.10
AR5	3.62	3.27	1.95	0.14	-10.70	4.96	5.93	9.21	0.77	-8.15	0.23	0.86	-9.94	-7.62
AR6	-2.18	-2.71	-2.90	-1.48	-4.93	-6.31	0.85	-19.71	1.12	-3.80	-6.67	0.22	-4.07	-7.39

Table 3.14: **Options data: Summary Statistics**. Mean, standard deviation (Std.), and number of observations for each moneyness/maturity category of out-of-the-money SPX options observed every last trading day of the month from January 1996 to December 2017, after applying the filtering criteria described in the text. Moneyness is the strike price divided by the spot asset price, K/S. σ^{bs} is the Black-Scholes implied volatility. Bid-Ask % is $100 * (ask\ price - bid\ price)/marketprice$. Maturity is measured in business days

Moneyness K/S		Maturity <60 Mean	Std.		60-120 Mean	Std.
<0.85	Put Price $	1.32	2.05	Put Price $	4.43	5.29
	σ^{BS} %	39.03	12.44	σ^{BS} %	35.07	10.65
	Bid-Ask %	31.11	43.93	Bid-Ask %	15.68	40.73
	Volumes	200.22	1422.96	Volumes	136.43	853.71
	Open Interest	5135.27	14906.66	Open Interest	6604.79	15440.84
	Delta %	-1.53	1.97	Delta %	-3.32	3.64
	Observations	35075.00		Observations	12175.00	
		Mean	**Std.**		**Mean**	**Std.**
0.85-1	Put Price $	10.82	11.38	Put Price $	32.90	18.04
	σ^{BS} %	20.85	6.89	σ^{BS} %	20.32	5.55
	Bid-Ask %	6.82	17.98	Bid-Ask %	4.31	3.64
	Volumes	735.60	2693.43	Volumes	395.11	1398.86
	Open Interest	8130.73	20563.74	Open Interest	9777.22	19181.20
	Delta %	-16.14	13.41	Delta %	-25.79	11.35
	Observations	51238.00		Observations	7375.00	
		Mean	**Std.**		**Mean**	**Std.**
1-1.15	Call Price $	8.56	11.18	Call Price $	21.23	19.70
	σ^{BS} %	13.33	5.65	σ^{BS} %	14.26	5.22
	Bid-Ask %	7.99	38.47	Bid-Ask %	5.65	22.71
	Volumes	661.74	2252.22	Volumes	288.35	1161.07
	Open Interest	6984.85	16651.28	Open Interest	7594.63	15801.82
	Delta %	17.05	15.68	Delta %	23.43	15.65
	Observations	32393.00		Observations	6304.00	
		Mean	**Std.**		**Mean**	**Std.**
>1.15	Call Price $	1.23	2.22	Call Price $	2.51	4.22
	σ^{BS} %	24.91	8.63	σ^{BS} %	17.74	6.06
	Bid-Ask %	45.82	53.96	Bid-Ask %	27.85	53.91
	Volumes	261.49	1297.35	Volumes	100.16	720.94
	Open Interest	10657.80	23800.44	Open Interest	8265.54	16989.17
	Delta %	2.77	3.40	Delta %	3.97	4.83
	Observations	1421.00		Observations	1619.00	

Table 3.15: **Monthly equity premium out-of-sample forecasting results for individual forecasts, and machine learning methods**. The R^2_{OS} is the Campbell Thompson (2008) out-of-sample R^2 statistic. Statistical significance for the R^2_{OS} statistic is based on the p-value for the Clark and West (2007) out-of-sample MPSE-adjusted statistic; the statistic corresponds to a one-sided test of the null hypothesis that the competing forecasting model has equal expected square prediction error relative to the historical average benchmark forecasting model against the alternative hypothesis that the competing forecasting model has a lower expected square prediction error than the historical average benchmark forecasting model. The results refer to monthly forecasts for the out-of-sample period 2001:01-2017:12. For predictions based on univariate forecasts the restrictions are the ones suggested by Campbell and Thompson (2008) while for the machine learning models when equity premium forecasts are negative they are replaced with zero. **Bold** indicates at least a significance level above 5%.

Standard	**2001-2017**		**Restricted**	**2001-2017**	
Predictor	$R^2_{OS}(\%)$	**pval**	**Predictor**	$R^2_{OS}(\%)$	**pval**
DP	0.13	0.20	DP	-0.02	0.24
DY	0.17	0.17	DY	-0.11	0.25
EP	-0.88	0.28	EP	1.23	0.08
DE	-1.34	0.69	DE	-0.31	0.51
SVAR	1.06	0.10	SVAR	0.73	0.10
BM	-0.10	0.24	BM	0.00	0.24
NTIS	-3.53	0.87	NTIS	-3.53	0.87
TBL	0.21	0.25	TBL	0.21	0.25
LTY	**0.49**	**0.03**	LTY	**0.49**	**0.03**
LTR	-0.01	0.34	LTR	-0.17	0.40
TMS	-1.15	0.76	TMS	-1.15	0.76
DFY	-0.28	0.92	DFY	-0.28	0.92
DFR	-0.33	0.43	DFR	-1.13	0.68
INFL lag	-0.86	0.93	INFL lag	-0.86	0.93

Model	$R^2_{OS}(\%)$	**pval**	**Model**	$R^2_{OS}(\%)$	**pval**
OLS	-6.63	0.36	OLS	-1.91	0.17
Pooled forecast: median	0.18	0.13	Pooled forecast: median	0.18	0.13
Pooled forecast: DMSFE	0.42	0.18	Pooled forecast: DMSFE	0.42	0.18
Sum-of-the-parts	0.89	0.10	Sum-of-the-parts	**1.35**	**0.03**
MARS	**1.18**	**0.04**	MARS	**1.29**	**0.01**
SVM SIC	0.16	0.17	SVM SIC	0.60	0.09
Lasso SVM	0.33	0.17	Lasso SVM	0.77	0.08
Random Forest	1.01	0.11	Random Forest	1.16	0.07
Diffusion index	0.36	0.27	Diffusion index	0.36	0.27
PLS	0.51	0.12	PLS	0.80	0.08
Neural Networks Median	5.77	0.13	Neural Networks Median	-2.19	0.29
Neural Networks 40^{th}	6.14	0.12	Neural Networks 40^{th}	-0.87	0.21

Table 3.16: **Monthly equity premium out-of-sample forecasting results for individual forecasts, and machine learning methods**. Utility gain (Δ Utility) is the portfolio management fee (in annualized percentage return) that an investor with mean-variance preferences and risk aversion coefficient of three would be willing to pay to have access to the forecasting model considered relative to the historical average benchmark forecasting model; the weight on stocks in the investor's portfolio is restricted to lie between -0.5 and 1.5 (inclusive). The restriction imposed for the restricted case are the same of Table 3.15. The results refer to monthly forecasts for the out-of-sample period 2001:01-2017:12. The division between Recession and Expansion months comes from the NBER database. Bold indicates a ΔUtility above 1.00%.

Δ Utility	**2001-2017**			**Δ Utility**	**2001-2017**		
Standard	**Total**	**Expansion**	**Recession**	**Restricted**	**Total**	**Expansion**	**Recession**
DP	**1.84**	-1.90	**26.15**	DP	**1.70**	-2.04	**26.05**
DY	**2.38**	-2.43	**33.89**	DY	**2.13**	-2.68	**33.67**
EP	**4.75**	-1.20	**44.07**	EP	**3.89**	-1.18	**37.23**
DE	**0.82**	0.13	**5.31**	DE	**1.24**	0.33	**7.18**
SVAR	**2.35**	**0.55**	**14.03**	SVAR	**2.21**	**0.50**	**13.27**
BM	**2.57**	-2.82	**38.05**	BM	**2.55**	-2.75	**37.44**
NTIS	-1.23	**1.38**	-18.24	NTIS	-1.23	**1.38**	-18.24
TBL	-0.71	**1.11**	-12.41	TBL	-0.71	**1.11**	-12.41
LTY	0.30	0.92	-3.65	LTY	0.30	**0.92**	-3.65
LTR	-0.09	-0.21	0.25	LTR	-0.24	-0.17	-0.97
TMS	-1.83	-0.02	-13.56	TMS	-1.83	-0.02	-13.56
DFY	-0.94	-0.14	-6.13	DFY	-0.94	-0.14	-6.13
DFR	**1.23**	-0.14	**9.95**	DFR	**0.96**	-0.45	**10.03**
INFL lag	-1.66	0.15	-13.04	INFL lag	-1.66	0.15	-13.04

Standard	**Total**	**Expansion**	**Recession**	**Restricted**	**Total**	**Expansion**	**Recession**
OLS	**4.57**	**1.95**	**21.56**	OLS	**4.56**	**2.05**	**21.04**
Pooled forecast: median	0.33	0.21	**1.15**	Pooled forecast: median	0.33	0.21	**1.15**
Pooled forecast: DMSFE	**1.18**	0.24	**7.45**	Pooled forecast: DMSFE	**1.18**	0.24	**7.45**
Sum-of-the-parts	**2.22**	**2.23**	**2.63**	Sum-of-the-parts	**2.40**	**2.31**	**3.40**
MARS	**1.78**	**1.93**	0.86	MARS	**1.85**	**1.93**	**1.40**
SVM SIC	**1.12**	**1.87**	-3.10	SVM SIC	**1.53**	**2.03**	-1.19
Lasso SVM	**1.15**	**1.64**	-1.48	Lasso SVM	**1.59**	**1.82**	0.47
Random Forest	**4.54**	0.22	**32.76**	Random Forest	**4.40**	0.27	**31.37**
Diffusion index	-1.25	**1.45**	-19.07	Diffusion index	-1.25	**1.45**	-19.07
PLS	**1.11**	**2.81**	-9.32	PLS	**1.40**	**2.91**	-7.88
Neural Networks Median	**2.93**	**4.20**	-4.97	Neural Networks Median	**2.49**	**3.82**	-5.62
Neural Networks 40^{th}	**2.75**	**3.81**	-3.73	Neural Networks 40^{th}	**2.44**	**3.6**	-4.35

Table 3.17: **Monthly equity premium out-of-sample forecasting results for individual forecasts, and machine learning methods**. This table reports R^2_{OS} and Δ Utility results for the out-of-sample period 2011:01-2017:12. The methodologies employed are the same explained in the tables above (3.15 3.16). **Bold** indicates a p-value for the R^2_{OS} under 0.05 or a ΔUtility above 1.00%

Standard	2011-2017	
Predictor	$R^2_{OS}(\%)$	**pval**
DP	-4.42	0.93
DY	-5.74	0.93
EP	-2.24	0.86
DE	0.78	0.10
SVAR	1.31	0.13
BM	-5.41	0.96
NTIS	**2.86**	**0.03**
TBL	2.25	0.06
LTY	**1.82**	**0.03**
LTR	-0.42	0.45
TMS	0.38	0.28
DFY	-0.20	0.88
DFR	0.22	0.31
INFL lag	0.45	0.16
Model	$R^2_{OS}(\%)$	**pval**
OLS	**2.12**	**0.04**
Pooled forecast: median	0.16	0.29
Pooled forecast: DMSFE	0.15	0.27
Sum-of-the-parts	2.23	0.07
MARS	**4.40**	**0.00**
SVM SIC	**3.22**	**0.04**
Lasso SVM	**3.19**	**0.05**
Random Forest	0.06	0.38
Diffusion index	**2.45**	**0.04**
PLS	**4.06**	**0.03**
Neural Networks Median	**3.08**	**0.05**
Neural Networks 40^{th}	**3.06**	**0.05**

Restricted	2011-2017	
Predictor	$R^2_{OS}(\%)$	**pval**
DP	-4.42	0.93
DY	-5.81	0.94
EP	-2.24	0.86
DE	0.78	0.10
SVAR	1.09	0.13
BM	-5.41	0.96
NTIS	**2.86**	**0.03**
TBL	2.25	0.06
LTY	**1.82**	**0.03**
LTR	-0.42	0.45
TMS	0.38	0.28
DFY	-0.20	0.88
DFR	-0.56	0.45
INFL lag	0.45	0.16
Model	$R^2_{OS}(\%)$	**pval**
OLS	**1.96**	**0.04**
Pooled forecast: median	0.16	0.29
Pooled forecast: DMSFE	0.15	0.27
Sum-of-the-parts	2.23	0.07
MARS	**4.40**	**0.00**
SVM SIC	**3.22**	**0.04**
Lasso SVM	**3.19**	**0.05**
Random Forest	0.06	0.38
Diffusion index	**2.45**	**0.04**
PLS	**4.06**	**0.03**
Neural Networks Median	**3.08**	**0.05**
Neural Networks 40^{th}	**3.08**	**0.05**

Δ Utility	2011-2017	
Predictor	**Standard**	**Restricted**
DP	-4.01	-4.01
DY	-5.05	-5.07
EP	-3.27	-3.27
DE	0.78	0.78
SVAR	**1.02**	0.93
BM	-5.09	-5.09
NTIS	**1.57**	**1.57**
TBL	**1.71**	**1.71**
LTY	**1.37**	**1.37**
LTR	-0.96	-0.90
TMS	0.56	0.56
DFY	-0.38	-0.38
DFR	0.15	-0.21
INFL lag	0.13	0.13
Model	**Standard**	**Restricted**
OLS	**4.02**	**3.94**
Pooled forecast: median	0.08	0.08
Pooled forecast: DMSFE	0.05	0.05
Sum-of-the-parts	**3.59**	**3.59**
MARS	**2.71**	**2.71**
SVM SIC	**2.99**	**2.99**
Lasso SVM	**2.63**	**2.63**
Random Forest	0.33	0.33
Diffusion index	**1.49**	**1.49**
PLS	**3.55**	**3.55**
Neural Networks Median	**2.34**	**2.34**
Neural Networks 40^{th}	**2.16**	**2.16**

Table 3.18: R^2_{OS} **of the six portfolios built double sorting on Size and the Book/Market ratio using the Welch and Goyal [2008] predictors.** The R^2_{OS} is the Campbell Thompson (2008) out-of-sample R^2 statistic. Statistical significance for the R^2_{OS} statistic is tested using the Clark and West [2007] p-value; the statistic corresponds to a one-sided test of the null hypothesis that the competing forecasting model has equal expected square prediction error relative to the historical average benchmark forecasting model against the alternative hypothesis that the competing forecasting model has a lower expected square prediction error than the historical average benchmark forecasting model. The results refer to monthly forecasts for the out-of-sample period 1986:01-2016:12. **Bold** indicates a p-value for the R^2_{OS} statistic less than 0.1.

R^2_{OS}

Predictor	SMALL LoBM	pval	ME1 BM2	pval	SMALL HiBM	pval	BIG LoBM	pval	ME2 BM2	pval	BIG HiBM	pval
DP	-1.11	0.22	-1.78	0.30	-2.97	0.16	-1.41	0.55	-1.75	0.43	-1.88	0.12
DY	-2.22	0.17	-3.67	0.23	-5.76	0.11	-2.11	0.53	-2.69	0.40	-2.99	0.11
EP	-0.51	0.27	-1.39	0.39	-2.18	0.36	-0.94	0.30	-1.82	0.27	-1.22	0.21
DE	-0.19	0.59	-0.32	0.84	-0.14	0.54	-0.29	0.59	-0.71	0.53	-0.58	0.70
SVAR	-1.02	0.91	-1.81	0.93	-3.10	0.95	-0.41	0.79	-1.03	0.89	-3.36	0.95
BM	-2.58	0.20	-4.91	0.28	-8.33	0.15	-2.50	0.64	-5.38	0.44	-6.04	0.15
NTIS	-3.48	0.77	-4.91	0.77	-8.10	0.90	-1.30	0.51	-3.59	0.75	-4.82	0.76
TBL	0.02	0.33	-0.08	0.56	-0.08	0.49	-0.29	0.92	-0.18	0.92	-0.24	0.91
LTY	0.05	0.29	-0.11	0.88	-0.07	0.90	-0.11	0.99	-0.07	0.88	-0.05	0.96
LTR	-0.04	0.25	-0.14	0.17	-0.44	0.21	-0.11	0.30	-0.53	0.30	-0.28	0.38
TMS	-1.48	0.73	-1.46	0.65	-1.65	0.62	-1.04	0.77	-0.91	0.77	-1.38	0.93
DFY	-0.26	0.37	-0.85	0.48	-1.85	0.55	-0.45	0.82	-0.89	0.78	-2.06	0.79
DFR	-0.18	0.54	-0.27	0.57	-1.40	0.97	0.12	0.28	-0.24	0.55	-0.71	0.90
INFL lag	-0.21	0.57	-0.74	0.69	-1.48	0.78	-0.32	0.79	-0.49	0.87	-1.52	0.95

R^2_{OS}

Model	SMALL LoBM	pval	ME1 BM2	pval	SMALL HiBM	pval	BIG LoBM	pval	ME2 BM2	pval	BIG HiBM	pval
OLS	-3.79	0.18	-8.14	0.21	-13.85	0.26	-4.66	0.51	-11.17	0.45	-14.51	0.66
Pooled forecast:median	0.14	0.20	**0.22**	**0.09**	0.16	0.19	0.03	0.39	0.08	0.23	0.03	0.35
Pooled forecast:MDSFE	0.18	0.25	-0.08	0.40	0.00	0.28	-0.11	0.54	-0.19	0.52	-0.14	0.39
Sum-of-the-parts	0.04	0.18	-2.12	0.28	-2.14	0.14	-1.81	0.57	-1.79	0.41	-1.36	0.17
MARS	0.60	0.09	-0.60	0.43	-0.70	0.46	-0.38	0.31	-1.21	0.45	-0.49	0.37
SVM SIC	-0.94	0.67	-1.51	0.81	-2.24	0.93	0.32	0.19	-1.56	0.79	-0.64	0.76
Lasso SVM	-0.94	0.80	-1.07	0.86	-0.53	0.88	-0.09	0.33	-1.13	0.91	-0.19	0.52
Radom Forest	**0.50**	**0.10**	0.23	0.16	-0.23	0.44	-0.16	0.47	0.05	0.31	0.42	0.12
Diffusion index	0.32	0.17	-0.03	0.37	0.07	0.36	0.06	0.35	-0.37	0.74	-0.29	0.58
PLS	-0.08	0.20	-1.47	0.46	-0.96	0.52	-0.52	0.48	-1.50	0.72	-0.62	0.41
Neural Networks Median	0.11	0.26	-0.06	0.05	**1.71**	**0.00**	-0.13	0.23	0.37	0.14	**0.69**	**0.09**

Table 3.19: **Δ Utility of the six portfolios built double sorting on Size and the Book/Market ratio using the Welch and Goyal [2008] predictors.** The Utility gain (Δ Utility) is the portfolio management fee (in annualized percentage return) that an investor with mean-variance preferences and risk aversion coefficient of three would be willing to pay to have access to the forecasting model considered relative to the historical average benchmark forecasting model; the weight on stocks in the investor's portfolio is restricted to lie between -0.5 and 1.5 (inclusive). The restriction imposed for the restricted case are the same of Table 1. The results refer to monthly forecasts for the out-of-sample period 1986:01-2016:12. **Bold** indicates a ΔUtility above 1.00%.

Δ Utility

Predictor	**SMALL LoBM**	**ME1 BM2**	**SMALL HiBM**	**BIG LoBM**	**ME2 BM2**	**BIG HiBM**
DP	-0.58	-1.96	-3.52	-1.37	-1.62	-4.90
DY	-1.17	-3.41	-4.32	-2.43	-3.37	-4.95
EP	**1.78**	**1.40**	**1.76**	**1.74**	**2.76**	**2.82**
DE	-0.23	-0.63	-0.79	0.97	**1.23**	-0.75
SVAR	-1.67	-1.15	-1.21	**1.22**	0.64	-2.27
BM	-1.75	-4.61	-6.31	-2.11	-4.57	-6.10
NTIS	-2.79	-0.70	-0.64	**1.59**	0.98	-1.81
TBL	-0.10	-0.44	-0.46	**1.26**	0.83	-1.68
LTY	0.10	-0.73	-0.20	**1.21**	0.65	-1.38
LTR	-0.23	0.49	**1.00**	**1.12**	**1.02**	-1.09
TMS	-3.37	-1.09	-0.99	0.54	0.19	-2.54
DFY	-1.54	-1.23	-1.80	0.97	0.31	-3.43
DFR	0.76	0.61	-0.95	**2.20**	**1.65**	-2.00
INFL lag	-0.97	-0.79	-1.13	**1.22**	0.25	-2.93

Δ Utility

Model	**SMALL LoBM**	**ME1 BM2**	**SMALL HiBM**	**BIG LoBM**	**ME2 BM2**	**BIG HiBM**
OLS	0.04	**1.24**	-1.74	0.60	-0.26	-3.34
Pooled forecast:median	0.14	-0.43	-0.45	**1.40**	0.79	-1.43
Pooled forecast:MDSFE	0.83	-0.28	-0.75	**1.08**	0.83	-1.31
Sum-of-the-parts	**1.43**	-0.35	0.09	-0.79	0.28	-0.79
MARS	**1.96**	-0.16	0.27	**1.21**	**2.05**	**1.86**
SVM SIC	0.18	-3.65	-3.33	-4.58	-3.50	-3.83
Lasso SVM	-1.44	-0.58	-0.88	**1.72**	0.80	-1.30
Radom Forest	**1.45**	-0.32	-0.57	0.72	**1.32**	-0.58
Diffusion index	0.64	-0.52	-0.81	**1.49**	0.97	-1.78
PLS	-0.48	0.58	-1.21	**1.36**	0.66	-1.19
Neural Networks Median	-0.02	**2.96**	-3.48	0.60	0.78	-1.26

Table 3.20: R^2_{OS} **of the six portfolios built double sorting on Size and the Momentum using the Welch and Goyal [2008] predictors.** The R^2_{OS} is the Campbell Thompson (2008) out-of-sample R^2 statistic. Statistical significance for the R^2_{OS} statistic is tested using the Clark and West [2007] p-value; the statistic corresponds to a one-sided test of the null hypothesis that the competing forecasting model has equal expected square prediction error relative to the historical average benchmark forecasting model against the alternative hypothesis that the competing forecasting model has a lower expected square prediction error than the historical average benchmark forecasting model. The results refer to monthly forecasts for the out-of-sample period 1986:01-2017:12. **Bold** indicates a p-value for the R^2_{OS} statistic less than 0.1.

R^2_{OS}												
Predictor	**SMALL LoPRIOR**	**pval**	**ME1 PRIOR2**	**pval**	**SMALL HiPRIOR**	**pval**	**BIG LoPRIOR**	**pval**	**ME2 PRIOR2**	**pval**	**BIG HiPRIOR**	**pval**
DP	-2.38	0.15	-2.51	0.16	-1.09	0.34	-2.88	0.45	-1.48	0.26	-0.50	0.33
DY	-4.14	0.10	-5.02	0.11	-2.24	0.29	-4.01	0.40	-2.35	0.25	-0.83	0.32
EP	-2.29	0.60	-1.68	0.41	-0.30	0.19	-3.07	0.59	-1.62	0.30	0.00	0.09
DE	**1.06**	**0.07**	-0.09	0.36	-0.31	0.81	-0.32	0.60	-0.54	0.72	-0.42	0.45
SVAR	-1.87	0.79	-3.16	0.92	-0.67	0.91	-1.40	0.89	-1.71	0.91	0.62	0.06
BM	-5.22	0.22	-6.71	0.19	-2.80	0.24	-6.37	0.60	-4.16	0.39	-1.22	0.33
NTIS	-3.50	0.61	-6.06	0.77	-4.96	0.93	-2.87	0.52	-2.22	0.52	-2.25	0.84
TBL	**0.55**	**0.08**	0.02	0.33	-0.17	0.74	-0.12	0.79	-0.22	0.71	-0.20	0.95
LTY	**0.39**	**0.04**	0.00	0.48	-0.08	0.91	-0.05	0.72	-0.08	0.85	-0.09	0.99
LTR	0.50	0.11	**0.59**	**0.07**	-0.13	0.30	0.49	0.10	-0.41	0.23	-0.21	0.51
TMS	-1.01	0.46	-2.08	0.65	-1.45	0.75	-0.72	0.51	-1.28	0.75	-0.69	0.81
DFY	1.15	0.11	-1.07	0.41	-0.99	0.72	-0.06	0.34	-0.43	0.57	-0.22	0.94
DFR	-0.63	0.89	-0.60	0.86	-0.09	0.44	-0.66	0.96	-0.28	0.59	0.46	0.18
INFL lag	-0.65	0.71	-1.12	0.79	-0.35	0.54	-0.43	0.93	-0.34	0.84	-0.29	0.68

R^2_{OS}												
Model	**SMALL LoPRIOR**	**pval**	**ME1 PRIOR2**	**pval**	**SMALL HiPRIOR**	**pval**	**BIG LoPRIOR**	**pval**	**ME2 PRIOR2**	**pval**	**BIG HiPRIOR**	**pval**
OLS	-5.82	0.11	-9.22	0.19	-6.33	0.23	-8.87	0.80	-8.90	0.65	-2.80	0.23
Pooled forecast:median	**0.53**	**0.04**	0.20	0.17	0.20	0.11	0.00	0.44	0.02	0.39	0.12	0.13
Pooled forecast:MDSFE	0.47	0.12	0.04	0.27	-0.03	0.39	-0.24	0.52	-0.02	0.37	0.18	0.19
Sum-of-the-parts	-0.16	0.37	-2.04	0.23	-2.36	0.15	-0.63	0.65	-1.58	0.44	-2.34	0.25
MARS	0.20	0.21	-0.07	0.25	-0.83	0.39	-0.87	0.45	-0.90	0.52	-1.21	0.28
SVM SIC	-0.13	0.30	-0.41	0.37	-0.62	0.52	-0.87	0.56	0.75	0.11	-0.21	0.30
Lasso SVM	-0.03	0.25	-0.73	0.51	-0.60	0.85	-0.51	0.48	-0.57	0.74	-0.43	0.37
Radom Forest	**0.44**	**0.08**	-0.02	0.29	0.60	0.05	0.18	0.18	0.20	0.19	-0.05	0.35
Diffusion index	0.32	0.11	0.17	0.17	-0.22	0.63	-0.72	0.41	0.23	0.23	-1.68	0.80
PLS	**0.98**	**0.04**	-1.23	0.31	-1.81	0.75	-1.62	0.72	-0.49	0.40	0.02	0.17
Neural Networks Median	-0.77	0.41	**1.01**	**0.02**	**2.05**	**0.00**	-0.71	0.55	-0.16	0.33	-0.04	0.08

Table 3.21: **Δ Utility of the six portfolios built double sorting on Size and the Momentum using the Welch and Goyal [2008] predictors.** The Utility gain (Δ Utility) is the portfolio management fee (in annualized percentage return) that an investor with mean-variance preferences and risk aversion coefficient of three would be willing to pay to have access to the forecasting model considered relative to the historical average benchmark forecasting model; the weight on stocks in the investor's portfolio is restricted to lie between -0.5 and 1.5 (inclusive). The restriction imposed for the restricted case are the same of Table 1. The results refer to monthly forecasts for the out-of-sample period 1986:01-2016:12. **Bold** indicates a ΔUtility above 1.00%.

Δ Utility						
Predictor	**SMALL LoPRIOR**	**ME1 PRIOR2**	**SMALL HiPRIOR**	**BIG LoPRIOR**	**ME2 PRIOR2**	**BIG HiPRIOR**
DP	-0.34	-3.53	0.28	-3.13	-2.20	0.33
DY	-0.10	-4.15	-1.10	-3.17	-3.28	0.17
EP	-0.34	**1.54**	**2.14**	-1.03	**2.57**	**2.59**
DE	-1.76	-1.13	-0.97	-1.84	0.44	0.33
SVAR	-3.95	-1.11	-1.03	-3.67	0.31	**2.28**
BM	-2.27	-5.30	-1.38	-5.35	-3.85	-0.03
NTIS	-10.36	-0.54	-1.10	-5.67	**1.17**	0.60
TBL	-1.57	-0.13	-0.59	-1.61	0.93	**1.05**
LTY	-0.95	-0.41	-1.03	-1.25	0.72	0.89
LTR	-1.55	**1.09**	0.19	-1.20	0.76	0.95
TMS	-4.91	-1.00	-0.89	-2.68	0.36	0.69
DFY	-6.11	-1.64	-0.94	-5.57	0.56	0.79
DFR	-1.69	-0.31	0.87	-1.90	**1.62**	**2.86**
INFL lag	-3.60	-0.79	-0.47	-1.94	0.60	0.93

Δ Utility						
Model	**SMALL LoPRIOR**	**ME1 PRIOR2**	**SMALL HiPRIOR**	**BIG LoPRIOR**	**ME2 PRIOR2**	**BIG HiPRIOR**
OLS	-2.06	0.23	0.91	-6.65	-1.60	**1.71**
Pooled forecast:median	-0.53	-0.49	-0.41	-1.16	0.75	**1.19**
Pooled forecast:MDSFE	-0.09	-0.11	0.02	-1.06	0.89	**1.25**
Sum-of-the-parts	0.75	-0.08	0.00	-0.85	-0.28	-0.83
MARS	0.84	**1.31**	-0.52	0.42	0.66	0.74
SVM SIC	-0.65	-0.55	0.76	-1.12	**1.85**	0.47
Lasso SVM	0.05	-0.67	-0.83	-0.33	0.48	0.42
Radom Forest	0.42	-0.30	0.65	-0.05	**1.11**	0.72
Diffusion index	0.46	-0.43	-0.55	-2.12	**1.32**	0.18
PLS	-1.60	0.52	0.08	-4.77	**1.57**	**1.45**
Neural Networks Median	-0.59	**2.90**	**2.97**	-0.98	-4.11	**1.31**

Table 3.22: R^2_{OS} **of the six portfolios built double sorting on Size and the Book/Market ratio using factor-anomalies returns spread as predictors.** The R^2_{OS} is the Campbell Thompson (2008) out-of-sample R^2 statistic. Statistical significance for the R^2_{OS} statistic is tested using the Clark and West [2007] p-value; the statistic corresponds to a one-sided test of the null hypothesis that the competing forecasting model has equal expected square prediction error relative to the historical average benchmark forecasting model against the alternative hypothesis that the competing forecasting model has a lower expected square prediction error than the historical average benchmark forecasting model. The results refer to monthly forecasts for the out-of-sample period 1986:01-2016:12. **Bold** indicates a p-value for the R^2_{OS} statistic less than 0.1.

R^2_{OS}

Predictor	SMALL LoBM	pval	ME1 BM2	pval	SMALL HiBM	pval	BIG LoBM	pval	ME2 BM2	pval	BIG HiBM	pval
SMB	-1.16	0.46	-0.68	0.26	-0.27	0.14	-0.61	0.46	-0.36	0.28	-0.29	0.33
HML	-0.32	0.14	-0.74	0.36	-0.67	0.65	0.30	0.12	-0.82	0.84	-0.63	0.80
RMW	-1.28	0.81	-0.47	0.68	-0.06	0.37	-0.83	0.56	-0.96	0.67	-0.49	0.53
CMA	**0.39**	**0.02**	**0.09**	**0.02**	-0.19	0.05	**0.40**	**0.04**	-0.27	0.11	0.17	0.11
LT	-0.21	0.38	-0.51	0.65	-0.63	0.96	0.05	0.17	-0.77	0.64	-0.65	0.70
ST	-0.69	0.47	**0.31**	**0.08**	**0.95**	**0.03**	-0.79	0.87	-0.58	0.66	-0.01	0.29
Mom	-0.32	0.52	**0.80**	**0.02**	**0.83**	**0.02**	-0.99	0.88	-0.50	0.78	0.07	0.30
Asset Growth	**13.47**	**0.00**	**5.09**	**0.00**	**1.19**	**0.00**	**19.15**	**0.00**	**5.92**	**0.00**	**3.89**	**0.00**
Gross Prof	-3.01	0.00	-0.57	0.00	-0.11	0.00	**0.72**	**0.00**	-0.98	0.03	-0.22	0.07
Inv to Assets	**12.83**	**0.00**	**7.00**	**0.00**	**3.61**	**0.00**	**13.50**	**0.00**	**7.90**	**0.00**	**4.72**	**0.00**
Net Stock Issues	**58.32**	**0.00**	**32.58**	**0.00**	**24.07**	**0.00**	**28.74**	**0.00**	**11.84**	**0.00**	**13.44**	**0.00**
NOA	-3.60	0.22	-2.72	0.36	-1.93	0.36	-2.85	0.30	-1.50	0.06	-0.72	0.16
Accruals	-1.90	0.00	-3.32	0.01	-2.83	0.05	-1.48	0.00	-2.28	0.04	-2.26	0.12
O	-1.15	0.28	-3.90	0.94	-3.93	0.74	**12.45**	**0.00**	**0.27**	**0.05**	-1.11	0.48
ROA	-7.85	0.13	-4.23	0.25	-2.30	0.35	-3.41	0.00	-4.01	0.14	-0.94	0.26
Distress	-0.86	0.45	**0.61**	**0.09**	**1.78**	**0.02**	-0.13	0.20	**1.51**	**0.03**	**3.14**	**0.00**
Comp Eq Issue	-0.48	0.16	-0.58	0.14	-0.29	0.10	-0.25	0.29	-0.92	0.91	-0.78	0.87
Model	**SMALL LoBM**	**pval**	**ME1 BM2**	**pval**	**SMALL HiBM**	**pval**	**BIG LoBM**	**pval**	**ME2 BM2**	**pval**	**BIG HiBM**	**pval**
OLS	**53.49**	**0.00**	**30.28**	**0.00**	**27.05**	**0.00**	**27.98**	**0.00**	**6.90**	**0.00**	**8.40**	**0.00**
Pooled forecast:median	**3.39**	**0.00**	**2.58**	**0.00**	**2.19**	**0.00**	**5.05**	**0.00**	**2.13**	**0.00**	**1.63**	**0.00**
Pooled forecast:MDSFE	**29.65**	**0.00**	**11.54**	**0.00**	**7.04**	**0.00**	**18.45**	**0.00**	**7.50**	**0.00**	**4.41**	**0.00**
MARS	**16.53**	**0.00**	**10.20**	**0.00**	**8.44**	**0.00**	-2.41	0.08	-0.52	0.01	**4.05**	**0.00**
SVM SIC	-19.89	0.05	-8.81	0.18	-3.67	0.17	-14.66	0.32	-8.57	0.37	-3.68	0.44
Lasso SVM	-22.86	0.10	-9.63	0.29	-3.36	0.21	-21.32	0.26	-5.15	0.34	-2.19	0.36
Radom Forest	0.11	0.21	-0.12	0.65	0.08	0.24	-0.15	0.63	-0.02	0.43	0.00	0.43
Diffusion index	**11.21**	**0.00**	**4.22**	**0.00**	**0.26**	**0.03**	19.27	0.00	**6.25**	**0.00**	**2.74**	**0.00**
PLS	-41.52	0.82	-25.67	0.78	-14.40	0.61	-48.62	0.95	-27.61	0.99	-14.38	0.94
Neural Network Median	**6.32**	**0.00**	-2.61	0.14	-2.45	0.43	-1.77	0.28	-0.04	0.25	**0.34**	**0.06**

Table 3.23: **Δ Utility of the six portfolios built double sorting on Size and the Book/Market ratio using factor-anomalies returns spread as predictors**.The Utility gain (Δ Utility) is the portfolio management fee (in annualized percentage return) that an investor with mean-variance preferences and risk aversion coefficient of three would be willing to pay to have access to the forecasting model considered relative to the historical average benchmark forecasting model; the weight on stocks in the investor's portfolio is restricted to lie between -0.5 and 1.5 (inclusive). The restriction imposed for the restricted case are the same of Table 1. The results refer to monthly forecasts for the out-of-sample period 1986:01-2016:12. **Bold** indicates a Δ Utility above 1.00%.

Δ Utility

Predictor	SMALL LoBM	ME1 BM2	SMALL HiBM	BIG LoBM	ME2 BM2	BIG HiBM
SMB	0.35	0.16	0.11	-0.43	0.23	-0.15
HML	-0.53	0.21	-0.45	**1.64**	-0.24	-0.65
RMW	-1.00	0.07	0.51	-0.03	-0.18	0.05
CMA	**4.35**	**1.90**	0.30	**2.05**	0.72	0.05
LT	-0.47	0.37	-0.30	**1.66**	0.51	0.85
ST	0.42	**1.37**	**2.11**	-0.80	-0.28	0.81
Mom	0.08	**1.25**	**1.14**	-0.69	-0.21	0.25
Asset Growth	**17.89**	**11.57**	**7.82**	**14.52**	**7.99**	**7.68**
Gross Prof	**4.01**	**6.14**	**5.11**	**2.92**	**2.65**	**2.39**
Inv to Assets	**16.62**	**11.82**	**8.80**	**11.82**	**8.18**	**8.68**
Net Stock Issues	**38.85**	**25.75**	**22.81**	**23.00**	**17.61**	**18.96**
NOA	**3.92**	**3.00**	**1.21**	-0.36	**4.88**	**2.54**
Accruals	**4.06**	**3.68**	**3.31**	**4.61**	**3.03**	**1.66**
O	-2.97	-0.39	0.32	**7.58**	0.35	-0.71
ROA	0.84	**1.10**	-0.07	**3.33**	0.51	-0.98
Distress	0.03	0.32	**1.83**	-0.06	**3.36**	**4.20**
Comp Eq Issue	**1.71**	**1.20**	0.50	0.02	-0.46	-0.41
Predictor	**SMALL LoBM**	**ME1 BM2**	**SMALL HiBM**	**BIG LoBM**	**ME2 BM2**	**BIG HiBM**
OLS	**36.28**	**24.01**	**23.77**	**17.54**	**9.14**	**10.72**
Pooled forecast:median	**6.40**	**1.66**	**1.59**	**3.97**	**2.26**	**1.43**
Pooled forecast:MDSFE	**27.60**	**12.96**	**7.96**	**15.41**	**7.75**	**5.95**
MARS	**12.07**	**6.29**	**7.83**	-3.77	0.22	**4.23**
SVM SIC	**2.16**	**2.13**	**3.30**	-0.22	**1.63**	**3.02**
Lasso SVM	**3.12**	**2.00**	**3.28**	-0.12	**1.24**	**3.15**
Radom Forest	0.50	0.01	0.05	-0.32	0.08	0.36
Diffusion index	**16.54**	**12.22**	**7.29**	**13.19**	**9.10**	**8.41**
PLS	-12.19	-7.58	-5.65	-7.51	-7.26	-5.47
Neural Network Median	**10.63**	**2.17**	**2.06**	-0.63	0.67	**2.77**

Table 3.24: R^2_{OS} **of the six portfolios built double sorting on Size and the Momentum using factor-anomalies returns spread as predictors.** The R^2_{OS} is the Campbell Thompson (2008) out-of-sample R^2 statistic. Statistical significance for the R^2_{OS} statistic is tested using the Clark and West [2007] p-value; the statistic corresponds to a one-sided test of the null hypothesis that the competing forecasting model has equal expected square prediction error relative to the historical average benchmark forecasting model against the alternative hypothesis that the competing forecasting model has a lower expected square prediction error than the historical average benchmark forecasting model. The results refer to monthly forecasts for the out-of-sample period 1986:01-2016:12. **Bold** indicates a p-value for the R^2_{OS} statistic less than 0.1.

R^2_{OS}

Predictor	SMALL LoPRIOR	pval	ME1 PRIOR2	pval	SMALL HiPRIOR	pval	BIG LoPRIOR	pval	ME2 PRIOR2	pval	BIG HiPRIOR	pval
SMB	-0.42	0.28	-0.45	0.21	-0.58	0.19	-0.66	0.99	-0.72	0.68	-0.40	0.16
HML	-0.54	0.42	-0.70	0.46	-0.69	0.18	-0.74	0.95	-0.48	0.55	-0.14	0.17
RMW	0.22	0.20	-0.25	0.54	-0.38	0.36	-1.58	0.69	-1.37	0.66	**0.61**	**0.06**
CMA	**0.53**	**0.04**	**0.46**	**0.01**	-0.26	0.03	-0.38	0.20	**0.12**	**0.05**	**0.30**	**0.04**
LT	-0.65	0.90	-0.57	0.67	-0.60	0.72	-0.69	0.66	-0.48	0.39	-0.46	0.45
ST	-0.57	0.33	**0.37**	**0.06**	-0.61	0.46	-1.07	0.80	-0.68	0.85	-0.41	0.68
Mom	0.31	0.19	**0.84**	**0.02**	-0.19	0.42	-0.97	0.82	-0.74	0.89	-0.72	0.80
Asset Growth	**12.38**	**0.00**	**8.18**	**0.00**	**5.19**	**0.00**	**14.95**	**0.00**	**10.57**	**0.00**	**6.04**	**0.00**
Gross Prof	**0.92**	**0.00**	**0.43**	**0.00**	-3.37	0.00	**1.74**	**0.01**	**0.20**	**0.00**	-3.62	0.00
Inv to Assets	**14.77**	**0.00**	**8.81**	**0.00**	**5.60**	**0.00**	**15.84**	**0.00**	**8.46**	**0.00**	**4.20**	**0.00**
Net Stock Issues	**37.70**	**0.00**	**26.58**	**0.00**	**42.36**	**0.00**	**18.99**	**0.00**	**13.90**	**0.00**	**25.17**	**0.00**
NOA	-2.74	0.21	-2.28	0.11	-2.43	0.26	-1.45	0.11	-2.75	0.16	-3.14	0.44
Accruals	-1.42	0.03	-3.13	0.01	-3.19	0.01	-1.13	0.04	-1.91	0.01	-2.86	0.02
O	-0.65	0.26	-3.41	0.95	-4.44	0.93	**7.25**	**0.00**	**3.87**	**0.00**	**0.51**	**0.03**
ROA	-0.13	0.10	-4.42	0.22	-6.21	0.06	-0.77	0.31	-4.08	0.07	-5.61	0.00
Distress	**18.36**	**0.00**	**4.52**	**0.00**	-1.97	0.33	**22.00**	**0.00**	**3.13**	**0.00**	-2.19	0.04
Comp Eq Issue	**0.16**	**0.06**	-0.38	0.07	-0.44	0.10	-0.96	0.98	-0.74	0.86	-0.14	0.25
Model	**SMALL LoPRIOR**	**pval**	**ME1 PRIOR2**	**pval**	**SMALL HiPRIOR**	**pval**	**BIG LoPRIOR**	**pval**	**ME2 PRIOR2**	**pval**	**BIG HiPRIOR**	**pval**
OLS	**53.42**	**0.00**	**28.94**	**0.00**	**38.00**	**0.00**	**37.95**	**0.00**	**9.11**	**0.00**	**16.69**	**0.00**
Pooled forecast:median	**3.39**	**0.00**	**3.03**	**0.00**	**3.46**	**0.00**	**2.08**	**0.00**	**2.63**	**0.00**	**4.01**	**0.00**
Pooled forecast:MDSFE	**14.98**	**0.00**	**10.86**	**0.00**	**17.85**	**0.00**	**13.71**	**0.00**	**9.94**	**0.00**	**11.46**	**0.00**
MARS	**33.80**	**0.00**	**14.20**	**0.00**	**19.44**	**0.00**	**14.96**	**0.00**	-0.37	0.01	**1.12**	**0.00**
SVM SIC	-5.29	0.06	-4.51	0.02	-13.68	0.04	-8.13	0.36	-9.68	0.28	-12.61	0.21
Lasso SVM	-9.23	0.12	-5.33	0.07	-15.09	0.14	-8.21	0.35	-5.83	0.19	-15.38	0.27
Radom Forest	**0.25**	**0.06**	**0.34**	**0.02**	0.00	0.38	-0.07	0.55	-0.01	0.41	-0.01	0.39
Diffusion index	**11.80**	**0.00**	**7.79**	**0.00**	**1.81**	**0.00**	**13.50**	**0.00**	**10.42**	**0.00**	**7.02**	**0.00**
PLS	-31.55	0.95	-27.02	0.88	-33.90	0.80	-39.06	0.98	-31.33	0.97	-36.41	0.89
Neural Network Median	**1.38**	**0.02**	-3.28	0.41	-1.49	0.19	-0.02	0.21	-0.85	0.26	-0.64	0.08

Table 3.25: **Δ Utility of the six portfolios built double sorting on Size and the Momentum using factor-anomalies returns spread as predictors.** The Utility gain (Δ Utility) is the portfolio management fee (in annualized percentage return) that an investor with mean-variance preferences and risk aversion coefficient of three would be willing to pay to have access to the forecasting model considered relative to the historical average benchmark forecasting model; the weight on stocks in the investor's portfolio is restricted to lie between -0.5 and 1.5 (inclusive). The restriction imposed for the restricted case are the same of Table 1. The results refer to monthly forecasts for the out-of-sample period 1986:01-2016:12. **Bold** indicates a Δ Utility above 1.00%.

Δ Utility

Predictor	**SMALL LoPRIOR**	**ME1 PRIOR2**	**SMALL HiPRIOR**	**BIG LoPRIOR**	**ME2 PRIOR2**	**BIG HiPRIOR**
SMB	0.74	0.29	0.54	-0.89	-0.47	0.66
HML	-1.86	-0.13	**1.00**	-0.85	0.48	**1.66**
RMW	-0.84	-0.14	**1.28**	-0.45	0.30	**1.94**
CMA	**2.98**	**2.95**	**2.01**	-0.61	**1.44**	**2.33**
LT	-1.50	0.40	-0.55	-0.10	**1.56**	0.42
ST	**1.10**	**1.55**	-0.39	-1.02	-0.60	0.04
Mom	0.30	0.90	-0.15	-1.10	-0.35	-0.30
Asset Growth	**9.98**	**12.12**	**15.20**	**11.72**	**10.25**	**11.74**
Gross Prof	-1.64	**6.42**	**6.68**	0.98	**2.95**	**2.67**
Inv to Assets	**11.70**	**12.19**	**14.00**	**12.03**	**8.97**	**9.18**
Net Stock Issues	**28.12**	**23.26**	**32.15**	**21.51**	**18.61**	**22.48**
NOA	0.87	**3.59**	**5.01**	-0.04	**2.32**	**1.02**
Accruals	**1.70**	**4.68**	**4.02**	**3.44**	**4.80**	**2.76**
O	-5.54	-0.38	-0.38	**3.10**	**2.81**	**2.15**
ROA	**3.57**	**1.21**	**4.33**	0.45	**1.21**	**5.34**
Distress	**8.62**	**4.91**	0.71	**12.73**	**4.46**	**2.85**
Comp Eq Issue	**1.16**	**1.52**	**2.20**	-0.92	-0.36	**1.11**
Model	**SMALL LoPRIOR**	**ME1 PRIOR2**	**SMALL HiPRIOR**	**BIG LoPRIOR**	**ME2 PRIOR2**	**BIG HiPRIOR**
OLS	**30.50**	**22.12**	**29.36**	**21.38**	**9.38**	**18.31**
Pooled forecast:median	**6.97**	**2.59**	**4.15**	**2.49**	**2.42**	**3.53**
Pooled forecast:MDSFE	**17.67**	**12.46**	**18.55**	**14.17**	**9.47**	**11.10**
MARS	**16.44**	**9.22**	**13.77**	**10.96**	0.40	**2.13**
SVM SIC	-2.39	**2.87**	**8.01**	-1.03	**2.00**	**2.30**
Lasso SVM	-0.96	**3.45**	**6.09**	-3.75	**2.12**	**1.57**
Radom Forest	0.50	0.61	0.37	-0.23	0.00	0.02
Diffusion index	**8.62**	**12.95**	**15.23**	**9.93**	**10.20**	**12.73**
PLS	-13.68	-8.16	-9.21	-10.04	-6.47	-5.98
Neural Network Median	**1.13**	**2.64**	**1.49**	0.22	-0.28	**2.48**

Table 3.26: **Out-of-sample predictability of spread portfolio returns with Welch and Goyal [2008] predictors: Δ Utility %.** In this table we compare the out-of-sample predictability of a set 17 spread portfolio returns: SMB (1), HML (2), RMW (3), CMA (4), LT (5), ST (6), Mom (7), Asset Growth (8), Gross Prof (9), Inv to Asset (10), Net Stock Issue (11), NOA (12), Accruals (13), O (14), ROA (15), Distress (16), Comp Eq Issue (17). The monthly out-of-sample period considered is the most recent 30% for each variable. Forecasts are based on Welch and Goyal [2008] predictors: we consider both univariate regression and all the machine learning techniques detailed in the second part of this paper. **Bold** indicates an yearly percentage utility gain of more than 1%.

Δ Utility	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**	**(16)**	**(17)**
DP	-1.49	**1.72**	-0.86	**1.39**	0.69	**4.63**	**2.27**	**1.69**	-2.07	0.64	0.30	-0.18	-0.79	0.34	**1.91**	-0.82	-0.32
DY	-2.17	**1.66**	-0.94	**1.42**	0.68	**4.43**	**2.21**	**1.69**	-2.16	0.64	0.30	-0.20	-0.79	0.18	**1.83**	-0.80	-0.40
EP	-1.47	**1.02**	-0.34	0.58	0.75	**3.50**	**3.81**	**1.69**	0.05	0.64	0.38	-0.26	-0.79	0.28	**1.22**	-0.59	-0.38
DE	0.36	-0.20	-0.59	0.60	**3.94**	0.15	**3.82**	**1.43**	**2.25**	0.64	0.40	-0.34	-0.85	0.61	**2.33**	-0.72	-0.41
SVAR	-0.77	-0.98	-0.72	0.59	**1.24**	0.13	**5.30**	**1.53**	0.51	0.56	0.04	-0.35	-0.79	**1.35**	**1.05**	-0.61	-0.33
BM	-1.14	**1.17**	0.46	0.71	0.96	**4.05**	**4.17**	**1.69**	0.02	0.64	0.34	-0.15	-0.79	0.40	0.59	-0.71	-0.34
NTIS	-0.30	**1.07**	0.06	0.71	**3.58**	0.33	**4.24**	**1.68**	0.11	0.81	0.40	-0.26	-0.79	-0.59	0.38	-0.61	-0.23
TBL	-0.02	0.28	0.46	-0.08	0.60	0.19	**3.80**	**1.51**	**1.45**	0.64	0.16	-0.07	-0.83	0.45	**2.33**	-0.66	-0.57
LTY	0.01	0.58	-0.44	0.34	0.72	0.20	**4.45**	**1.55**	**1.14**	0.64	0.28	-0.15	-0.79	0.12	**2.52**	-0.73	-0.50
LTR	-0.78	0.51	0.31	0.35	**1.42**	0.57	**5.11**	**1.56**	**1.06**	0.62	0.11	-0.36	-0.79	0.30	**1.08**	-0.78	-0.44
TMS	0.16	0.86	-0.41	0.43	0.30	0.39	**4.08**	**1.57**	**2.02**	0.64	0.44	-0.27	-0.89	**1.75**	**2.46**	-0.75	-0.20
DFY	-0.14	-0.29	0.16	0.62	**1.35**	0.98	**4.05**	**1.66**	-0.07	0.64	0.22	-0.20	-0.79	0.10	**2.54**	-0.87	-0.48
DFR	0.10	**1.67**	0.20	0.14	**1.34**	0.11	**4.95**	**1.55**	0.66	0.64	0.26	-0.34	-0.79	0.66	**1.97**	-0.71	-0.42
INFL lag	0.14	-0.32	0.20	0.46	0.77	-0.06	**4.67**	**1.64**	**2.04**	0.64	0.43	-0.31	-0.79	0.73	**2.99**	-0.68	-0.39
Δ Utility																	
OLS	-2.52	**4.26**	-1.50	0.58	**2.61**	**1.21**	0.60	-3.04	-2.28	-1.66	-2.49	-0.28	**4.36**	-1.04	-9.47	-4.89	-5.65
Pooled forecast:median	-0.34	**1.94**	-1.76	-0.17	**1.96**	**3.03**	**2.56**	-3.50	-2.24	-1.80	-2.09	0.17	**1.38**	-0.78	-7.10	-4.46	-5.02
Pooled forecast:MDSFE	-0.71	**1.68**	-1.76	-0.17	**1.79**	**3.22**	**2.28**	-3.50	-2.21	-1.80	-2.09	0.17	**1.38**	-0.67	-7.26	-4.45	-5.02
MARS	-0.84	**1.77**	-1.60	-1.16	**2.59**	**4.52**	**10.87**	-5.23	-3.75	-4.54	-3.42	-1.01	**4.27**	-0.98	-9.13	-7.90	-8.21
SVM SIC	-0.34	**1.66**	-1.76	-0.30	**1.50**	**3.65**	**1.53**	-3.50	-2.16	-1.80	-2.09	0.17	**1.34**	-1.89	-6.77	-4.95	-5.02
Lasso SVM	-1.21	**1.64**	-1.76	-0.03	**1.52**	**3.91**	0.93	-3.50	-2.88	-1.80	-2.09	0.17	**1.38**	-1.77	-7.08	-5.80	-5.02
Radom Forest	-0.87	**2.13**	-1.76	-0.17	**1.64**	**2.80**	**2.70**	-3.50	-2.20	-1.80	-2.09	0.17	**1.38**	-1.02	-7.05	-4.39	-5.02
Diffusion index	-1.38	**2.21**	-1.76	-0.14	**2.20**	**3.88**	0.84	-3.50	-2.69	-1.80	-2.13	0.17	**1.37**	-1.10	-6.10	-5.00	-5.02
PLS	-1.13	**1.15**	-1.77	-0.41	**2.11**	**2.55**	**1.79**	-4.09	-2.36	-2.10	-2.17	0.17	**1.19**	0.89	-8.55	-5.77	-5.02
Neural Networks Median	0.65	**2.74**	-3.21	-2.24	**3.90**	**2.54**	**2.71**	-2.33	0.85	-1.74	-1.70	-2.32	**0.74**	0.55	-4.86	-4.88	-2.61

Table 3.27: **Out-of-sample predictability of spread portfolio returns with lagged spread portfolio returns predictors: Δ Utility %.** In this table we compare the out-of-sample predictability of a set 17 spread portfolio returns: SMB (1), HML (2), RMW (3), CMA (4), LT (5), ST (6), Mom (7), Asset Growth (8), Gross Prof (9), Inv to Asset (10), Net Stock Issue (11), NOA (12), Accruals (13), O (14), ROA (15), Distress (16), Comp Eq Issue (17). The monthly out-of-sample period considered is 1:1986-12:2016. Forecasts are based on lagged (t-1) spread portfolio returns predictors: we consider both univariate regression and all the machine learning techniques detailed in the second part of this paper Bold indicates an yearly percentage utility gain of more than 1%.

Δ Utility	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
SMB	0.52	-0.71	-0.44	-0.40	-0.67	0.27	-0.26	-0.43	-0.03	-0.02	0.15	-0.04	-0.08	**2.26**	0.73	-0.24	-0.42
HML	-0.31	**3.41**	0.08	-0.24	0.24	**1.12**	**1.62**	-0.32	-0.22	-0.03	0.09	0.11	-0.02	-0.66	-0.41	-0.26	-0.45
RMW	-1.41	-1.51	**2.41**	-0.68	0.46	**2.10**	-0.22	-0.14	-0.21	0.00	-0.94	-0.11	0.05	0.56	0.24	-1.30	-0.53
CMA	**2.65**	**2.09**	-0.46	0.32	0.25	**2.13**	-0.71	-0.14	-0.22	0.29	-0.17	0.93	0.07	-0.55	0.05	-0.13	-0.35
LT	-0.28	**2.13**	**1.22**	0.79	**1.70**	0.27	-0.67	-0.05	-0.39	0.00	-0.24	0.00	-0.01	-0.35	-0.55	-0.04	0.08
ST	**3.21**	**1.84**	-0.63	0.15	0.16	-1.57	-1.88	-0.01	-0.37	0.00	0.91	0.23	0.14	0.40	-0.54	-0.58	0.05
Mom	**2.04**	0.39	0.10	-0.28	0.63	-0.64	-1.24	-0.49	-0.17	-0.01	0.42	-0.14	-0.03	0.34	-0.58	-0.64	-0.72
Asset Growth	**1.46**	**12.61**	-0.01	**12.61**	**9.24**	**2.26**	-2.15	-0.71	-0.06	-0.06	-0.37	0.04	-0.25	0.98	-0.62	-0.06	**3.84**
Gross Prof	**3.91**	**4.27**	**3.83**	**2.82**	-0.47	**1.68**	-2.89	-0.25	0.28	0.00	0.10	0.61	0.09	**1.06**	-0.17	0.14	-0.31
Inv to Assets	0.84	**7.87**	0.21	**10.10**	**6.60**	**2.49**	**4.44**	-0.77	0.83	-0.31	-0.28	0.06	0.20	**1.54**	-0.50	-0.32	**2.79**
Net Stock Issues	**6.91**	**9.23**	**10.15**	**7.67**	-0.05	**3.83**	-0.02	-0.17	0.07	-0.01	0.80	0.08	-0.15	0.36	-0.58	-0.10	**12.04**
NOA	**2.45**	**4.47**	**6.89**	-0.38	**1.43**	0.08	**2.99**	-0.22	0.23	-0.13	0.54	0.71	0.15	0.33	-0.78	0.95	**1.43**
Accruals	**1.11**	**5.25**	0.14	**3.63**	**3.58**	-0.33	-0.47	-0.71	-0.51	-0.24	-0.34	-0.25	-0.24	-0.13	-0.48	0.06	0.35
O	**6.06**	**11.79**	-0.58	**6.32**	**4.51**	-1.07	0.25	-0.15	-0.27	0.00	-0.19	0.26	-0.06	**1.00**	-0.42	-0.11	0.40
ROA	**2.32**	**8.88**	**4.97**	**3.31**	**6.27**	0.83	**9.98**	-0.21	-0.96	0.03	-0.22	0.08	-0.23	0.06	-0.10	-0.01	-0.64
Distress	0.45	**3.31**	-1.38	-0.05	-0.85	**12.59**	**23.23**	-0.49	-0.65	-0.31	0.44	0.55	-0.08	**1.07**	-0.21	-0.81	-0.40
Comp Eq Issue	**1.66**	0.84	**1.76**	-0.62	-0.30	0.62	-0.02	-0.05	-0.38	0.35	-0.58	-0.12	0.27	-0.43	0.57	-0.16	0.55
Δ Utility																	
OLS	**16.06**	**18.32**	**11.60**	**11.84**	**10.38**	**12.74**	**22.85**	-1.93	0.17	-1.61	0.45	0.16	-1.04	**1.52**	**1.02**	-4.20	**11.59**
Pooled forecast:median	**2.39**	**5.25**	**1.54**	**2.63**	**2.24**	**1.11**	0.63	-0.04	0.07	0.00	-0.10	0.03	-0.02	0.35	-0.15	-0.02	0.18
Pooled forecast:MDSFE	**6.01**	**15.15**	**5.93**	**10.04**	**8.03**	**5.84**	**13.19**	-0.07	-0.04	0.00	-0.05	0.04	-0.01	0.66	-0.29	0.00	**7.28**
MARS	**10.36**	**6.73**	**5.18**	**5.55**	**3.79**	**9.19**	**13.33**	-5.15	-2.68	-6.57	-2.23	-5.05	-5.45	0.65	-1.44	-5.86	**4.16**
SVM SIC	**2.35**	0.46	**1.07**	-0.46	0.81	0.18	-1.37	-0.81	-0.17	0.00	0.15	0.11	0.09	0.57	0.19	-0.30	-2.16
Lasso SVM	**1.30**	0.56	0.74	-0.40	0.80	-0.52	**1.24**	-0.82	-0.03	0.00	-0.41	0.11	0.17	0.54	0.24	-0.29	-0.90
Radom Forest	0.38	**1.15**	-0.12	0.72	0.59	0.11	0.95	0.00	0.05	0.00	0.01	0.03	0.01	0.12	-0.04	0.01	0.02
Diffusion index	**1.11**	**11.54**	-0.10	**10.78**	**8.49**	**4.01**	-1.01	-2.41	-0.35	-0.09	-0.21	0.28	-0.05	**1.59**	-0.46	-0.23	**2.05**
PLS	-0.33	-0.26	-0.63	-1.98	**1.11**	-1.01	-5.75	-3.15	-0.58	-0.26	-0.02	-0.36	-0.58	**1.54**	-0.19	-1.33	-2.23
Neural Network Median	-12.52	0.43	0.97	**2.66**	-1.30	-13.96	-22.74	-5.75	-0.14	-0.23	-0.04	0.59	0.39	**0.72**	-1.05	-0.81	-0.32

Table 3.28: **Out-of-sample predictability of swaps and volatility-correlations risk premia: yearly percentage Δ Utility.**. We report the results employing the 17 spread returns portfolios as predictors for the monthly out-of-sample period 1:2005-12:2017. The variable forecasted are: the 30 and 90 days ahead Implied Correlation (IC 30 and IC 91), the 30 and 90 days ahead Implied Volatility (IV 30 and IV 90), the Implied Variance Risk Premium at 30 and 90 days ahead (VRP 30 and VRP 91) the 30 and 90 days ahead Implied Downside Variance Risk Premium (IVD 30 and IVD 90) and the 30 days-91 days Realized Correlation (RC 30 and RC 90). **Bold** indicates a percentage Δ Utility above 1%.

Δ Utility	**IC 30**	**IC 91**	**IV 30**	**IV 91**	**VRP 30**	**VRP 91**	**IVD 30**	**IVD 91**	**RC 30**	**RC 91**
SMB	-2.87	-3.32	-2.91	-1.59	**24.87**	**2.47**	-3.06	-1.60	-5.00	-0.05
HML	0.06	-0.72	-0.84	0.41	**24.98**	**2.36**	-1.20	0.17	-2.94	-1.06
RMW	-1.91	-3.44	-3.94	-1.85	**25.04**	**2.46**	-5.28	-2.04	-12.63	-0.45
CMA	-8.28	-10.03	-5.90	-4.20	**25.05**	**2.21**	-5.52	-3.99	-6.41	-10.29
LT	-12.01	-15.32	-9.16	-8.44	**25.02**	**2.26**	-9.55	-8.04	-9.06	-5.26
ST	-1.64	-2.63	-2.09	-0.14	**25.10**	**2.35**	-2.38	-0.39	-4.82	-4.38
Mom	0.20	-0.26	-0.99	0.57	**24.97**	**2.44**	-1.34	0.29	-2.96	-2.22
Asset Growth	-15.47	-20.78	-5.97	-5.95	**24.65**	**1.55**	-5.47	-4.64	-9.04	-20.21
Gross Prof	-1.72	-0.64	-2.28	-0.11	**25.01**	**2.57**	-2.38	-0.15	-4.73	0.80
Inv to Assets	-11.47	-11.94	-4.21	-2.64	**24.79**	**1.75**	-4.37	-3.06	-11.61	-12.04
Net Stock Issues	-23.45	-26.43	-9.29	-9.32	**25.54**	**2.56**	-8.74	-8.42	-11.21	-31.30
NOA	-4.40	-7.09	-2.30	-1.60	**25.25**	**2.78**	-2.45	-1.47	-2.91	-5.69
Accruals	-3.16	-6.80	-1.22	-0.84	**24.58**	-0.08	-1.54	-1.08	-3.39	-7.74
O	-24.59	-21.71	-11.65	-11.25	**24.83**	**2.96**	-10.38	-10.09	-7.99	-28.04
ROA	-1.88	-2.04	-1.72	-0.53	**24.92**	**2.60**	-1.83	-0.49	-4.53	-4.35
Distress	**1.84**	0.77	0.29	**1.39**	**24.94**	**2.56**	-0.03	**1.19**	-2.71	-0.24
Comp Eq Issue	0.85	-0.66	-0.81	0.23	**24.98**	**2.45**	-1.14	-0.02	-2.75	0.64
Model										
OLS	-4.12	**6.14**	-18.15	-10.93	-557.29	-466.70	-16.98	-30.09	-13.57	**6.21**
Pooled forecast:median	0.27	0.80	0.38	0.25	**1.95**	-0.18	0.61	0.70	0.11	0.91
Pooled forecast:MDSFE	**1.37**	**2.94**	**1.60**	**2.31**	-2.20	-1.07	**1.57**	**1.75**	0.10	**2.06**
MARS	-0.15	**2.51**	-4.62	0.80	**23.91**	0.09	-2.10	-1.41	-5.50	-0.30
SVM SIC	-5.60	-4.24	-8.31	-6.28	**23.98**	**1.38**	-9.46	-7.08	-8.88	**2.70**
Lasso SVM	-10.25	-9.17	-12.53	-6.81	**24.01**	0.14	-15.09	-9.75	-8.23	**3.43**
Radom Forest	-0.40	0.63	-0.09	0.20	**2.42**	**1.16**	0.15	0.56	-0.08	-0.71
Diffusion index	-6.06	-2.98	-7.63	-4.56	**24.98**	**2.99**	-8.69	-8.06	-7.59	**1.61**
PLS	-9.95	-9.08	-19.45	-17.93	**23.07**	-0.22	-22.75	-22.75	-7.80	-7.61
Neural Networks Median	**3.87**	**3.33**	0.42	**3.27**	**26.53**	**5.64**	-0.10	**3.90**	-5.82	**11.47**

Table 3.29: **Out-of-sample predictability the moments contracts: Δ Sharpe ratio.** We document the Δ Utility metric. We report the results employing as predictors the 17 spread returns portfolios (Anomalies), or the Welch and Goyal [2008] (W-G) variables for the monthly out-of-sample period 1:2005-12:2017. The predictive approaches used are the same detailed in section 3.1. The variables forecasted are the returns of the first four 20 and 40 business days ahead moments contract (M1 20, M1 40, M2 20, M2 40, M3 20, M3 40, M4 20, M4 40) built following Bakshi et al. [2003]. **Bold** indicates a Δ Sharpe ratio higher than 0.5.

	M1 20	**M2 20**	**M3 20**	**M4 20**	**M1 40**	**M2 40**	**M3 40**	**M4 40**
Benchmark	-0.33	0.60	0.29	-0.44	-0.46	-0.47	-0.32	3.57
Δ SR Anomalies								
OLS	0.29	-0.20	-0.01	0.18	0.49	0.18	**0.58**	-3.17
Pooled Forecast median	-0.03	0.00	0.01	0.01	-0.04	-0.01	0.00	-0.97
Pooled Forecast MDSFE	-0.03	0.00	0.01	0.02	-0.03	-0.02	0.00	-0.93
MARS	**6.59**	**10.32**	0.08	**3.34**	**2.26**	**0.97**	**0.63**	**7.08**
SVM SIC	**0.67**	0.18	-0.55	**2.05**	**1.10**	**0.76**	**0.58**	**4.13**
Lasso svm	**0.65**	0.40	**0.77**	**3.46**	**0.94**	**0.80**	0.07	**7.10**
Random Forest	-0.01	-0.02	0.01	0.00	0.01	0.38	0.00	-2.09
Diffusion Index	0.45	**1.77**	-0.27	**3.39**	**0.73**	**0.85**	**0.66**	**7.07**
PLS	**0.74**	0.57	**0.55**	**3.26**	**0.55**	0.29	0.11	**1.75**
Neural Netwok Median	**1.06**	**0.69**	-0.47	**1.41**	**1.71**	**0.82**	0.07	0.31
Δ SR W-G								
OLS	**0.54**	-0.04	-0.01	0.07	**0.77**	0.04	**0.61**	-3.89
Pooled Forecast median	-0.23	-0.07	-0.01	-0.01	-0.26	0.20	**0.58**	-3.51
Pooled Forecast MDSFE	-0.22	-0.04	-0.03	0.02	-0.11	0.24	**0.62**	-3.46
MARS	0.24	0.36	**1.04**	**1.79**	0.04	**0.76**	**0.61**	-2.23
SVM SIC	-0.01	-0.33	0.25	**1.19**	-0.04	**0.88**	**0.62**	-2.27
Lasso svm	-0.07	-0.38	-0.34	**1.38**	0.10	**0.88**	**0.62**	-2.33
Random Forest	-0.21	-0.09	-0.01	0.00	-0.29	0.13	0.00	-3.46
Diffusion Index	-0.13	-0.70	-0.01	0.86	-0.34	**0.95**	**0.60**	-2.78
PLS	-0.02	-0.92	-0.04	**1.23**	0.00	**0.92**	**0.61**	-2.28
Neural Netwok Median	0.19	-0.91	0.10	0.15	0.38	**0.79**	-0.01	-2.83

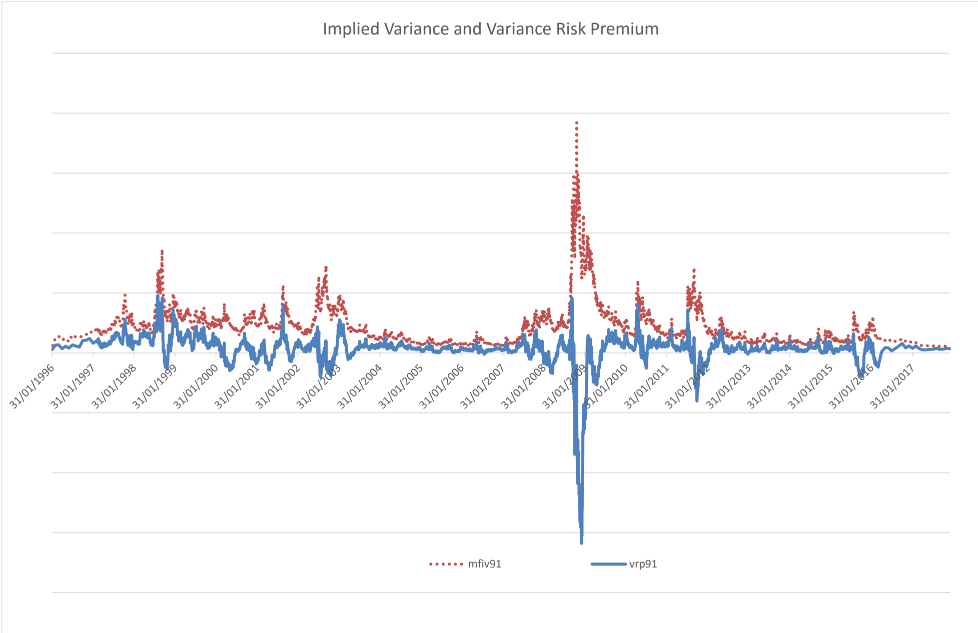

Figure 3.3: **Implied Variance and Variance Risk Premium.** This table plots the time series of the model free impled variance swap computed following Martin and Wagner [2019] and the related Variance Risk Premium. Monthly data sapans the period 1996:1-2017:12.

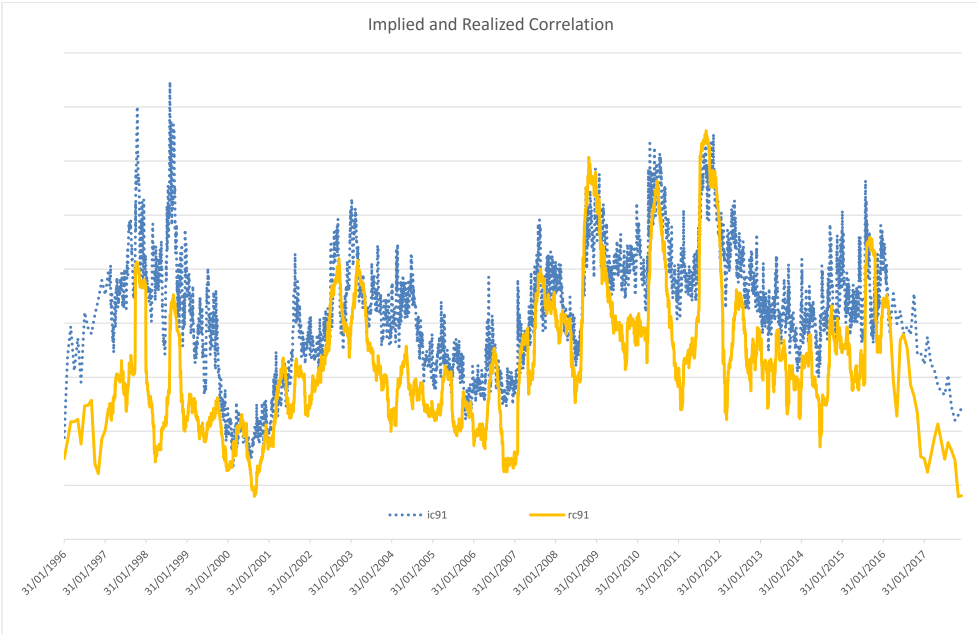

Figure 3.4: **Implied and Realized Correlation.** This table plots the time series of the model free Implied Correlation Swaps built following Buss et al. [2018] and of the related Realized Correltion. Monthly data sapans the period 1996:1-2017:12.

Chapter 4

The Magnificent Enigma

4.1 Introduction

This paper links equity predictability and pricing through the study of the rationale underpinning predictability. The cornerstone of this article is equity premium predictability: the magnificent enigma. This enigma is of the utmost relevance not only because of its apparent economic value but also because the analysis of predictability's rationale allows us to shed new light on the link between behavioral and neoclassical finance. Indeed, the capability to understand the genesis of out-of-sample predictability implies that we have gained a deep understanding about the dynamics of risk and risk pricing[1].
From a theoretical point of view, this study is linked to the ongoing debate between behavioral and neoclassical finance. Indeed, the theory on asset pricing is divided into two main conflicting schools of thought: the neoclassical approach which states that higher expected returns are consequence of higher risks[2] and the behavioral approach, which explain how human biases lead investors to deviate from full rationality[3]. We show how the interaction among risks and the pricing of risks is at the very base of predictability, and consequently, both behavioral and neoclassical theories provide useful tools in understanding financial markets.
All the results provided in this paper are built on the key idea that real knowledge of financial markets should imply the capability to forecast their behavior and to explain the rationale which is driving the predictions. Consequently, we start analyzing the out-of-sample predictive power of a comprehensive set of behavioral and

[1]The idea that predictability and pricing are intimately related is not new and is formulated in the seminal work of Campbell [1991].

[2]Among the most complete books which summarizes the state of the art we cite the remarkable works of Ross [2004], Cochrane [2005], and Duffie [2001]

[3]In the list of books which offer a rich analysis of the main achievements in the field we list Shleifer [2000], Thaler [2005], Shefrin [2008], and Forbes [2009]

fundamental predictors, both unconditionally and conditionally to being in period of economic recession-expansion. Consistently, with the prevailing literature[4], we observe how it is possible to beat the forecasts provided by the mean returns both in terms of positive R^2_{OS} and Utility gains. Even more importantly, we observe how the predictability detected by our econometric and machine learning models is higher during the more recent 2001-2016 out-of-sample period than during the longer 1986-2016 one, suggesting how the phenomenon is not disappearing. Remarkably, some of the proposed spread returns predictors (Asset Growth, Net Stock Issue and Investment to Assets)[5] achieve statistically significant monthly R^2_{OS} values well above the 10% threshold matched by equally important utility gains. After that, we document how predictability is on average higher during periods of economic recession and conditionally on the subsequent return being negative.

After that, we start considering individual predictors and their capability to forecast the discount rate and cash flows component of asset prices. We observe how all the three most powerful predictors (Asset Growth, Net Stock Issue and Investment to Assets) are especially effective in forecasting the cash flow component of returns suggesting that the fundamental component is the pivotal one. After that, we notice how fundamentally based predictors (e.g., the dividend-price the dividend-yield, the book-to-market), are especially effective in forecasting the $S\&P500$ returns in periods of economic recession, while behaviourally based predictors (e.g., Net Equity Expansion, Momentum, Long and Short Term reversal) are more effective predictors during periods of economic expansion. These results jointly point out toward an interpretation of financial markets in which fundamentals play the dominant role during recessions while behavioral variables become more relevant during expansions.

To gain a better understanding of the drivers of predictability we employ three behavioural (the Greed index of Huang et al. [2015][6], the Fear index coming from the corridor variance approach of Andersen and Bondarenko [2007][7], and the Financial Uncertainty index of Jurado et al. [2015]) and five fundamental variables (the five Fama and French [2015] factors) and we perform a pooled regression analysis on all the returns time series of the R^2_{OS} previously estimated. Our results

[4]See e.g. Rapach et al. [2009], Neely et al. [2014] and Rapach and Zhou [2013]

[5]We employed the 11 anomalies considered by Stambaugh et al. [2012] following the detailed report in the appendix of the work of Stambaugh and Yuan [2017]

[6]In the original paper the authors named this paper as a Sentiment index but Barone-Adesi et al. [2018] show how this index is effective only in the timely detection of abnormally low levels of risk aversion

[7]Fear index which we employ in this paper is the downside variance risk premium estimated by Grigory Vilkov. Our choice is motivated by the empirical analyse performed by Feunou et al. [2017]

show how both fundamental and behavioral variables are important in explaining predictability. Motivated by the concern that the Fama and French factors could be largely affected by market behavioral dynamics (Stambaugh et al. [2012]) we employ alternative macroeconomic variables: the five principal components (which we name Income, Industrial Production, Labor, House, and Inflation) estimated from five large sets of macroeconomic time series clustered on the base of their economic meaning[8]. Subsequently, we employ the three behavioral variables and the new five macroeconomics ones as independent variables in the adaptive elastic net framework of Zou and Zhang [2009] while the dependent variable is now the total market predictability computed as the average R^2_{OS} return of all the univariate OLS and multivariate machine learning predictive models. The results which arise confirm how both fundamental and behavioral factors are linked to predictability. Importantly, even the interactions between behavioral and fundamental variables are critical components in explaining predictability. These finding on predictability are consistent with a theory of equity prices which involves both fundamental and behavioral components[9].

Subsequently, we estimate VAR(1) models which include the time series of the total R^2_{OS} returns and a rich set of five macroeconomic (Income, Industrial Production, House, Labor, and Inflation) and the three behavioral variables (Greed, Fear, and Uncertainty). In the first case considered the returns of the macroeconomic and behavioral variables are included in the VAR(1) system while in the second case, we include the levels of the variables. The related impulse response functions show us how predictability reacts to macroeconomic and behavioral shocks. After that, we employ regime Markov Switching Regressions to test which macroeconomic and behavioral variables explain the dynamics of aggregate predictability in the bull and bear market regimes. Finally, we computed threshold regressions based on the prevailing filtered probabilities to perform a regime dependent pairwise causality analysis between behavioral and fundamental variables. Overall our results document how changes in fundamentals trigger changes in the behavioral variables, and the effects are stronger during bear markets.

Our results have broad theoretical implications because they offer a different empirical approach to test the mainstream asset pricing theories: the long-term-risk model of Bansal and Yaron [2005], the habit model introduced by Campbell and Cochrane [1999] and the rare disaster approach of Barro [2006] and Gabaix [2012]. At first, we point out how the widespread evidence that Fear is a key element in explaining predictability in bear market regimes brings favorable evidence in favor

[8] We followed an approach close to the one successfully employed byLudvigson and Ng [2007] and Ludvigson and Ng [2009]

[9] Among the pioneering studies which propose this understanding of securities prices we report the works of Shefrin and Statman [2000], Shefrin and Statman [1994], Shefrin [2008], and Barone-Adesi et al. [2016]

of the rare disaster theory[10]. After that, the impact of current income changes on the dynamics of predictability shows how short term changes in consumption have a relevant impact on investors risk aversion. In conclusion, our empirical evidence, while does not exclude the influence of changes in long-term risks, is more favorable to the habit asset pricing model.

The paper proceeds as follows; Part II briefly reviews and comments on the literature. Part III details the data employed. Part IV studies the out-of-sample predictive performance of the chosen models-variables. Part V studies the interactions and characteristics of the forecasts generated by our sets of predictors. Part VI studies aggregate equity market predictability in terms of macroeconomic and behavioral variables. Part VII studies the interaction between behavioral and fundamental variables. Finally, part VIII discusses our results and concludes.

4.2 Literature review

The theory of finance is largely divided into competing approaches: the neoclassical one which explains the dynamics of prices in terms of changes in the underlying fundamental risks and the behavioral one, which studies the impact of human psychology on the dynamics of financial markets. In this brief review, we focus on the main attempts to reconcile the evidence coming from the two pieces of literature. An effort to reconcile these positions is due to Shefrin and Statman [1994] and Daniel et al. [2002]. In their innovative works, these authors explain how asset prices reflect both covariance risk and misperceptions of firms' prospects. The cited studies have subsequently led to a new formulation of the modern portfolio theory (Shefrin and Statman [2000]) and a related approach to estimate the pricing kernel (Barone-Adesi et al. [2016]).

Another attempt to reconcile the existing positions involves the theory of rational bubbles (Diba and Grossman [1988b] and Diba and Grossman [1988a]), it assumes that rational investors with short expected holding periods (i.e., traders) are driven only by expectations of future price increments (Froot et al. [1992]) while ignoring fundamentals. This approach is fascinating because it introduces a behavioral component while retaining the Campbell and Shiller [1988] decomposition framework (C-S from now). C-S assume that the rational bubble component is zero, and an empirical investigation performed by Cochrane [2008] seems to confirm this assumption. Still, Cochrane assumes expectations about a continuous growth in prices, while rational bubbles, by definition, involve both price surges and falls. Consequently, the evidence of an unconditional expected return of zero naturally arises from the "boom and bust" dynamics of the bubble but it does not rule out

[10] Our results are consistent with the ones provided by Andersen et al. [2015] and Wachter [2013]

the possibility that conditionally to the current market's regime, the rational bubble component of the C-S decomposition can be significantly different from zero. Finally, a third possible approach to reconcile the opposing theories comes from Campbell and Cochrane [1999]. The authors assume that investors have a utility function affected by habit. This implies that losses can change the risk aversion of individuals leading them to follow a behavior which would be labeled "irrational" if their utility curve were wealth invariant. This reasoning calls for the introduction of multi-dimensional utility functions which can account for the complexity of human psychology and in a setting were investors have both financial and real sources of income[11].
The second literature closely related to our study involves market predictability. The literature on market predictability stems from the traditional asset pricing one. At the beginning market predictability was studied to test the efficient market hypothesis (Fama [1970]), but over time; the focus has switched toward market predictability itself (Welch and Goyal [2008], Lettau and Van Nieuwerburgh [2008]). The debate on the amount and the rationale of financial markets predictability is still in its infancy. Luckily, at least on some points, the consensus is broad:

- Equity premium predictability to some extent exists[12], ;
- It is linked to the the business cycle[13];
- It is linked to sentiment and liquidity[14]
- It is stronger in bear markets[15]
- It is time varying and affected by financial research[16].
- it can be enhanced by imposing economically motivated constraints[17]

[11] Cochrane [2013] explain the relevance of understanding the source of real income in portfolio optimization

[12] See, e.g., , Dangl and Halling [2012], F et al. [2010], Golez and Koudijs [2018]

[13] See, e.g., the seminal work of Fama and French [1989] and the recent works coming from F et al. [2010] and Cochrane [2011]

[14] Chen et al. [2018] show how to isolate a powerful liquidity predictor while Huang et al. [2015] propose a powerful sentiment one.

[15] Julien and Michael [2017] explain this phenomenon through the existence of a risk premium for uncertainty.

[16] Lo [2004] formulates a fascinating adaptive market hypothesis while Mclean and Pontiff [2015] proving how academic research reduce predictability implicitly confirm the hypothesis.

[17] Campbell and Thompson [2008] impose constraints on the regression coefficients and on the predicted returns (when the predicted returns are negative, they are replaced with zero) while Pettenuzzo et al. [2014] successfully introduces a constraint on the conditional Sharpe ratio.

After that, it has become clear how employing more and more powerful predictive models the capability to forecast the equity premium out-of-sample is steadily increasing. Among the most successful methodologies we report the Kalman filter approach of Van Binsbergen and Koijen [2010], the Markov Switching approach of Guidolin and Timmermann [2008], and the bayesian system approach of Pastor and Stambaugh [2009].
Another, closely linked, line of works proposes new powerful predictors. Huang et al. [2015] introduce a partial least squares sentiment index, Rapach et al. [2016] show the predictive power of short interest, Huang and Kilic [2019] propose the Gold-Platinum ratio, Kelly and Pruitt [2013] employ their three-pass regression filter (Kelly and Pruitt [2015]) to extrapolate a powerful predictor from the cross-section of stock returns, and Almeida et al. [2017] prove how the left tail of their non-parametric pricing kernel exhibits a strong predictive power.
While far from the mainstream financial literature two others lines of research have provided relevant contributions to the research on market predictability:

- the Bayesian data-science oriented approach
- the machine learning approach.

Among the relevant contributions inside the first line of research, we report the Bayesian latent threshold approach of Nakajima and West [2013], the dynamic dependent sparse factor model of Zhou et al. [2014], the dynamic dependence networks methodology of Yi et al. [2016], the simultaneous graphical dynamic linear proposal of Gruber and West [2016], and the Bayesian predictive synthesis of Johnson and West [2018].
Among the most intriguing works on machine learning financial forecasting we report the the stochastic neural network combination approach of Sermpinis et al. [2012], the adaptive evolutionary neural networks methodology of Georgios et al. [2015], the evolutionary support vector machines model of Karathanasopoulos et al. [2015], and the genetic programming approach of Karatahansopoulos et al. [2014][18].
Finally, we consider the two open debates which are related with our study. The first debated issue is about long and short-term predictability. The early literature (Fama and French [1988a] and Fama and French [1988b]) found evidence of weak predictability at the short horizons but higher predictability at long horizons peaking at five years. With time, some studies have questioned the soundness of the econometric procedure employed[19] and pointed out the role played by parameter

[18] A comprehensive review of the existing literature on machine learning financial forecasting can be found in the works of Dunis et al. [2016] and de Prado [2018]

[19] See. e.g., Nelson and Kim [1993], Valkanov [2003], Campbell and Yogo [2006], and Boudoukh et al. [2008]

and model uncertainty at long horizons (Pastor and Stambaugh [2012]). These findings led to a new wave of studies which ultimately reverted the early results: equity premium predictability is higher at the short horizon (Dangl and Halling [2012], and Kostakis et al. [2015]).
The second widely debated issue involves the predictability of dividend growth. Indeed, the work of C-S implies that returns and dividend growth predictability are intimately related, as explained in the influential work of Cochrane [2008]. Here the author explains how the weak predictive power of the dividend yield is mainly due to the positive correlation between dividend growth and discount rates. Consequently, the inclusion of a dividend growth predictor can significantly improve the out of sample predictive power of dividend yields (Golez [2014]). Similarly, Ang [2012] has shown how dividend yields can predict future dividends, and that the predictability of dividend growth is much stronger than the predictability of returns on a yearly horizon. It follows that coherently with the Campbell-Shiller present value identity, the combination of expected dividend growth and dividend yield results in an enhanced capability to forecast returns as detailed in Detzel and Strauss [2016]. Finally, the time-varying dynamics of returns and dividend growth predictability are discussed in McMillan [2015], Zhu [2015] and Ghosh and M. Constantinides [2010]. In the current study we prove how dividend growth is effectively predicted by machine learning models.
In conclusion, the literature on these topics is extensive but often polarized in conflicting interpretations on the rationale underpinning financial markets dynamics. With the current study we dissect financial market predictability to gain novel insights into the mechanism driving financial markets. Finally, we use the results emerging from our analyses to test empirically the most prominent asset pricing theories: the habit model of Campbell and Cochrane [1999], the long term risk model of Bansal and Yaron [2005] and the rare disaster theory of Barro [2006].

4.3 Data

In this section we detail the data employed in the subsequent analysis. For seek of brevity the full list of macroeconomic time series, with the related transformations, is reported in the appendix.

4.3.1 Welch and Goyal Predictors

The study of Welch and Goyal [2008] (W-G) is a benchmark and a challenge for the existing literature on market predictability. Consequently, we start with the fourteen predictors used in this provocative work. The updated database is coming directly from the website of Goyal[20]. In more detail, the predictors are:

- log Dividend-price ratio (DP): the difference between the log of dividends paid on the S&P 500 index and the log of prices, where dividends are measured using a twelve-month moving sum.
- log Dividend yield (DY): the difference between the log of dividends and the log of lagged prices.
- log Earnings-price ratio (EP): the difference between the log of earnings on the S&P 500 index and the log of prices, where earnings are measured using a twelve-month moving sum.
- log Dividend payout ratio (DE): the difference between the log of dividends and the log of earnings.
- Stock variance (SVAR): the sum of squared daily returns on the S&P 500 index.
- Book to market (BM): the ratio of book value to market value for the Dow Jones Industrial Average.
- Net equity expansion (NTIS): the ratio of twelve-month moving sums of net issues by NYSE-listed stocks to the total end-of-year market capitalization of NYSE stocks.
- T-bill rate (TBL): the interest rate on a 3-month Treasury bill (secondary market).
- Long-term yield (LTY): long-term government bond yield.
- Long-term return (LTR): return on long-term government bonds.
- Term spread (TMS): the difference between the long-term yield and the T-bill rate.
- Default yield spread (DFY): the difference between BAA- and AAA-rated corporate bond yields.
- Default return spread (DFR): the difference between long-term corporate bond and long-term government bond returns.
- Inflation (INF lag): calculated from the CPI (all urban consumers); since inflation rate data are released in the next month, we use $x_{i,t-1}$.

[20]http://www.hec.unil.ch/agoyal/

4.3.2 Spread Returns

In this section, we detail the factors and anomalies employed in this study. An anomaly is a statistically significant difference in cross-sectional average returns that persist after the adjustment for exposures to the Fama and French [1993] three factors model. Our empirical analysis makes use of i) the eleven anomalies proposed by Stambaugh and Yuan [2017], ii) the five factors of the extended Fama and French [2015] model iii) Momentum, Long and Short term reversal. All data are monthly and span the period from 01-1965 to 12-2016 except the net operating assets, the accruals, the return on assets, and the distress anomaly for which data are available respectively only from 8-1965, 1-1970, 5-1976, and 1-1977. The considered factors-anomalies are:

- Financial distress. Campbell et al. [2008] show that firms with high failure probability have lower, not higher, subsequent returns (Distress). Another closely related measure of distress is the Ohlson [1980] O-score (O).

- Net stock issues and composite equity issues. Loughran and Ritter [1995] show that, in post-issue years, equity issuers under-perform non-issuers with similar characteristics (Net Stock Issues). Daniel and Titman [2006] propose an alternative measure, composite equity issuance (Comp eq Issue), defined as the amount of equity issued (or retired by a firm) in exchange for cash or services.

- Total accruals. Sloan [1996] demonstrates that firms with high accruals earn abnormal lower returns on average than firms with low accruals (Accruals).

- Net operating assets. Hirshleifer et al. [2004] find that net operating assets, computed as the difference on the balance sheet between all operating assets and all operating liabilities divided by total assets is a negative predictor of long-run stock returns (NOA).

- Momentum. The momentum effect, proposed by Jegadeesh and Titman [1993] is one of the most widespread anomalies in asset pricing literature (Mom).

- Gross profitability premium. Novy-Marx [2013] shows that sorting on gross-profit-to-assets creates abnormal benchmark-adjusted returns, with more profitable firms having higher returns than less profitable ones (Gross Prof).

- Asset growth. Cooper et al. [2008] show how companies that grow their total assets more earn lower subsequent returns (Asset Growth).

- Return on assets. Chen et al. [2011] show that firms with higher past return on assets gain higher subsequent returns (ROA).

- Investment-to-assets. Titman et al. [2003] show that higher past investment predicts abnormally lower future returns (Inv to Assets).

- The four factors proposed by the extended model of Fama and French [2015]: Small Minus Big (SMB), High Minus Low (HML), Robust Minus Weak (RMW), and Conservative Minus Aggressive (CMA).

- The Short and Long Term Reversal factors (ST, LT): as presented in the website of Professor Kenneth R. French.

Data for the four factors chosen by Fama and French [2015], the Momentum, and the two Short-Long Reversal Factors comes from the website of Professor Kenneth R. French[21] while anomalies are build matching CRSP and Compustat data following the approach detailed in Stambaugh and Yuan [2017].

4.3.3 Fundamental and Behavioural Data

In a closely related study Barone-Adesi et al. [2018] show how commonly employed sentiment proxies[22] are effective in capturing abnormally low level of risk aversion (Greed) while option-based measures of fear are needed to timely detect abnormally high levels of risk-aversion (Fear). Consequently, we employ sentiment index of Huang et al. [2015] as a proxy for Greed[23] and the Downside Variance Risk Premium (estimated trough the corridor variance approach of Andersen and Bondarenko [2007]) as a proxy for Fear[24]. After that, we employ the three month ahead financial uncertainty index proposed by Jurado et al. [2015] as our Uncertainty measure (UNC)[25].
The construction of the five macroeconomic proxies is performed in the following way. At first each time series[26] is, where needed, transformed following the guidelines of Ludvigson and Ng [2007]. Then, the transformed time series are clustered in five sets on the basis of their economic rationale: Income, Industrial Production, Labor, House, and Inflation. Finally, the first principal component is recurrently

[21] $http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html$

[22] Among the most influential sentiment proxies we liste the ones of Baker and Wurgler [2006], Baker et al. [2012] and Huang et al. [2015]

[23] Data comes from the website of Professor Guofu Zhou http://apps.olin.wustl.edu/faculty/zhou/

[24] Data come from the website of Gergory Vilkov https://www.vilkov.net/codedata.html

[25] Data coming from the website of Professor Sydney Ludvingson, https://www.sydneyludvigson.com/data-and-appendixes/

[26] All data comes from the Federal Reserve of St. Louis, https://fred.stlouisfed.org/

estimated from each macroeconomic set. The resulting five time series are employed as inputs in our subsequent analyses. The full list of macroeconomic time series with the related transformations is in Appendix 10.3 on Macro Data.

4.4 Out-of-sample Predictability

This part is a comprehensive study of the out-of-sample performance of a rich set of predictors and predictive models when applied to forecast the S&P500 returns and dividend growth. We start introducing the performance metrics and the models employed, and subsequently, we report the results coming from our empirical analysis on the out-of-sample capability to predict the returns and the dividend growth of the $S\&P500$

4.4.1 Performance Metrics

To assess the out-of-sample predictive performance of the models and predictors considered in this study we follow the literature[27] and employ the R^2_{os} and Δ utility metrics. The former metric is further decomposed to disentangle the capability of the proxy to forecast positive and negative returns only. For the analysis, the out-of-sample performance metrics considered are:

- The R^2_{os} statistic

$$R^2_{os} = 1 - \frac{\sum_{t=1}^{T}(r_t - \hat{r}_t)^2}{\sum_{t=1}^{T}(r_t - \bar{r}_t)^2} \tag{4.1}$$

  R^2_{os} measures the percent reduction in mean squared forecast error (MSFE) between the forecasts generated by the chosen predictive model, $\hat{r}$, and the historical average benchmark forecast, $\bar{r}$. To assess the statistical significance of R^2_{os} we employ the p-values coming from the Clark and West (2007) MSFE-adjusted statistic. This indicator tests the null hypothesis that the historical average MSFE is less than or equal to the forecasting method MSFE against the alternative that the historical average MSFE is greater than the forecasting method MSFE (corresponding to $H_0 : R^2_{os} <= 0$ against $H_1 : R^2_{os} > 0$).

- The Δ Utility measure. Following the original paper, we estimate the variance using a ten-year rolling window of returns. We consider a mean-variance investor who forecasts the equity premium using the historical averages. She

[27]Both these measures are introduced in the seminal work of Campbell and Thompson [2008] and subsequently employed in a number of studies among which F et al. [2010], Detzel and Strauss [2017] and Rapach et al. [2016]

will decide at the end of period t to allocate the following share of her portfolio to equity in the subsequent period t+1:

$$w_{0,t} = \frac{1}{\gamma}\frac{\bar{r}_{t+1}}{\hat{\sigma}_{t+1}} \tag{4.2}$$

where $\hat{\sigma}_{t+1}$ is the rolling-window estimate of the variance of stock returns. Over the out-of-sample period, she will obtain an average utility of:

$$\hat{v}_0 = \hat{\mu}_0 - \frac{1}{2}\gamma\hat{\sigma}_0^2 \tag{4.3}$$

where $\hat{\mu}_0$ and $\hat{\sigma}_0^2$ are the sample mean and variance, over the out-of-sample period for the return on the benchmark portfolio formed using forecasts of the equity premium based on the historical average. Then we compute the average utility for the same investor when she forecasts the equity premium using one of the predictive approaches proposed in this paper. In this case, the investor will choose an equity share of:

$$w_{j,t} = \frac{1}{\gamma}\frac{\hat{r}_{t+1}}{\hat{\sigma}_{t+1}} \tag{4.4}$$

and she will realize an average utility level of:

$$\hat{v}_j = \hat{\mu}_j - \frac{1}{2}\gamma\hat{\sigma}_j^2 \tag{4.5}$$

where $\hat{\mu}$ and $\hat{\sigma}_{t+1}$ are the sample mean and variance, over the out-of-sample period for the return on the portfolio formed using forecasts of the equity premium based on one of the methodologies proposed. In this paper, we measure the utility gain as the difference between $\hat{v}_j$ and $\hat{v}_0$, and we multiply this difference by 100 to express it in average annualized percentage return. In our analysis, following the existing literature[28], we report results for $\gamma = 3$.

4.4.2 Predictive models

In this subsection, we list the predictive models employed while a detailed description will follow in the following subsections. To study the informative content which is possible to extrapolate from the joint use of predictors, we employ a wide list of models coming from the empirical financial literature and the Machine Learning one. Our approach combines model selection with machine learning and statistical approaches. Our list of models includes)[29].:

[28]Among the most cited works on the subject Campbell and Thompson [2008] and F et al. [2010] impose the same level of risk aversion

[29]Codes comes from http://apps.olin.wustl.edu/faculty/zhou/

1. Univariate OLS regressions for each predictor.
2. A predictive OLS multivariate regression model (kitchen-sink) that incorporates all predictors jointly ("OLS" in the Tables).
3. A median combination forecasts approach which employ the median forecast among the ones generated by the univariate OLS regressions ("Pooled forecast: median", in the Tables).
4. The pooled DMSPE forecasts method proposed by Stock and Watson [2004] and successfully employed by F et al. [2010] ("Pooled forecast: MDSFE" in the Tables).
5. The Multivariate Adaptive Regression Splines approach Friedman [1991] for variable selection and a multivariate Support Vector Machine regression model (Boser et al. [1992] and Drucker et al. [1997]) to make out-of-sample forecasts ("MARS", in the Tables).
6. The SIC (Schwartz Information Criterion) for the variable selection and a multivariate Support Vector Machine regression model (Boser et al. [1992] and Drucker et al. [1997]) to make out-of-sample forecasts ("SVM SIC", in the Tables)
7. The Lasso for the variable selection and a multivariate Support Vector Machine regression model (Boser et al. [1992] and Drucker et al. [1997]) to make out-of-sample forecasts ("Lasso SVM" in the Tables).
8. The diffusion index approach employed by Ludvigson and Ng [2007] to filter the information and the univariate Support Vector Machine regression model (Boser et al. [1992] and Drucker et al. [1997]) to make out-of-sample forecasts ("Diffusion Index", in the Tables).
9. The sum-of-the-parts approach of Ferreira and Santa-Clara [2011]

4.4.3 Out-of-Sample Predictability

To gain a first insight into the problem considered we plot the time series of the cumulative square prediction error using the historical average mean return minus the cumulative square prediction error of the total average forecast of all the predictive models considered (times 100). We also disaggregate the second average in the average forecast coming from all univariate OLS regression and of all the machine learning predictive models.

Insert Figure 4.1 about Here

We observe how, on average, the models considered provide an improvement in terms of R^2_{OS} with respect to the historical average. After that, it is immediately apparent how predictability on average rises during bear markets characterized by high uncertainty and economic recessions, while it is stable or even decline during periods of prolonged economic expansions and of bullish markets like the ones of the nineties or the ones which followed the 2008 financial crisis. In Figure 4.2 upper plot, we draw the cumulated returns for the S&P500 index and the uncertainty proxies proposed by Jurado et al. [2015]. We observe how the uncertainty indexes rise before the market crisis and pick during recessions. These results are consistent with the work of Barone-Adesi et al. [2018], who shows how uncertainty is already high when extreme market movements occur, and consequently, there is limited evidence in favor of an uncertainty risk premium. Subsequently, in the lower plot of Figure 4.1 we represent the cumulated returns of the S&P500 with the PLS Sentiment index of Huang et al. [2015] and with the Downside Variance Risk Premium of Andersen and Bondarenko [2007]: the former measure is effective in the detection of abnormally low levels of risk pricing (it captures overbought or greed) while the latter is effective in detecting abnormally high levels of risk pricing (it is an index of oversold or fear) Barone-Adesi et al. [2018]. The figure shows how the sentiment index of Huang et al. [2015] rises before market crashes and declines subsequently, while the downside volatility premium rises during market crashes and declines quickly afterward.

Insert Figure 4.2 about Here

We start our empirical analysis on the genesis of predictability by considering the out-of-sample performance generated both by univariate OLS regression and a set of advanced predictive models considering both the R^2_{OS} metrics and the Δ Utility one. The two measure capture two different aspects of the same phenomenon: the R^2_{OS} metric is about the capability to forecast precisely subsequent returns while the delta utility provides a measure of the profitability of the model employed. The two measure do not necessarily generate similar results. Indeed, a predictive model could detect the direction of the subsequent market returns while missing precision. On the other hand, the Δ Utility measure relies on the choice of a risk aversion parameter and not necessarily a higher degree of precision traduce itself into a higher utility because of the timing of the risk-return relationship. In Table 4.1, we present the results for univariate OLS forecasts and machine learning models which employ the predictors employed in the influential study of Welch and Goyal [2008]. We consider monthly forecasts for the out-of-sample periods 1986:01-2017:12 and 2001:01-2017:12. Similarly, in Table 4.2 we consider the monthly out-of-sample forecasts for the periods 1986:01-2016:12 and 2001:01-2016:12 employing as predictors the spreads returns coming from the 11 anomalies chosen by Stambaugh et al. Stambaugh and Yuan [2017] and from the four factors of Fama and French [2015] extended model. The R^2_{OS} metrics are matched by the related Clark and West [2007] p-values.

Insert Table 4.1 about Here

Our results from Table 4.1 are largely consistent with the existing literature: for the long 1986-2017 period no individual predictors can generate a positive and statistically significant R^2_{OS} while the delta utility gains are above 1% only for the EP ratio. The picture changes slightly for the briefer 2001-2017 window where the R^2_{OS} statistic is variance, and long term yield predictors achieve positive and statistically significant values. Even more, interestingly, the delta utility gains generated by profitability ratios like the Dividend-Price, Dividend Yield, Earning Price and Book to Market now positive and above the 1% threshold. After that, among predictive models, only the MARS SVM reaches R^2_{OS} values of 0.9% and 1.18% which are statistically significant at the 5% for, respectively, the 1986-2017 and the 2001-2017 periods. In conclusion, the predictive power of the Welch and Goyal [2008] predictors appear weak while surprisingly rising in the more recent out-of-sample window.

Insert Table 4.2 about Here

The findings emerging from Table 4.2 are different. At first, it is clear how the four anomalies return spreads (Asset Growth, Investment to Assets, Net Stock Issues and the Ohlson metric) generate out-of-sample return forecasts which are both accurate and economically valuable. Indeed, the R^2_{OS} metric for Net Stock Issue univariate OLS forecasts reach record-high values of 23.5% and 28.7% for the 1986-2016 and 2001-2016 periods with p-values well under 1% and with related Δ Utility gains above 23% and 28%. The predictive models which select and combine spread returns predictors are equally powerful. Differently from Table 4.1 now multivariate OLS and pooled forecasts methods can generate strong and highly significant R^2_{OS} values matched by equally robust Δ Utility gains. Even the simple multivariate OLS approach provides remarkable Utility gains of 14% and 12% for the two out-of-sample time windows considered. After that, the Diffusion Index and the MARS SVM approach provide statistically robust R^2_{OS} values of 11.8% and 4.1% for the 1986-2016 period.
These results are not entirely unexpected, Greenwood and Hanson [2012] show how the difference between the characteristics of firms which issue stocks and firms which repurchase stocks can forecast characteristic factor returns. The aggregate short interest measure of Rapach et al. [2016] shows is a powerful predictors both for the aggregate market and for the cross-sectional returns Maio and Santa-Clara [2017]. Similarly, Wen [2018] shows how the aggregate asset growth can forecast the $S\&P500$ index and Kelly and Pruitt [2013] extrapolate from the cross-section

of Book-Market portfolios returns a powerful predictor for the $S\&P500$. In conclusion, it is apparent how predictability is a stable and rising feature of US equity markets.

4.5 On predictors

In this section, we focus on the forecasts generated by predictors in univariate OLS regressions only. At first, we present the summary statistics for the time series of return forecasts generated by the univariate OLS models which consider both the Welch and Goyal [2008] and the spread returns predictors individually for the monthly out-of-sample window 1986:01-2016:12. For each model, we report the mean and median of the forecasted returns, the 1st and the 99th percentile of the forecasted returns, the standard deviation, and the skewness of the forecasted returns.

Insert Table 4.3 about Here

The results which emerge from these tables provide evidence on the characteristics of effective predictors. First, effective predictors like Asset Growth, Investment to Asset, and Net Stock Issue spread returns generate time series of expected returns with high median values and high standard deviations. Interestingly, these extremely well-performing predictors generate both extremely high (99th) and low (1st) percentiles of the distribution of forecasted returns are more extreme than the average ones while the skewness is of marginal relevance. On average the predictors employed in this univariate OLS setting generate an average monthly return forecast of 0.4% a median return of 0.5% and a null skewness and a weak standard deviation of 0.8. Realized monthly market returns for the S&P500 on the same 1986:01-2016:12 period generates an average return of 0.4%, a median return of 0.8% and negative skewness of -0.68 and a high standard deviation of 4. In conclusion, many predictors fail to be effective because the median of the forecasted returns is too low, and the volatility of the predicted returns are too low to match the realized ones. After that, we report the correlation matrix of the time series of forecasted monthly returns for all the predictive models considered.

Insert Table 4.4 about Here

The correlation between the time series of predicted returns are surprisingly low and often even slightly negative. The results confirm that the predictors' studied capture different economic dimensions. After that, we focus on the highest correlations. At first, we notice how, as expected, financial ratios (Dividend Price, Dividend Yield, Earning Price, Book to Market) provide time series of forecasted returns which are extremely highly correlated among themselves: Pearson correlation values are well above 0.5. After that, we stress how the forecasts coming from

the four most powerful spread return predictors are strongly correlated among themselves with correlation values above 0.3. Subsequently, we notice how the forecasts coming from the four Fama and French spread returns factors are also highly correlated among themselves with correlation values ranging between 0.13 and 0.72. Finally, we point out how the Composite Equity Issue spread return generates forecasts which are highly correlated with the Fama and French spread factor returns ones while the correlation with the forecasts coming from the Net Stock Issue spread return are weak (0.08).
To gain a better insight on what the individual predictors capture we borrow the methodology introduced by Rapach et al. [2016]. The authors propose a way to assess whether return predictability stems by anticipating discount rate and/or cash flows news, where news components are measured using the VAR methodology of Campbell [1991] and Campbell and Ammer [1993]. Following Campbell and Shiller [1988] the log stock return $r_{t+1} = log[(P_{t+1} + D_{t+1})/P_t]$, where P_t (D_t) is the month-t stock price (dividend), can be approximated by

$$r_{t+1} \approx k + \rho p_{t+1} + (1-\rho)d_{t+1} - p_t \tag{4.6}$$

where

$$\rho = \frac{1}{1 + exp(\overline{d-p})} \tag{4.7}$$

$$k = -log(\rho) - (1-\rho)log[(1/\rho) - 1] \tag{4.8}$$

where p_t (d_t) is the log stock price (dividend), and $\overline{d-p}$ is the mean of $d-p$. We can rewrite equation (6) as

$$p_t \approx k + \rho p_{t+1} + (1-\rho)d_{t+1} - r_{t+1} \tag{4.9}$$

Solving this equation forward and imposing the no-bubble transversality condition we recover the Campbell and Shiller [1988] stock price decomposition:

$$p_t = \sum_{j=0}^{\infty} \rho^j (1-\rho) d_{t+1+j} - \sum_{j=0}^{\infty} \rho^j r_{t+1+j} + \frac{k}{1-\rho} \tag{4.10}$$

Letting E_t denote the expectation operator conditional on information through month t it is possible to recover the following decomposition for the log stock innovation:

$$r_{t+1} - Er_{t+1} = (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j r_{t+1+j} \tag{4.11}$$

This last equation implies that the stock return innovation can be decomposed into cash flow news and discount rate news components:

$$\Psi^r_{t+1} = \Psi^{CF}_{t+1} - \Psi^{DR}_{t+1} \tag{4.12}$$

where

$$\Psi^r_{t+1} = r_{t+1} - E_t r_{t+1} \quad (\textit{stock return innovation}) \tag{4.13}$$

$$\Psi^{CF}_{t+1} = (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} \quad (\textit{cash flow news}) \tag{4.14}$$

$$\Psi^{DR}_{t+1} = (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j r_{t+1+j} \quad (\textit{discount rate news}) \tag{4.15}$$

Following Campbell [1991] we use a VAR framework to extract the cash flow and discount rate news components of stock return innovations. Consequently, we introduce the following VAR(1) model:

$$y_{t+1} = Ay_t + u_{t+1} \tag{4.16}$$

where $y_t = (r_t, d_t - p_t, z_t')'$, z_t is an n-vector of predictor variables, A is an (n+2)-by-(n-2) matrix of VAR slope coefficients, and u_t is an (n+2)-vector of zero-mean innovations. Letting e_1 denote an (n+2)-vector with one as its first element and zeros for the remaining elements, the stock return innovation and discount rate news components can be rewritten as:

$$\Psi^r_{t+1} = e_1' u_{t+1} \tag{4.17}$$

and

$$\Psi^{DR}_{t+1} = e_1' \rho A (I - \rho A)^{-1} u_{t+1} \tag{4.18}$$

The cash flow news is then residually defined:

$$\Psi^{CF}_{t+1} = \Psi^r_{t+1} + \Psi^{DR}_{t+1} \tag{4.19}$$

The expected stock return for t+1 based on information through t can expressed as:

$$E_t r_{t+1} = e_1' A y_t \tag{4.20}$$

Now knowing that $r_{t+1} = E_t r_{t+1} + \Psi^r_{t+1}$ the log stock return can be decomposed as

$$r_{t+1} = E_t r_{t+1} + \Psi^{CF}_{t+1} - \Psi^{DR}_{t+1} \tag{4.21}$$

With sample observations for y_t, (with $t = 1, ..., T$) we can use OLS to estimate A and u_{t+1} (with t=1,...,T-1) for the VAR model given by Eq. (16); It is possible to estimate even ρ using Eq (7) and the sample mean of the log dividend-price ratio. The related estimates are $\hat{A}$ and $\hat{u}_{t+1}$ and $\hat{\rho}$ which plugged into equations (17), (18), (19) and (20) yields $\hat{\Psi}^{DR}_{t+1}$ $\hat{\Psi}^{CF}_{t+1}$ $\hat{\Psi}^r_{t+1}$ and $\hat{E}_t r_{t+1}$, for t=1,...,T-1.
Now it becomes possible to analyze the sources of each predictor x_t's predictive

power for future stock returns by investigating its capability to predict the individual components comprising the total stock return. At first, we run a simple regression model for the log stock return based on the chosen predictor x_t:

$$r_{t+1} = \alpha + \beta x_t + \epsilon_{t+1} \quad for \quad t = 1, ..., T-1 \tag{4.22}$$

We then consider the following predictive regression models for the individual components on the right side of equation (21).

$$\hat{E}_t r_{t+1} = \alpha_{\hat{E}} + \beta_{\hat{E}} x_t + \epsilon_{t+1}^{\hat{E}} \tag{4.23}$$

$$\hat{\Psi}_{t+1}^{CF} = \beta_{CF} x_t + \epsilon_{t+1}^{CF} \tag{4.24}$$

$$\hat{\Psi}_{t+1}^{DR} = \beta_{DR} x_t + \epsilon_{t+1}^{DR} \tag{4.25}$$

for t=1,...,T-1. By the properties of the OLS the following relation holds:

$$\hat{\beta} = \hat{\beta}_{\hat{E}} + \hat{\beta}_{CF} + \hat{\beta}_{DR} \tag{4.26}$$

By comparing the estimated slope coefficients we can understand the extent to which x_t's ability to predict total stock returns relate to its capability to anticipate the individual components on the right-hand-side of equation (12).

Insert Table 4.5 about Here

Our results document how, among the Welch and Goyal [2008] predictors, only the dividend-price (DP) and the dividend yield (DY) exhibit an in-sample predictive power which is statistically significant and this predictive power is largely due to the capability to forecast the expected return. The results change remarkably for spread return predictors. Here, eight out of eleven spread return built following Stambaugh exhibit statistically significant betas. Among these eight predictors, we find the three (Asset Growth, Investment to Assets and Net Stock Issues) which recorded record high values in terms of R^2_{OS}. Importantly, for all these three predictors the Cash Flow component is the most important one while the Expected returns component while of statistically significant is of secondary relevance. Finally, for all the remaining five spread returns predictors the most relevant and statistically significant beta component arises is the expected return one. In conclusion, our results suggest that the most powerful predictors are the ones which capture changes in the economic fundamentals.
Having analyzed which components of stock returns each predictor forecasts, now we want to shed light on how predictability changes across different market conditions. Following the literature we consider two complementary approaches: first, we report the R^2_{OS} metrics conditionally on being in a period of expansion or recession as identified by the national bureau of economic research, second, we consider

the R^2_{OS} generated in forecasting returns conditionally on being subsequently positive or negative. To make our result robust, we focus on the longest out-of-sample windows which are 1986:1-2017:12 for the Welch and Goyal [2008] predictors and 1986:1-2016:12 for the spread returns predictors.

Insert Table 4.6 about Here

Now we observe how the average R^2_{OS} for the Welch and Goyal [2008] and spread returns univariate OLS predictors are, respectively, equal to -0.9% and to 1.68% during periods of economic expansion against -0.28% and 6.28% in periods of economic recession. Similarly, the capability to forecast returns which are ex-post positive results in averages R^2_{OS} of -6.24% and 1.70% for the Welch and Goyal [2008] and the spread returns predictors against average R^2_{OS} of 2.94% and 3.30% for returns which are ex-post negative. In conclusion, the average R^2_{OS} are higher for the periods characterized by economic recession and for returns, which are ex-post negative. After that, we notice how only three predictors produces positive and statistically significant R^2_{OS} in all the four cases considered: Asset Growth, Investment to Assets, and Net Stock Issue spread returns. On the other hand, ten predictors exhibit no statistically significant R^2_{OS} values in either case: Treasury Bill (TBL), Default Yield (DFY), Default Returns (DFR), Lagged Inflation (INF lag), Long Term (LT) spread returns, Short Term (ST) spread returns, Momentum (Mom) spread returns, Net Operating Assets (NOA) spread returns, Accruals spread returns (Accruals), Return on Assets (ROA) spread returns, Distress (Distress) spread returns, and Composite Equity (Comp Eq Issue) spread returns. All the other predictors are effective in forecasting returns only conditionally to economic conditions or to the subsequent sign of the predicted returns.

4.6 Dissecting Predictability

In what follows, we want to study the relationship between macroeconomic-behavioral variables and predictability. To achieve this goal, we proceed in two stages. In the first stage, we conduct time-series tests based on the Fama-French multi-factors model and behavioral indexes. In the second stage, we perform a model selection analysis based on the adaptive elastic net approach of Zou and Hastie [2005] and Zou and Zhang [2009]. Here we employ the behavioral indexes previously considered plus a list of 12 principal components: each one synthesizing a rich set of financial or macroeconomic variables.

The first part of the analysis involves the estimation of a series of factor models, using time-series regressions on the monthly difference between historical average benchmark forecasting model square prediction error minus predictive model forecasting model square prediction error.

$$(r_{t+1}-\overline{FC}_{t+1})^2-(r_{t+1}-FC_{j,t+1})^2 = \hat{\alpha}_j+\hat{\beta}_{j,MKT}(R_{m,t}-R_{f,t})+\sum_{i=1}^{4}\hat{\beta}_{j,i}Factor_{i,t}+e_{j,t+1} \tag{4.27}$$

In this model r_{t+1} is the S&P500 return at time t+1, $\overline{FC}_{t+1}$ is the forecast made at month t for the S&P500 return at month t+1 using the historical average benchmark model, $FC_{j,t+1}$ is the forecast made at month t for the S&P500 return at month t+1 using the predictive model j. $R_{mt} - R_{ft}$ is the return on the value-weighted market portfolio minus the U.S. one month T-bill rate. The 4 Fama and French [2015] factors considered are: SMB_t, HML_t, RMW_t and CMA_t.
Following Jo et al. [2018], to incorporate behavioral variables into the multifactor approach, we estimate general specifications involving the five Fama-French factors, two complementary behavioral proxies for greed and fear (Barone-Adesi et al. [2018]) and the financial uncertainty index of Jurado et al. [2015]. The specification considered are as follow:

$$\begin{aligned}(r_{t+1}-\overline{FC}_{t+1})^2-(r_{t+1}-FC_{j,t+1})^2 = \\ \hat{\alpha}_j+\hat{\beta}_{j,MKT}(R_{m,t}-R_{f,t})+\sum_{i=1}^{4}\hat{\beta}_{j,i}Factor_{i,t}+\sum_{m=1}\hat{\beta}_{j,m}BI_{m,t}+e_{j,t+1}\end{aligned} \tag{4.28}$$

$$\begin{aligned}(r_{t+1}-\overline{FC}_{t+1})^2-(r_{t+1}-FC_{j,t+1})^2 = \\ \hat{\alpha}_j+\hat{\beta}_{j,MKT}(R_{m,t}-R_{f,t})+\sum_{i=1}^{4}\hat{\beta}_{j,i}Factor_{i,t}+\sum_{m=1}\hat{\beta}_{j,m}BI_{m,t}+\sum_{i=1}^{4}\hat{\beta}_{j,i}Factor_{i,t}{*}ret\ BI_t+e_{j,t+1}\end{aligned} \tag{4.29}$$

where the behavioral indexes considered (BI) are the level (return) of the Huang et al. [2015] index (Greed in the tables), the Downside-Variance Risk Premium of Andersen and Bondarenko [2007] (Fear in the tables), and the uncertainty index introduced by Jurado et al. [2015](UNC in the tables). Equation (29) can be regarded as a version of a standard factor pricing model, but where factor loadings are functions of behavioral indicators and the interaction between the return of behavioral indicators and the Fama and French [2015] factors. In this regard, the estimation of equation (29) indicates how behavioral indicators impact the direction and magnitude of each factor on the predictive performance of the models considered. We repeat the same analyses regressing the monthly difference between historical average benchmark forecasting model square prediction error minus predictive model forecasting model square prediction error at time t on the factor

and behavioral indicator at the contemporaneous time t. The two analysis are complementary because they present two different aspects of predictability. When we regress the predictability metric on the contemporaneous factor-behavioral returns, we are analyzing how predictability originates, while when we regress the predictability metric at time t+1 on the factor-behavioral returns at time t we are studying what factors-behavioral returns forecast predictability.
To summarize our finding on the explanatory power of the variables considered we estimate the pooled versions of equations (27), (28) and (29) including all the time series of squared predictive error between the benchmark return forecast and the forecasts of the predictive models listed in tables 4.4 and 4.5. The estimation is based on the approach introduced by Hjalmarsson [2010] and Rapach et al. [2013] which imposes that $\beta_{j,i}=\bar{\beta}_i$ for all j and i. The results are based on the monthly time series spanning the period 1986:01-2016:12.

Insert Table 4.7 about Here

Table 4.7 reports the results for the pooled contemporaneous regressions considering all individual predictors or models time series of predictive performances. The results which emerge from this table are striking. First, when we consider the base model with only the intercept and the 4 Fama and French factors the betas of the market and the SMB factors are, as expected, negative and statistically significant while the beta of the CMA factor is positive. These results are coherent with our previous ones, which highlight how predictability in negatively correlated with market returns. The statistically robust values of the SMB and CMA factors for both Predictors and models pooled regressions confirm how predictability is linked to fundamentals. On the other hand, the presence of a positive and statistically significant intercept suggests the need for the inclusion of additional regressors. When we add the Greed and Fear indexes in our analysis, we observe two fundamental changes: the intercept is no more statistically significant, and the beta for the levels of the Greed and Fear indexes are positive and statistically significant. Consequently, we can argue that behavioral components matters in explaining the dynamics of predictability. The further inclusion of the financial uncertainty index results in the raising of the statistical significance of the fear index at the expense of the greed one while the significance of the beta of the uncertainty index itself remains mixed. Finally, we consider the interaction between factors and fear-greed returns. We observe how the interaction between greed returns and the five Fama and French [2015] factors give rise to factor loadings, which are not statistically significant. On the other hand, the interaction between fear returns and the market factor give rise to highly negative and statistically significant betas while the interaction between fear returns and the HML is positive and statistically significant. These results point out how fear interacts with fundamentals in the genesis of predictability.

Insert Table 4.8 about Here

Table 4.8 repeats the same analysis for the predictive performance t time t+1, which implies the capability to forecast the predictive performance of the models under scrutiny. The outcomes which we observe are different from the previous ones. At first, for the most parsimonious model specification, which involves only the 5 Fama and French factor, the only statistically significant factor loadings are the intercept and the one coming from the CMA factor. Interestingly, adding uncertainty, fear, and greed indexes in the pooled regression model generate positive and statistically significant factor loading for the greed and fear index but not for uncertainty. Finally, the factor loading for the interaction between the Greed level and market returns is positive and statistically significant while the factor loading for the interaction between the fear return and the market return is negative and statistically significant. Even more strikingly the level of fear interacts in a statistically significant manner with both the HML and the RMW factors while the fear returns interact in a positive statistically significant manner with the SMB return. In conclusion, greed and especially fear do not only directly drive financial market predictability, but they interact with fundamental factors in the genesis of predictability.
The second approach considered involves the elastic net methodology of Zou and Hastie [2005] and Zou and Zhang [2009]. The approach proposed by these authors is extremely powerful because it performs both parameter shrinkage and variable selection, providing stable and interpretable estimates in models with a large number of regressors. Indeed, this weighted version of adaptive elastic net achieves optimal large-sample performance in terms of variable selection and parameter estimation. Formally the adaptive elastic net estimation is based on a penalized sum of squared errors objective functions[30]:

$$\min_{\beta_i} \left[\sum_{t=0}^{T-1} (R^2_{OS,i,t+1} - x_t^{'} \beta_i)^2 + \lambda_1 \sum_{k=1}^{K} w_k |\beta_{i,k}| + \lambda_2 \sum_{k=1}^{K} \beta^2_{i,k} \right] \tag{4.30}$$

where λ_1 and λ_2 are regularization parameters corresponding to l_1 and l_2 penalty terms, and $w = (w_1, w_2, ..., w_k)'$ is a $K * 1$ vector of weighting factors for the $\beta_{i,k}$ parameters in the l_1 penalty. We select λ_1 and λ_2 employing twenty-fivefold cross-validation. To assess the statistical significance of the betas estimated by the adaptive elastic net, we employ the wild bootstrapping confidence intervals approach. The methodology reported is the one proposed by Rapach et al. [2013] and Clark and McCracken [2012]. The authors employ the fixed-design boostrap

[30]We thank Guofu Zhou for sharing the code on his website

in time-series contexts. Given the regression model

$$y_{t+1} = \beta_0 + \beta_1 X_t + \epsilon_{t+1} \qquad i = 1, ..., N \tag{4.31}$$

Let

$$\hat{\epsilon}_{t+1} = r_{t+1} - (\hat{\beta}_0 + \hat{\beta}_1 X_t) \qquad i = 1, ..., N \tag{4.32}$$

where $\hat{\beta}_0$ and $\hat{\beta}_1$ are the OLS estimates of the parameters equation (84). After that, we simulate data for $r_{i,t+1}$ via the following process:

$$r^*_{t+1} = \hat{\beta}_0 + \hat{\beta}_1 X_t + \hat{\epsilon}_{t+1} w_{t+1}, \qquad i = 1, ..., N. \tag{4.33}$$

where w_{t+1} is a draw from the standard normal distribution. This procedure employs the regressor observations from the original sample, making it a "fixed-design" wild bootstrap. We use this last equation and the the original observations to generate 2,000 pseudo samples. For each simulated sample, we calculate the OLS estimates and store the $\hat{\beta}_j$ estimates. Based on the empirical distributions, we compute a biased-corrected bootstrapped confidence interval for each β_j. Let $[\hat{\beta}^*_{j,b}]^B_{b=1}$ denote the bootstrapped draws of $\hat{\beta}_j$, where B=2.000. Define the bootstrap standard error as:

$$s^*_{\beta_j} = \Big[\frac{1}{B-1}\sum_{b=1}^{B}(\hat{\beta}^*_{j,b} - \bar{\beta}^*_j)^2\Big]^{0.5} \tag{4.34}$$

where $\bar{\beta}^*_j = (1/\beta)\sum_{b=1}^{B}\hat{\beta}^*_{j,b}$. The bias-corrected wild bootstrapped 90% confidence interval for β_j is then given by:

$$[2\hat{\beta}_j - \bar{\beta}^*_j - s^*_{\beta_j}1.645, 2\hat{\beta}_j - \bar{\beta}^*_j + s^*_{\beta_j}1.645] \tag{4.35}$$

Instead of feeding predictors directly into the adaptive elastic net, we employ an indirect methodology. Our goal is to maximize the informative content of our analysis while retaining a parsimonious model specification which can be highly interpretable. Consequently, we follow an approach close to the one proposed by Ludvigson and Ng [2007] and Ludvigson and Ng [2009]. We start considering a broad list of financial and macroeconomic variables, and we cluster them in five macroeconomic (Income, Industrial Production, Labor, House, Inflation) and four financial (Fixed Income, Forex, Commodities, Industries) sets[31]. After that, for each cluster, the time series of the first principal component is extrapolated. Finally, the resulting nine principal components are employed in the adaptive elastic

[31] The full list of the time series considered with the related transformations is available in Table A1 of the appendix, the clustering is done following the guidelines of Ludvigson and Ng [2007]. The out-of-sample predictive performance, both in terms of R^2_{OS} and of ΔUtility, of each transformed variable for the monthly period 2000-2017, is reported in the Appendix in Tables A5 and **??**

net model. In addition to the newly introduced macroeconomic and financial predictors, we include the Greed, Fear and Uncertainty proxies previously employed in Tables 4.7 and 4.8 and the interaction between the return of these three behavioral variables and the five macroeconomic principal components.
At first, we report how often a variable is selected (in percentage) by the Adaptive Elastic Net. Precisely, we consider the time series of the predictive performances for all the individuals OLS models and machine learning predictive approaches reported in Tables 4.3 and 4.4 and for each of them we employ the adaptive elastic net to select the relevant predictors. The results in Table 4.9 show the percentage of times a variable is chosen in a given model specification. In the left panel (Time t) results come from an adaptive elastic net where the dependent variable and the independent ones are all contemporaneous while in the right panel (Time t+1) results come from an adaptive elastic net where the dependent variable is more recent than the independent ones. In the following analysis for each model specification, we perform model selection considering either the levels or the returns of the variables employed. All results in Tables 4.9-4.11 are based on monthly returns for the period 1986:01-2016:12.

Insert Table 4.9 about Here

When we specify the model to include only the five macroeconomic principal components we observe how for the contemporaneous case (Time t) the variable which is selected most often is the Inflation, with a high ratio of 72% for the level and of 65% for the return case, followed by Income, with a ratio of 59% for the level and of 35% for the return case. The results change for the predictive case (Time t+1): here the most selected variables are Income (50%), Industrial Production (54%) and Labor (48%) for the Level and Income (24%) and Labor (33%) for the Return case. After that, when behavioral variables are introduced we observe how the outcomes for both the Time t and Time t+1 are homogeneous: when the level of the behavioral indexes are employed the chosen variables are the Greed and Fear ones while when the returns are employed the most chosen variable is Uncertainty (with percentage above 60% in both cases). Subsequently, when the four financial principal components are added we observe how, as expected, the one which is chosen more often, both in the Time t and Time t+1 cases, is the one extrapolated from the industries returns indexes. When we introduce the interaction between the returns of the Greed and Fear indexes and the macroeconomic principal components we observe how the percentages of selection are almost unanimously higher for the interaction between fear returns and macroeconomic principal components than for the interaction between greed returns and macroeconomic principal components. For the model specifications, which employs the Level of the principal components, the interaction variables most commonly selected are fear-Labor and fear-Industrial-Production both for the Time t and Time t+1 cases. Remarkably, for the Time t+1 specification only, the Labor-Ret-Fear interaction variable achieves a high selection percentage of 63. Finally, we document how, for both the Time t and Time t+1 cases, the interaction between the uncertainty return and the returns of the Income-Inflation principal components are selected in a relevant number of cases: a steady 37% for the Uncertainty-Income returns interaction case and 57% (Time t) and 46% (Time t+1) for the Uncertainty-Inflation returns interaction case. Having studied the percentage of cases the adaptive elastic net chooses a given parameter, we apply the same adaptive elastic net model to the time series of the historical mean benchmark forecast model cumulative square prediction error minus the average of all individual and machine learning predictive models (Figure 4.2, Total). The 95% confidence intervals are estimated through the wild bootstrapping procedure presented above.

Insert Table 4.10 about Here

Insert Table 4.11 about Here

The outcomes resulting from Tables 4.10 and 4.11 provide us further confirmation of our previous results. First, looking at the variable selected among macroeconomic, financial, and behavioral returns, we observe how only uncertainty is always selected, and the resulting factor loadings are always positive and statistically significant. Other return variables which are the product of uncertainty returns and the returns of the principal components of macroeconomic variables (Income, Labor, Inflation) are also chosen and overall augment the original effect of uncertainty returns. Second, when we look at the levels, we observe how, for Table 4.10, all macroeconomic and behavioral variables are selected, and the estimated factor loadings are statistically significant. Table 4.11 confirms these findings, but now the factor loadings for Inflation and Industrial Production are negative while the principal component extracted from Labor is discarded. The interaction variables between uncertainty returns and the level of the macroeconomic principal components are almost always selected. Finally, differently from the Return case, some of the interaction variables between Greed-Fear and the macroeconomic level of the principal component are selected, and the resulting beta coefficients are inside the confidence intervals.
In conclusion, three key results emerge from the analyses performed in this section:

- both fundamental and behavioral factors concur in the genesis of predictability.

- the interactions between fundamental and behavioral variables are also key drivers of equity market predictability.

- the level of uncertainty has weak explanatory power for predictability, but uncertainty returns are very powerful.

4.7 The link between behavioral and neoclassical finance

One of the main implications of the previous analyses is that both behavioral and fundamental factors drive market predictability. The previous results open the question of how the different predictability drivers coevolve over time. To investigate this issue, we employ Vector Auto Regression (VAR) models that focus on the dynamic relationship between the R^2_{OS} metrics and their drivers. The VAR model is an elegant extension of the univariate autoregressive model to a dynamic multivariate time series and is a tool to observe predictable relationships among variables. In the VAR model, all variables are assumed endogenous, indicating that one equation exists for each variable as a dependent variable, and each equation has lagged values of all of the included variables as independent variables, including the dependent variable itself. The VAR model also captures the linear interdependencies among multiple time series because they include the joint generation mechanisms of the variables involved.
A VAR(p) model for the set of m variables $y_{1t}, ..., y_{mt}$ listed in the $mx1$ vector $y_t = (y_{1t}, ..., y_{mt})'$ is:

$$\underset{mx1}{y_t} = \underset{mx1}{\mu} + \underset{mxm}{\Phi_1}\, y_{t-1} + ... + \underset{mxm}{\Phi_p}\, y_{t-p} + \underset{mx1}{\epsilon_t}, \quad \epsilon_t \sim WN\left(0, \underset{mxm}{\Sigma}\right) \tag{4.36}$$

Consequently, in a VAR(p) each variable depends on up to p of its own lags and up to p lags of each other variable, with coefficients grouped in p matrices $\Phi_1, ..., \Phi_p$, each of dimension mxm. After that, it depends on intercepts grouped in the $mx1$ vector $\mu = (\mu_1, ..., \mu_m)'$ and on an error term grouped into $\epsilon_t = (\epsilon_{1t}, ..., \epsilon_{mt})'$, such that the error term of each equation has zero mean and it is uncorrelated over time and homoskedastic, but it can be contemporaneously correlated with the errors in other equations.
In our analyses, we separately consider a VAR model for both the returns and the levels of the variables considered. In each case, we always include the returns of the total R^2_{OS} index, which is the average predictability performance for all the predictors and machine learning approaches considered. After that, we include the five macroeconomic principal components (Inflation, House, Industrial Production, Labor, and Income) and the three behavioral ones (Greed, Fear, and Uncertainty). All the time series analyzed are monthly and span the period 01:1996-12-2016.
At first, we consider the VAR for the time series of returns. We observe how both the four lags Augmented Dickey-Fuller and the four lags Phillips-Perron Unit Root

test are in favor of the absence of unit roots for all the series considered. After that, we perform a battery of tests (Akaike information criterion, Hannan–Quinn information criterion, the Schwarz Criterion and the Final Prediction Error Criterion (FPE)) to identify the proper number of lags for the VAR system. All the four tests considered confirm that the best approach is the most parsimonious one which includes only on lag. Table 4.12 reports our results for the VAR(1) system while Figure 4.3 shows the related impulse response functions when the dependent variable is the total R^2_{OS}, and we perturb one of the nine variables under study.

Insert Table 4.12 about Here

Insert Figure 4.3 about Here

The results which emerge from these analyses confirm and augment our previous ones: returns of the uncertainty measure are the most robust predictors of the subsequent total R^2_{OS} measure. Interestingly all the other variables studied exhibit a low statistical significance confirming the results of the Adaptive Elastic Net. Differently, the impulse response functions provide novel insights on the dynamics of predictability. At first, a positive shock to the R^2_{OS} measure results in a subsequent positive values at time t+1 which abruptly turn negative in the subsequent periods. As expected shocks to the Fear and Uncertainty measures trigger a higher level of the R^2_{OS} measure in the subsequent periods while the pattern for shocks to the Greed measure are more complex: null at time t+1, negative at time t+2 and positive for longer horizons. After that, shocks to the House and to the Income factors are associated to positive response at time t+2 which vanish at longer horizons. Finally, we remark how shocks to the inflation measure trigger a positive response for the R^2_{OS} variable in the short term (first two periods) and negative one at longer horizons while the opposite holds for shocks to the Labor and industrial production variables.
The analyses for the VAR in levels pose new challenges. While the tests for the selection of the most appropriate number of lags unanimously confirm the VAR(1) structure the tests for stationarity highlight how for 4 time series (Greed, Uncertainty, Labour and House) the presence of a unit root cannot be rejected[32]. This poses the challenge of the estimation of a VAR system with both stationary and non-stationary time series. To address this issue, we follow Stock et al. [1990]. The authors prove how "individual coefficients in the estimated autoregressive equations are asymptotically normal with the usual limiting variance unless they are coefficients of a variable which is nonstationary and which does not appear in any of the system's stationary linear combinations". Consequently, we perform

[32]All details for the 4 lags Augmented Dickey-Fuller and the 4 lags Phillips-Perron Unit Root test are reported in Table A6 in the Appendix

the Engle-Granger pairwise cointegration tests and the Johansen test, which considers all the four non-stationary time series jointly. The empirical results[33] all unanimously suggest that the series considered are cointegrated: the Johansen test points out how the number of cointegration vectors is equal to one while the pairwise Engle-Granger tests suggest that all the series are cointegrated. Our empirical results jointly confirm that the estimation of a simple VAR(1) model is not inappropriate in this setting. As before we always include the returns of the total R^2_{OS} index, with the level of the five macroeconomic principal components (Inflation, House, Industrial Production, Labor, and Income) and of the three behavioral ones (Greed, Fear and Uncertainty). All the time series analyzed are monthly and span the period 01:1996-12-2016.

Insert Table 4.13 about Here

The results emerging from Table 4.13 confirm that the level of fear has a positive and statistically significant impact on subsequent predictability, while the level of uncertainty lacks statistical significance. After that, we notice how uncertainty has a positive and statistically significant impact on the subsequent levels of both Greed and Fear, while these two latter variables are, as expected, negatively related. Remarkably, the Industrial Production and the Labor variables have a strong statistically significant relationship with the Greed and Fear measures while the Inflation index has a robust negative relationship with the subsequent level of the Fear proxy. In conclusion, the level of the Greed and Fear measures are linked with the level of uncertainty and to some macroeconomic variables while uncertainty is connected with the level of Industrial Production and of Labor.
The impulse response functions for the R^2_{OS} returns of this second VAR(1) system which employs the time series of levels confirm the previous results coming from the VAR(1) system which employs the time series of returns. The only significant differences come from the response to shocks to Greed (the subsequent effect R^2_{OS} are now positive) and to Income (after an initial positive impact for the first two periods the effect turns negative).
Having studied how the different macroeconomic and behavioral variable trigger changes in the predictability of financial markets, we are now ready to study how behavioral and macroeconomic variables interact one with the others in different market regimes. To achieve this goal, we employ two regimes Markov Switching Dynamic models. At first, we propose a formulation in which the intercept, all the regression coefficients, and the volatility of the normal errors change across regimes. We propose different combinations of independent variables, while the dependent variable is the total average of all R^2_{OS} previously employed in our analyses. We focus on contemporaneous regression to identify which fundamental and

[33]For brevity the results of the cointegration tests are reported in table A6 in the Appendix

behavioral components explain predictability in the two different market regimes identified in this study. To perform our empirical analysis, we make use of monthly returns for the period 01:1996-12:2016. For seek consistency, the predictors employed the same as before, and all details can be found in Section 3 and the online appendix.

$$y_t = \beta_{0,S_t} + \sum_{i=1}^{n} \beta_{i,S_t} x_t + \epsilon_t \tag{4.37}$$

$$\epsilon_t \sim N(0, \sigma^2_{i,S_t}) \tag{4.38}$$

Figure 4.3 shows us the different, forward regimes probabilities identified by our empirical approach. It is immediately apparent how one regime is linked to financial and economic turmoil, is less frequent, and when is dominant lasts less: it is a bear regime. The specular applies for the other regime which we label as a bull regime.

Insert Figure 4.3 about Here

Insert Table 4.14 about Here

The result which emerges from Table 4.14 help us to gain a better understanding of the genesis of predictability. The upper panel, which employs the time series of returns as independent variables provides a clear picture. At first, when we consider only the intercept and the three behavioral variables (Greed, Fear, and Uncertainty), we observe how as expected, the intercept is negative in bull regimes and positive in bear ones. After that, the only statistically significant coefficient is the one for Fear returns in the bear regime. Interestingly, the Greed and Uncertainty coefficients flip signs in the two regimes being positive during bull regimes and negative in bear ones. Subsequently, we find no statistically significant regressors when including only the five macroeconomic returns time series (Income, Labor, House, Industrial Production, and Inflation). Subsequently, we regress the returns of the three behavioral time series and the product of return uncertainty and the return of the five macroeconomic time series. We observe now how uncertainty returns are positively related to predictability only during bull regimes and that always only in bull regimes the interaction between the Labor, House and Inflation returns and the uncertainty returns are statistically significant. Finally, we employ as independent variables the greed and fear return time series plus the product of the fear returns and the returns of the five macroeconomic time series. We observe how the fear returns are positively linked to predictability only during bear markets and that the only statistically significant regression coefficient are the ones for the interaction between fear returns and the returns of income and industrial production time series. In conclusion, uncertainty returns are positively

linked to predictability during bull regimes, while fear returns are linked to predictability only during bear ones[34]
The lower panel of Table 4.14 repeats the same analyses employing the levels of the same variables. Before entering into the detail of the different model formulations, one results appear strikingly clear: the signs of the relationship between the level of the studied variables and the dynamics of predictability flip sign in the large majority of the cases considered suggesting the relevance of employing a Markov Switching regression model. We observe how the level of uncertainty is positively related to predictability only during bull regimes while fear negatively related to predictability only in bear ones. Subsequently, we observe how the level of the Industrial production variable and the Labor one are positively linked to predictability respectively in the bear and bull regime only. Finally, our results show how the interaction between the level of uncertainty and the level of the five macroeconomic variables are statistically robust only in bull regimes while the interaction between the level of fear and the level of the same five macroeconomic variables is more pronounced in bear ones.
Having understood the relevance of market regimes in the understanding of predictability, it becomes pivotal to understand the relationships between fundamental and behavioral variables. Indeed, the understanding of the link between fundamental and behavioral variables provides further guidance not only for dissecting the genesis of predictability but also for the related pricing of financial securities. To address this challenging task at first, we make use of the impulse response functions coming from our VAR(1) system based on the time series of macroeconomic and behavioral returns (Table 4.12). At first, the impulse response function shows how when Greed rises, it triggers a decline in Fear, and the vice versa holds. After that, coherently with Barone-Adesi et al. [2018], we observe how a shock to uncertainty triggers a positive reaction for both Greed and Fear. Subsequently, we found how shocks to Greed have a weak impact on subsequent macroeconomic variables, while shocks to Fear trigger an unambiguously negative response to the Labor variable. Finally, in the short shocks to uncertainty trigger, an increase for all the macroeconomic variables but the Inflation one[35].
After that, we employ the pairwise Granger causality approach employed by Rapach et al. [2013]. Accordingly, we consider the five macroeconomic and the three behavioral time series of returns, and we perform a univariate regression of each

[34]Employing Greed instead of Uncertainty provides no statistically significant results, confirming how in this framework Uncertainty captures and subsumes the informational content of Greed.
[35]For seek of brevity the impulse response functions are reported in the Appendix Figures 4.6, 4.7 and 4.8

variable on all the other ones.

$$r_{i,t+1} = \beta_{i,0} + \beta_{i,j} r_{j,t} + \epsilon_{i,t+1} \quad i \neq j \tag{4.39}$$

The employed Newey-West t-statistic is heteroskedasticity and autocorrelation robust. Subsequently, to account for the differences across regimes, we repeat the same analysis making use of the following threshold regression:

$$r_{i,t+1} = \begin{cases} \beta_{i,0,Bull} + \beta_{i,j,Bull} r_{j,t,Bull} + \epsilon_{i,t+1,Bull} & i \neq j \quad if \quad p_{t,Bull} > p_{t,Bear} \\ \beta_{i,0,Bear} + \beta_{i,j,Bear} r_{j,t,Bear} + \epsilon_{i,t+1,Bear} & i \neq j \quad if \quad p_{t,Bull} < p_{t,Bear} \end{cases} \tag{4.40}$$

where the probabilities $p_{t,Bull}$ and $p_{t,Bear}$ are the filtered probabilities coming from the previously estimated regression Markov switching model (Equation 37) which employs only the three behavioral variables returns as regressors. All data employed in this analysis are monthly and span the period 1996:01-2016:12.

Insert Figure 4.4 about Here

Insert Table 4.15 about Here

The key result which emerges from Table 4.15 is that fundamentals drive behavioral variables and that this relationship is much stronger during the Bear regime. Indeed, looking at the upper panel, which makes use of all the data available, we observe how Incomes predicts both fear and uncertainty while the vice versa does not hold. After that, we notice how the results from this table confirm the ones coming from the impulse response functions previously discussed.

Looking at the lower panel, the results coming from the threshold regressions are insightful. In the Bull regime, the sign, magnitude, and statistical significance of almost all the betas are close to the ones found for the case which make use of all data. Differences emerge from the results of the Bear regime side of the threshold regression. Here we observe how Income predicts all the three behavioral variables considered and how Industrial Production and Labor forecast Fear while House Granger cause Uncertainty. Even more importantly, not only the significance of the relationships detected is higher, but the absolute value of betas are two orders of magnitude bigger than in the bull regime case. These results confirm how the interaction between fundamental and behavioral variable is more relevant in the bear regime than in the bull ones confirming our previous results on the higher predictive power of fundamental predictors during recessions. All the considered macroeconomic variables are not Granger-caused by the behavioral ones in the bear regime (except Industrial Production which is predicted by the Greed variable).

In conclusion, we have empirically proved how predictability reacts to changes in macroeconomic and behavioral variables and the variables which are linked to predictability changes across market regimes. Finally, we showed how fundamentals drive behavioral variables and how this relation is especially strong during the bear regime.

4.8 Conclusions

After years of restless efforts, our understanding of financial markets predictability (the magnificent enigma) is still in an early stage. With this work, we provide some first empirical insight into the rationale and dynamics of predictability and on their implications for our understanding of asset pricing. Our study is relevant not only because of its economic implications for traders and portfolio managers but even because it allows us to better understand the interaction between risks and risks premia (or the link between the neoclassical and behavioral finance).
At first, the results which emerge from our empirical analyses confirm and augment the ones coming from Barone-Adesi et al. [2018], where the authors prove how the dynamics of uncertainty (the heterogeneity of investors views) drive the risk pricing (both greed and fear). High uncertainty and a high level of sentiment imply that prices are driven by the most optimist investors while high uncertainty and a high level of fear imply that the investors are likely overestimating the real risks. In any case, when uncertainty is high volatility is likely to follow because subsequent fundamental news has a bigger impact on a pool of investors with heterogeneous beliefs. Importantly for our understanding of financial markets, uncertainty rises before markets crashes and remains high during all the bear market regime to steadily decrease while the new bullish regime starts to gain momentum. As previously accounted by Barone-Adesi et al. [2018], these findings are against the existence of an uncertainty risk premium. In the presence of high uncertainty and high greed, the arrival of negative fundamentals news can trigger a strongly negative reaction of equity markets. In these cases, the endogenous dynamics of financial market play a role in amplifying negative returns. Indeed, stop losses and Value at Risk constraints can trigger further sells even for investors with positive fundamental views with the final effect of a fast reversal of excessively low-risk premia into excessively high ones. These endogenous dynamics of financial markets make prices (on which stop losses and VaR levels are based) more informative (and relevant for traders) during bear market regimes than during bull markets ones. The same dynamics joint with the high level of uncertainty makes prices even more responsive to fundamental news during bear markets than during bull ones[36]. During bull markets, the opposite hold and prices are both less informa-

[36] There is a whole blossoming literature on the informative nature of financial crises (Brancati and Macchiavelli [2019] and Dang et al. [2019]) and on the different influence of fundamental

tive and less responsive to fundamental news. Importantly, from our empirical results, it is apparent how fundamental changes trigger changes in the risk premia, which amplify the outcome. Consequently, our view of financial markets is one in which both fundamentals and behavioral components have an important role. The dynamics of risks and risk premia interact one with other: changes in fundamentals trigger changes in the pricing of risks. Consequently, both neoclassical and behavioral components are reflected in equity prices and are important in our understanding of out-of-sample predictability[37].

Our understanding of financial markets and predictability are intrinsically related. We started our analysis showing how predictability is a common and rising feature of financial markets both in terms of R^2_{OS} and Δ Utility. Consistently with the existing literature[38] we show how predictability is, on average, higher during recessions and in forecasting negative returns. Importantly the most powerful predictors considered (Asset Growth, Investment to Assets and Net Stock Issues spread returns) are the ones which exhibit a higher capability to forecast cash flows in the Campbell and Shiller [1988] frameworks: a first confirmation of the dominant role of fundamentals in forecasting financial markets. After that, our results combined with the ones of Barone-Adesi et al. [2018] and Neely et al. [2014] confirm how technical predictors and the Sentiment index of Huang et al. [2015] are effective in detecting abnormally low levels of risk aversion (and perform better in period of economic expansion), while option-based fear indicators and fundamental predictors are effective in detecting abnormally high levels of risk aversion (and perform better in periods of economic recessions). These results combined suggest how different typologies of market predictors have a changing predictive power accordingly to the prevailing market regime. Consequently, fundamentals are the main drivers and are more precisely incorporated into prices, during bear markets, while during bullish markets the dynamics of risk pricing are more relevant, and non-fundamental (technical, trend following, behavioral) signals have a higher impact.

Having understood predictors, we subsequently studied aggregate predictability itself. At first, we included three behavioral motivated variables (Greed, Fear, and Uncertainty) and the five Fama and French risk factors. Our results confirm that aggregate predictability is linked with contemporaneous changes in both fundamental and behavioral variables. Even more, interestingly, even the interaction between risk and behavioral factors is linked with predictability, but the interaction between greed and risk factor is much weaker than the interaction between fear and risk factors confirming our previous results on the changing relevance of

information disclosure in these times Loh and Stulz [2018]

[37] This view of financial market is consistent with the work of Shefrin [2008]

[38] See, e.i. Rapach et al. [2009] and Rapach and Zhou [2013]

fundamentals through market regimes. These results do not change fundamentally when instead of the five Fama and French factors we employ five macroeconomic variables (Income, Labor, House, Industrial Production and Inflation) which are extrapolated (taking the first principal components) from a rich pool of variables characterizing each macroeconomic area. Another interesting result which emerges from our analyses is that when both Greed and Uncertainty are included in the same model, Uncertainty becomes the most significant variable subsuming Greed (from Barone-Adesi et al. [2018] we know that Uncertainty and Greed, the Huang et al. [2015], are cointegrated and that Uncertainty Granger causes Greed). Subsequently, we studied how predictability reacts to shocks. We document how predictability rises after positive shocks to Fear and Uncertainty while declines after shocks to Greed. The impact of shocks to macroeconomic variables is less straightforward, being overall positive only for the Inflation and Income variables. The in sample analysis of the predictive power of the behavioral and macroeconomic variables on the subsequent (t+1) aggregate predictability returns follow a similar pattern confirming the results coming from the impulse response functions. The results just stated suggests that the relationships among behavioral and fundamental variables and out-of-sample predictability are regime dependent. Our results on Markov Switching regressions confirm and augment our previous results. At first, we observe how in the vast majority of the cases considered the betas of the regression of the behavioral and fundamental variables on predictability returns flip the sign when regimes change. After that, it is clear how uncertainty and the interactions between uncertainty and the macroeconomic variables are statistically significant only during bull markets while fear and the interactions between fear and the macroeconomic variables are statistically significant only during bull ones.

Another important set of results regards the link between fundamental and behavioral variables. At first, impulse response functions show how when sentiment rises, it triggers a decline in Fear, and the vice versa holds. After that, coherently with Barone-Adesi et al. [2018], we observe how a shock to uncertainty triggers a positive reaction for both Greed and Fear. Subsequently, we found how shocks to greed have a weak impact on subsequent macroeconomic variables, while shocks to Fear trigger an unambiguously negative response to the Labor variable. Finally, an uncertainty shock triggers an increase for all the macroeconomic variables but the Inflation one. Finally, we study the causality dynamics among behavioral and fundamentals variables, and we document how, on average, are changes in fundamentals (risks) which trigger changes in behavioral variables (risk premia). These relations are stronger (in terms of magnitude, statistical power and the number of statistically significant predictors) during the bear than during the bull regime. This explains the dominant role played by fundamentals in forecasting market returns during recessions. Our results, reject the theory advanced by Julien and Michael [2017] who explain the higher probability detected in recession markets through the existence of an uncertainty risk premium. Indeed, all our analyses confirm how the level of uncertainty has no explanatory power for predictability dynamics. In bull markets, on the other hand, the impact of fundamentals is weaker, and the dynamics of uncertainty have a larger impact in explaining predictability. Indeed, uncertainty is the dispersion of investors views (which leads risk premia Barone-Adesi et al. [2018]), and consequently, individual signals are more commonly employed by investors and non-fundamental predictors become more valuable in forecasting markets returns out-of-sample.

The results just listed allow us to shed new light on the closely related field of asset pricing (Campbell [1991]). Indeed, our improved understanding of predictability allows us to identify better what the market ultimately reflects into prices or what are the key elements of the pricing kernel. Indeed, it is well known since Shiller [1981] that changes in dividends (or equivalently changes in fundamental risks) are not enough to explain the high level of volatility detected into financial markets. More recent studies link the volatility of macroeconomic variables with the market volatility (Engle et al. [2009] and Engle et al. [2013]), confirming that only part of the observed volatility can be linked to changes in fundamentals. Our results confirm that the interaction between risk and risk premia is critical in explaining out-of-sample predictability, and consequently, both components are reflected in asset prices. The predictability of equity markets suggests how mispricing is a structural feature of equity markets: they cyclically become overpriced and suddenly crash when fundamental news disappoint the optimist investors who were pushing prices too high. Behavioral and endogenous dynamics foster market crashes, which are the results of negative changes in fundamentals. This evidence suggests how Rare disaster theories[39] which explain the excess of return volatility in terms of extreme negative expectations of events which are unlikely to occur (and that ex-post do not materialize) are partially consistent with our understanding of financial markets: in the bear regime underpricing materialize and the dynamics of risk diverge from the dynamics of risk pricing (Andersen et al. [2015]). Another really popular theoretical framework to understand asset pricing is Recursive Utility long term risk one introduced by Bansal and Yaron [2005]. The long term risk model is entirely based on changes in the long-run consumption growth while current changes in consumption are irrelevant (as pointed out by Cochrane [2017]). Our results strongly reject the long-term risk theories because we proved how changes in Income trigger a change in risk pricing (fear and uncertainty): this is especially true during the bear market regime. Finally, the habit theory introduced by Campbell

[39] The most prominent studies comes from Barro [2006], Gabaix [2012] and Wachter [2013]. The authors explain predictability in terms of fear.

and Cochrane [1999] which explains market time-varying risk premia through a utility function which discount more risks in bad than in good times is largely consistent with our empirical evidence: prices are driven by changes in current fundamentals (risks) which trigger changes in behavioral variables (risks pricing) . While our study provides a first pioneering analysis on the genesis of predictability and the related link between neoclassical and behavioral finance, much is left to subsequent research. At first, our study focuses on short-term (one month ahead) predictability while the study of long-term predictability is completely unexplored. Second, we largely focus on understanding the total (aggregate) predictability changes while we do not study the predictability detected by individual's predictive models: it would be interesting to analyze which aspects of the financial market predictability each model capture to understand when and how to employ each model. Finally, we detected an asymmetric behavior in the dynamic interactions among risks and risks pricing in bull and bear market regimes, which is not accounted for in the original habit model of Campbell and Cochrane [1999]. Our results suggest how the original model of Campbell and Cochrane [1999], while fundamentally correct, may be improuved by the inclusion of the complex markets features emerging from our study.

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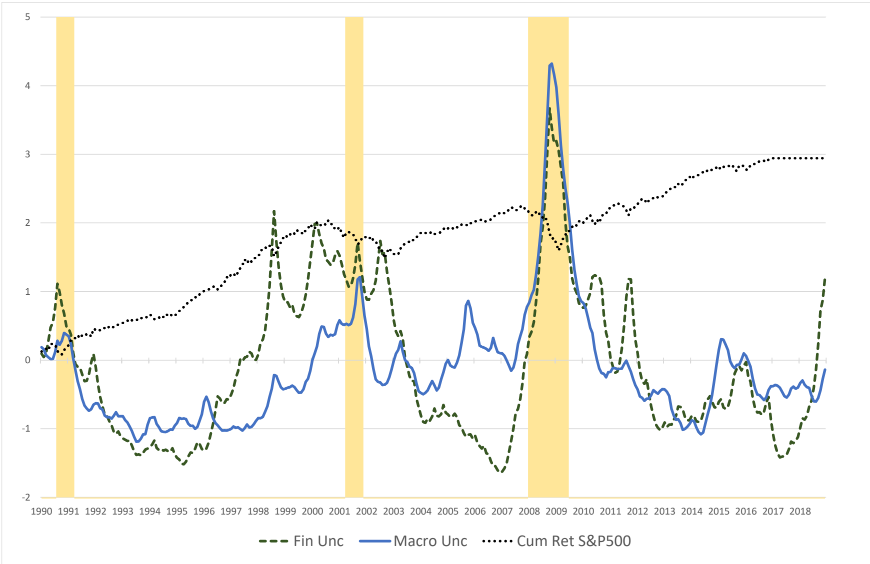
4.9 Tables and Figures

Figure 4.1: **Sentiment, Fear, Uncertainty and the S&P500**. The upper plot draws the 3 months macroeconomic and financial uncertainty indexes of Jurado et al. [2015] with S&P500 cumulated returns. The lower plot represents the Sentiment index of Huang et al. [2015] with the Downside variance risk premium of Andersen and Bondarenko [2007] and the S&P500 index. The shaded areas highlight periods of economic recession. All series are monthly and standardized, and span the period 01-1990/12-2016.



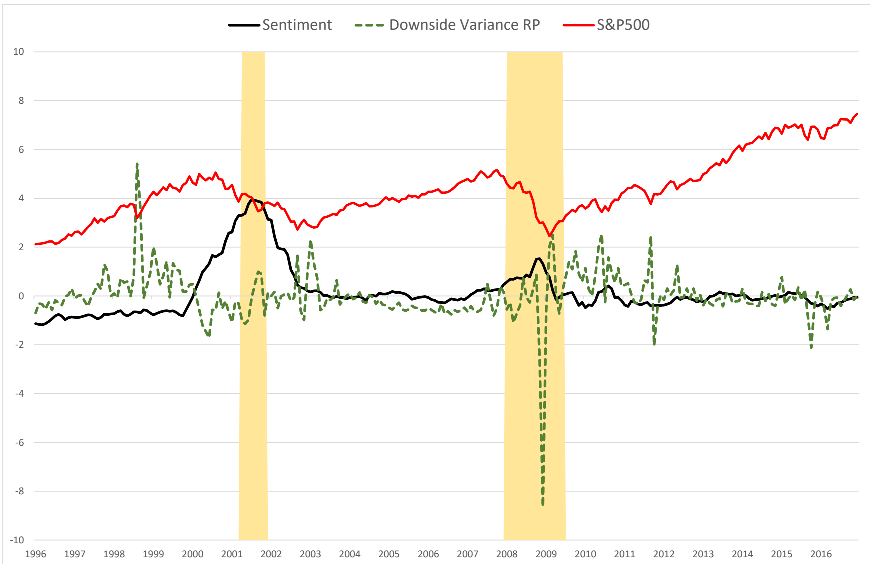
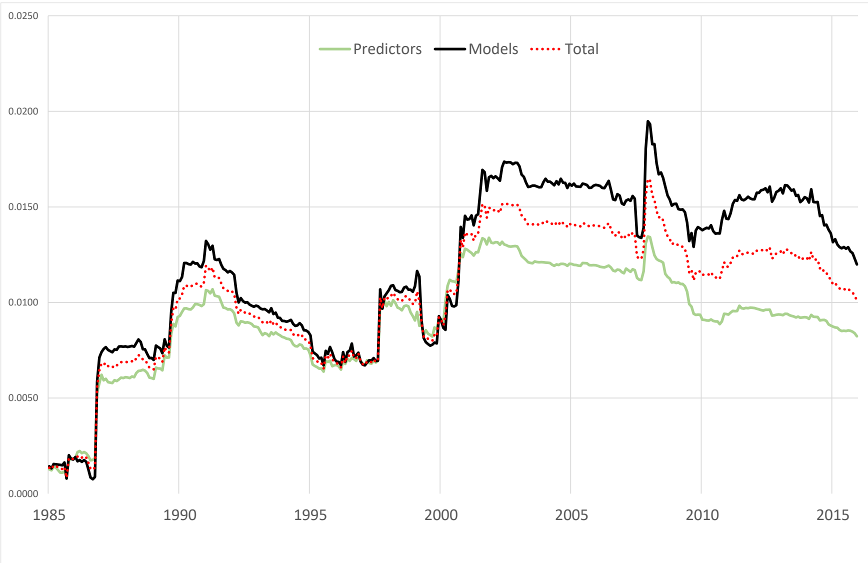
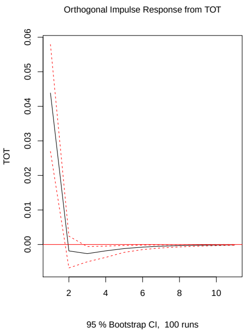
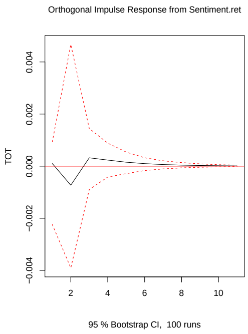


Figure 4.2: **Aggregate** R^2_{OS}. Historical average benchmark forecast model cumulative square prediction error minus: i) average individual predictive regression forecast model cumulative square prediction error (Predictors in the Plot) ii) average models forecast cumulative square prediction error (Models in the Graph) iii) the average of the previous two values (Total in the Graph).





(a)



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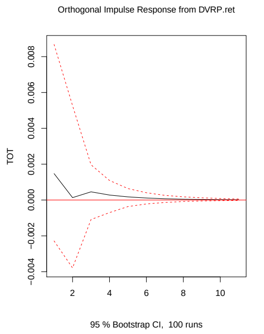

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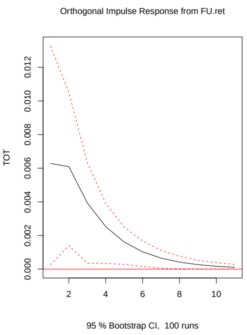

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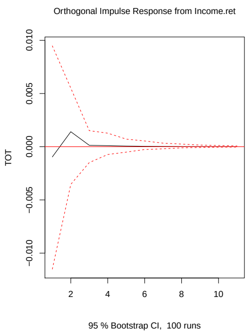

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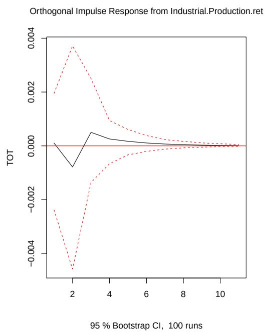

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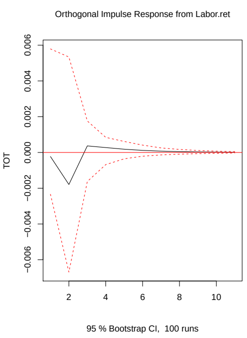

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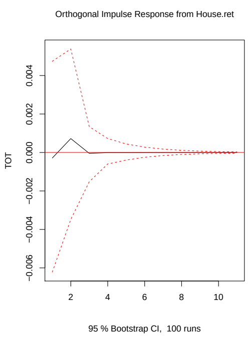

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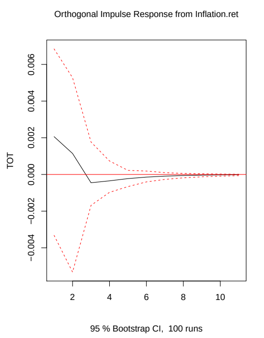
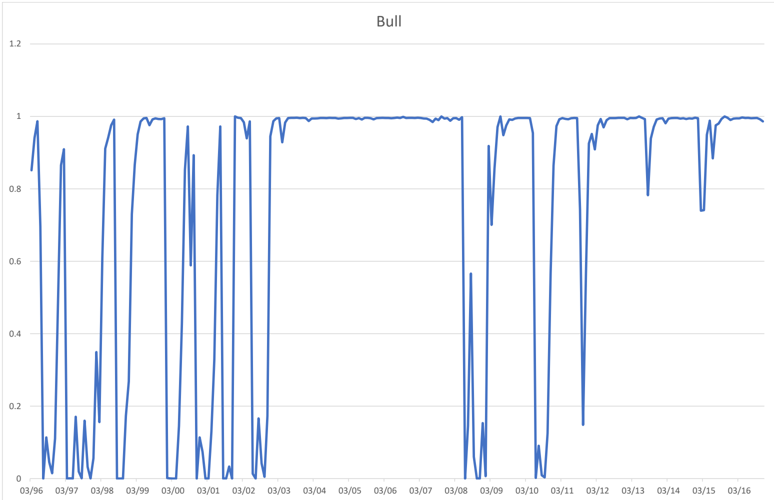


(i)

Figure 4.3: **Impulse Response Function R^2_{OS} returns**. This Figure shows the response of the Total R^2_{OS} to the following impulses: (a) R^2_{OS}, (b) Greed, (c) Fear, (d) Uncertainty, (e) Income, (f) Industrial Production, (g) Labor, (h) House, (i) Inflation. All details are in Section 3 on data an in the Appendix

Figure 4.4: **Markov Switching Regression Filtered Probabilities**. This figure plots the filtered probabilities of a two regimes markov switching regression model which employs as independent variable the Total R^2_{OS} returns and as dependent ones the returns of the three behavioural variables considered in this study (Greed, Fear and Uncertainty). All details are in Section 3.
$y_t = \beta_{0,S_t} + \sum_{i=1}^{n} \beta_{i,S_t} x_t + \epsilon_t \quad \epsilon_t \sim N(0, \sigma^2_{i,S_t})$
Monthly data span the period 01:1996-12:2016. It is immediately apparent how the orange regime is linked to high volatility market periods while the opposite holds for the blue regime. Consequently, in this study, we address the blue probability as the probability of being in a bull market regime and the orange probability as the probability of being in a bear regime. Finally, we distinguish between being in a bull or bear market at time t accordingly to which probability is higher at that time.



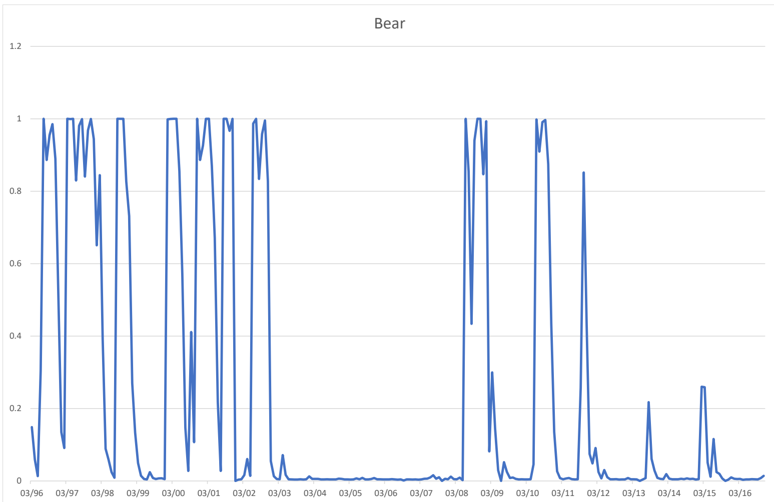


Table 4.1: **Welch and Goyal [2008] predictors: monthly equity premium out-of-sample forecasting results for individual forecasts, and machine learning methods**. We consider two monthly out-of-sample windows: 1957:1-2017:12 and 2001:1-2017:12. The R^2_{OS} is the Campbell and Thompson [2008] out-of-sample R^2 statistic. Statistical significance for the R^2_{OS} statistic is based on the p-value for the Clark and West [2007] out-of-sample MPSE-adjusted statistic; the utility gain (Δ Utility) is the portfolio management fee (in annualized percentage return) that an investor with mean-variance preferences and risk aversion coefficient of three would be willing to pay to have access to the forecasting model considered relative to the historical average benchmark forecasting model; the weight on stocks in the investor's portfolio is restricted to lie between 0 and 1.5 (inclusive). For the R^2_{OS} statistic *,** and *** indicate significance level at the 10%, 5% and 1%. **Bold** indicates an Utility gain or a R^2_{OS} above 1.00%.

	1986-2017		**2001-2017**	
Predictor	R^2_{OS}	**pval**	R^2_{OS}	**pval**
DP	-1.34	0.52	0.13	0.20
DY	-1.99	0.48	0.17	0.17
EP	-1.41	0.32	-0.88	0.28
DE	-0.54	0.54	-1.34	0.69
SVAR	0.39	0.16	1.06*	0.10
BM	-2.28	0.57	-0.10	0.24
NTIS	-1.77	0.65	-3.53	0.87
TBL	-0.21	0.47	0.21	0.25
LTY	-0.06	0.44	0.49**	0.03
LTR	-0.31	0.40	-0.01	0.34
TMS	-0.83	0.64	-1.15	0.76
DFY	-0.20	0.92	-0.28	0.92
DFR	0.18	0.29	-0.33	0.43
INF_lag	-0.35	0.84	-0.86	0.93
	1986-2017		**2001-2017**	
Model	R^2_{OS}	**pval**	R^2_{OS}	**pval**
OLS	-5.83	0.36	-6.63	0.36
Pooled Forecast: median	0.08	0.32	0.18	0.13
Pooled Forecast: MDSFE	-0.01	0.42	0.42	0.18
Sum-of-the-parts	0.24	0.21	0.89*	0.10
MARS SVM	0.89**	0.02	**1.18****	**0.04**
SIC SVM	0.49*	0.06	0.16	0.17
LASSO SVM	0.37*	0.10	0.33	0.17
Diffusion Index	0.22	0.25	0.36	0.27

	1986-2017	**2001-2017**
Predictor	**Δ Utility**	**Δ Utility**
DP	-2.59	**1.75**
DY	-2.66	**2.37**
EP	**1.83**	**4.93**
DE	-0.26	-0.20
SVAR	-0.58	-0.40
BM	-2.67	**2.62**
NTIS	-0.66	-0.08
TBL	0.00	0.08
LTY	0.06	0.32
LTR	-0.18	0.22
TMS	-1.08	-1.21
DFY	-0.90	-1.33
DFR	0.96	**1.22**
INF_lag	-0.74	-1.47
	1986-2017	**2001-2017**
Model	**Δ Utility**	**Δ Utility**
OLS	-3.78	-5.35
Pooled Forecast: median	0.07	-0.28
Pooled Forecast: MDSFE	-0.05	0.33
Sum-of-the-parts	0.60	**1.78**
MARS SVM	0.30	-0.12
SIC SVM	**1.20**	**1.63**
LASSO SVM	0.61	0.89
Diffusion Index	-0.23	-0.29

Table 4.2: **Spread return predictors: monthly equity premium out-of-sample forecasting results for individual forecasts, and machine learning methods**. We consider two monthly out-of-sample windows: 1986:1-2016:12 and 2001:1-2016:12. The R^2_{OS} is the Campbell and Thompson [2008] out-of-sample R^2 statistic. Statistical significance for the R^2_{OS} statistic is based on the p-value for the Clark and West [2007] out-of-sample MPSE-adjusted statistic; the utility gain (Δ Utility) is the portfolio management fee (in annualized percentage return) that an investor with mean-variance preferences and risk aversion coefficient of three would be willing to pay to have access to the forecasting model considered relative to the historical average benchmark forecasting model; the weight on stocks in the investor's portfolio is restricted to lie between 0 and 1.5 (inclusive). For the R^2_{OS} statistic *,** and *** indicate significance level at the 10%, 5% and 1%. **Bold** indicates an Utility gain or a R^2_{OS} above 1.00%.

	1986-2016		**2001-2016**	
Predictor	R^2_{OS}	**pval**	R^2_{OS}	**pval**
SMB	-0.45	0.29	-0.98	0.49
HML	-0.22	0.35	0.07	0.33
RMW	-0.40	0.43	-0.41	0.41
CMA	0.19*	0.07	0.55	0.17
LT	-0.42	0.39	-0.87	0.54
ST	-0.76	0.82	-2.15	0.97
Mom	-0.78	0.90	-1.12	0.89
Asset Growth	**13.20*** **	**0.00**	**3.55*** **	**0.00**
Gross Prof	-0.15	0.00	-11.67	0.83
Inv to Assets	**11.13*** **	**0.00**	-1.17	0.01
Net Stock Issues	**23.54*** **	**0.00**	**28.67*** **	**0.00**
NOA	-2.95	0.36	-4.18	0.80
Accruals	-1.72	0.01	-10.18	0.56
O	**6.43*** **	**0.00**	**6.69** **	**0.01**
ROA	-3.64	0.04	-12.88	0.95
Distress	0.71*	0.08	0.14	0.25
Comp Eq Issue	-0.38	0.49	-0.19	0.32
	1986-2016		**2001-2016**	
Model	R^2_{OS}	**pval**	R^2_{OS}	**pval**
OLS	**15.71*** **	**0.00**	**17.69*** **	**0.00**
Pooled Forecast median	**2.37*** **	**0.00**	**3.50* **	**0.00**
Pooled Forecast MDSFE	**10.89*** **	**0.00**	**12.36*** **	**0.00**
MARS SVM	**11.82** **	**0.00**	**4.90* **	**0.00**
SIC SVM	-20.13	0.34	-12.36	0.18
LASSO SVM	-12.46	0.24	-9.03	0.18
Diffusion Index	**4.16*** **	**0.01**	**13.54*** **	**0.00**

	1986-2016	**2001-2016**
Predictor	**Δ Utility**	**Δ Utility**
SMB	-0.58	-1.44
HML	0.11	**1.23**
RMW	0.39	**1.20**
CMA	0.99	**1.51**
LT	0.45	0.46
ST	-0.68	-2.20
Mom	-0.61	-0.66
Asset Growth	**11.47**	**6.96**
Gross Prof	**1.06**	-6.68
Inv to Assets	**10.30**	**6.29**
Net Stock Issues	**23.56**	**28.53**
NOA	-2.31	-3.64
Accruals	**2.39**	-1.85
O	**4.53**	**5.43**
ROA	0.05	-5.50
Distress	**2.36**	**2.59**
Comp Eq Issue	-0.10	0.77
	1986-2016	**2001-2016**
Model	**Δ Utility**	**Δ Utility**
OLS	**14.13**	**12.39**
Pooled Forecast median	**5.05**	**3.38**
Pooled Forecast MDSFE	**12.76**	**10.56**
MARS SVM	**5.11**	**13.10**
SIC SVM	0.24	0.16
LASSO SVM	0.00	0.86
Diffusion Index	**10.97**	**7.11**

Table 4.3: **Out-of-sample forecasts: Summary Statistics**. We consider the out-of-sample window 1980:1-2016:12 for the 14 Welch and Goyal [2008] predictors and the 17 Factors-Anomalies. DP is the log dividend-price ratio, DY is the log dividend yield, EP is the log earnings-price ratio, DE is the log dividend-payout ratio, SVOL is the volatility of excess stock returns, BM is the book-to-market value ratio for the Dow Jones Industrial Average, NTIS is net equity expansion, TBL is the interest rate on a three-month Treasury bill, LTY is the long-term government bond yield, LTR is the return on long-term government bonds, TMS is the long-term government bond yield minus the Treasury bill rate, DFY is the difference between Moody's BAA- and AAA-rated corporate bond yields, DFR is the long-term corporate bond return minus the long-term government bond return, and INFL is inflation calculated from the CPI for all urban consumers. SMB is the Small minus Big F&F factor, HML is the High minus Low F&F factor, RMW is the Robust minus Weak F&F factor, CMA is the Conservative minus Aggressive F&F factor, Mom is the momentum French factor, LT is the long term French factor, ST is the short term French factor. Asset Growth, Gross Prof, Inv to Assets, and Net Stock Issues are the asset growth, Gross Profitability, Investment to Assets and net stock issues anomalies (spread portfolios returns), built following Stambaugh and Yuan [2017]. Finally, NOA, Accruals, O, ROA, Distress and Comp Eq Issue are the Net Operating Assets, the Accruals, the Ohlson, the return on asset, the distress and the composite equity issue anomalies (spread portfolios returns), are also built following Stambaugh and Yuan [2017].

Summary Stat.	Mean	Median	1st Percentile	99th Percentile	Std. dev.	Skewness
DP	0.21	0.25	-1.39	1.95	0.58	-0.08
DY	0.20	0.24	-1.37	1.59	0.56	-0.14
EP	0.33	0.40	-1.47	1.40	0.46	-1.67
DE	0.53	0.51	-1.88	1.93	0.55	-1.54
SVAR	0.45	0.54	-1.51	1.53	1.03	10.79
BM	0.37	0.43	-1.39	1.61	0.52	-1.29
NTIS	0.56	0.49	-0.91	2.88	0.72	1.05
TBL	0.70	0.72	-0.63	1.34	0.35	-1.20
LTY	0.61	0.64	-1.04	1.51	0.44	-0.11
LTR	0.45	0.48	-0.63	1.61	0.40	0.22
TMS	0.57	0.56	-0.32	1.21	0.31	-0.22
DFY	0.36	0.42	-0.43	2.23	0.38	2.08
DFR	0.42	0.46	-2.07	2.40	0.74	-0.49
INF_lag	0.40	0.48	-1.34	0.96	0.41	-1.83
SMB	0.38	0.38	-0.85	1.71	0.49	0.48
HML	0.44	0.49	-0.74	1.55	0.45	0.10
RMW	0.41	0.42	-0.51	1.26	0.35	-0.82
CMA	0.46	0.49	-1.26	2.89	0.74	1.54
LT	0.43	0.43	-0.63	1.33	0.40	0.00
ST	0.42	0.46	-0.66	1.37	0.27	-1.08
Mom	0.42	0.45	-0.43	1.07	0.26	-0.60
Asset Growth	0.28	0.58	-6.80	6.43	2.43	-0.50
Gross Prof	0.35	0.32	-3.57	4.29	1.55	-0.03
Inv to Assets	0.44	0.53	-7.34	6.10	2.36	-0.48
Net Stock Issues	0.51	0.56	-4.38	6.03	1.93	0.25
NOA	0.34	0.42	-2.98	2.87	0.96	-0.69
Accruals	0.44	0.51	-3.53	4.94	1.52	-0.21
O	0.40	0.38	-3.44	3.13	1.17	-1.52
ROA	0.34	0.49	-5.26	4.10	1.61	-0.76
Distress	0.39	0.43	-2.25	1.95	0.66	-1.37
Comp Eq Issue	0.43	0.46	-0.42	1.19	0.32	-0.01

Table 4.4: **Out-of-sample forecasts: Pearson correlations**. We consider the out-of-sample window 1980:1-2016:12 for the 14 Welch and Goyal [2008] predictors and the 17 Factors-Anomalies. DP is the log dividend-price ratio, DY is the log dividend yield, EP is the log earnings-price ratio, DE is the log dividend-payout ratio, RVOL is the volatility of excess stock returns, BM is the book-to-market value ratio for the Dow Jones Industrial Average, NTIS is net equity expansion, TBL is the interest rate on a three-month Treasury bill, LTY is the long-term government bond yield, LTR is the return on long-term government bonds, TMS is the long-term government bond yield minus the Treasury bill rate, DFY is the difference between Moody's BAA- and AAA-rated corporate bond yields, DFR is the long-term corporate bond return minus the long-term government bond return, and INFL is inflation calculated from the CPI for all urban consumers. SMB is the small minus big F&F factor, HML is the high minus Low F&F factor, RMW is the robust minus weak F&F factor, CMA is the conservative minus aggressive F&F factor, Mom is the momentum F&F factor, LT is the long term F&F factor, ST is the short term F&F factor. Asset Growth, Gross Prof, Inv to Assets, and Net Stock Issues are the asset growth, Gross Profitability, Investment to Assets and net stock issues anomalies (spread portfolios returns), built following Stambaugh and Yuan [2017]. Finally, NOA, Accruals, O, ROA, Distress and Comp Eq Issue are the Net Operating Assets, the Accruals, the Ohlson, the return on asset, the distress and the composite equity issue anomalies (spread portfolios returns), built following Stambaugh and Yuan [2017].

Correlations	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
DP (1)	1.00														
DY (2)	0.92	1.00													
EP (3)	0.51	0.42	1.00												
DE (4)	-0.39	-0.33	0.17	1.00											
SVAR (5)	-0.03	-0.04	0.10	0.20	1.00										
BM (6)	0.86	0.77	0.68	-0.18	0.02	1.00									
NTIS (7)	-0.24	-0.17	-0.02	0.09	-0.01	-0.14	1.00								
TBL (8)	-0.14	-0.05	0.33	0.62	0.19	0.16	-0.10	1.00							
LTY (9)	-0.01	0.12	0.33	0.39	0.16	0.13	-0.05	0.79	1.00						
LTR (10)	0.05	0.16	0.13	0.12	0.06	0.18	0.11	0.21	0.19	1.00					
TMS (11)	-0.40	-0.35	-0.13	0.51	0.06	-0.23	-0.14	0.53	0.08	-0.06	1.00				
DFY (12)	-0.01	0.15	-0.10	0.16	0.07	-0.22	0.02	0.08	0.37	0.05	-0.23	1.00			
DFR (13)	0.05	0.03	0.06	0.13	0.06	0.05	-0.02	0.15	0.11	-0.43	0.12	0.02	1.00		
INF_lag (14)	0.12	0.12	0.52	0.21	0.09	0.31	-0.12	0.57	0.65	0.19	0.01	0.06	0.10	1.00	
SMB (15)	0.04	0.07	0.08	0.18	0.02	0.12	-0.03	0.35	0.30	-0.02	0.14	0.14	0.25	0.25	1.00
HML (16)	-0.01	0.16	0.09	0.13	-0.02	0.06	0.08	0.36	0.39	0.09	0.04	0.17	0.06	0.25	0.31
RMW (17)	-0.04	-0.01	0.16	0.18	0.16	0.11	0.01	0.35	0.32	0.08	0.08	0.02	0.19	0.27	0.13
CMA (18)	-0.04	0.10	0.04	0.08	0.02	-0.03	0.03	0.21	0.25	0.07	-0.01	0.19	0.05	0.16	0.20
LT (19)	-0.05	-0.01	0.13	0.13	0.18	0.06	0.13	0.26	0.31	0.21	-0.03	0.06	-0.01	0.22	-0.11
ST (20)	0.08	0.10	0.32	0.28	0.10	0.23	-0.01	0.47	0.50	0.14	0.11	0.07	0.16	0.48	0.17
Mom (21)	0.17	0.10	0.36	0.23	-0.02	0.29	-0.02	0.37	0.36	0.19	-0.04	0.06	0.07	0.45	0.18
Asset Growth (22)	-0.03	0.00	-0.01	-0.08	-0.04	-0.06	0.08	-0.03	0.01	-0.03	-0.08	0.01	0.03	-0.01	-0.06
Gross Prof (23)	0.02	0.08	-0.06	0.01	-0.08	-0.02	0.01	0.09	0.08	0.03	0.03	0.11	-0.01	-0.02	0.15
Inv to Assets (24)	0.00	0.02	0.02	-0.03	-0.09	-0.01	0.08	0.01	0.05	0.01	-0.07	0.02	0.02	0.04	0.00
Net Stock Issues (25)	0.02	0.01	0.03	0.00	-0.01	0.02	0.02	0.03	0.04	0.02	-0.06	0.00	-0.01	0.02	-0.02
NOA (26)	-0.11	-0.09	0.06	0.14	0.09	-0.01	-0.01	0.24	0.19	0.07	0.10	-0.03	0.06	0.15	0.10
Accruals (27)	0.00	0.04	0.00	-0.01	-0.02	0.03	0.04	0.01	-0.01	0.15	-0.04	0.00	-0.06	-0.01	0.00
O (28)	-0.06	-0.04	-0.05	0.06	-0.04	-0.04	0.00	0.04	0.00	0.05	0.02	-0.02	-0.08	-0.06	-0.02
ROA (29)	0.07	0.07	0.07	-0.01	-0.03	0.08	0.14	0.01	0.02	-0.04	-0.06	-0.04	0.06	-0.05	0.01
Distress (30)	0.20	0.18	0.10	-0.08	0.01	0.25	0.00	0.04	0.05	-0.02	-0.06	-0.18	-0.01	-0.02	0.06
Comp Eq Issue (31)	-0.03	0.04	0.16	0.21	0.12	0.06	-0.04	0.39	0.41	0.04	0.10	0.13	0.20	0.33	0.44

Correlations	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)
DP (1)																
DY (2)																
EP (3)																
DE (4)																
SVAR (5)																
BM (6)																
NTIS (7)																
TBL (8)																
LTY (9)																
LTR (10)																
TMS (11)																
DFY (12)																
DFR (13)																
INF_lag (14)																
SMB (15)																
HML (16)	1.00															
RMW (17)	0.26	1.00														
CMA (18)	0.72	0.20	1.00													
LT (19)	0.47	0.25	0.44	1.00												
ST (20)	0.15	0.38	0.06	0.23	1.00											
Mom (21)	0.13	0.20	-0.04	0.20	0.52	1.00										
Asset Growth (22)	0.11	0.03	0.13	0.14	-0.07	-0.09	1.00									
Gross Prof (23)	0.12	0.03	0.12	0.00	0.04	-0.08	0.36	1.00								
Inv to Assets (24)	0.09	0.03	0.11	0.11	-0.03	-0.04	0.83	0.28	1.00							
Net Stock Issues (25)	0.09	0.11	0.06	0.12	0.00	0.05	0.35	0.01	0.35	1.00						
NOA (26)	0.08	0.09	0.13	0.14	0.11	0.09	0.36	0.13	0.39	-0.14	1.00					
Accruals (27)	0.08	0.05	0.13	0.08	-0.03	-0.06	0.42	0.24	0.33	0.13	0.14	1.00				
O (28)	0.11	0.00	0.03	0.13	0.03	0.15	0.30	0.10	0.24	0.22	-0.06	0.14	1.00			
ROA (29)	0.03	-0.05	-0.02	0.08	0.04	-0.03	0.49	0.49	0.38	0.01	0.19	0.21	0.08	1.00		
Distress (30)	0.03	0.07	-0.06	0.05	0.02	-0.01	-0.03	0.00	-0.04	0.15	-0.19	-0.01	0.03	0.25	1.00	
Comp Eq Issue (31)	0.53	0.54	0.44	0.26	0.19	0.12	0.01	0.02	0.03	0.08	0.10	0.01	0.04	-0.09	0.01	1.00

Table 4.5: **Predictive regression estimation results for market return components**. We consider the monthly out-of-sample windows 1977:1-2016:12.The table reports the ordinary least squares estimate of by for the predictive regression model,
$y_{t+1} = \alpha_y + \beta_y x_t + \epsilon_{t+1}$ for $t = 1, ..., T-1$
where y_t is the S&P 500 log return or one of three estimated components of the S&P 500 log return for month t and x_t is one of the predictors considered. The three estimated components of the S&P 500 log return are the expected return ($\hat{E}r_{t+1}$), cash flow news ($\hat{\Psi}^{CF}_{t+1}$), and discount rate news ($\hat{\Psi}^{DR}_{t+1}$). The beta for the S&P 500 log return is β_{Tot} while the betas for the three components are $\hat{\beta}_{Ex}$, $\hat{\beta}_{CF}$ and $\hat{\beta}_{DR}$, respectively. The components are estimated using the Campbell [1991] and Campbell and Ammer [1993] vector autoregression (VAR) approach. The VAR includes the first three principal components extracted from the non x_t predictors. The intercept term is set to zero for the cash flow news and discount rate news predictive regressions. The t-statistics, reported in brackets, are heteroskedasticity and autocorrelation robust. ***, ** and * indicate significance at the 10%, 5%, and 1% levels, respectively. **Bold** is used to highlight the main beta component for predictors which own a Total beta t-stat value above 1.

Predictor	β_{Tot}		β_{Ex}		β_{CF}		β_{DR}	
DP	0.39**	(1.97)	**0.35*****	(3.55)	0.18	(1.00)	0.14	(1.18)
DY	0.41**	(2.08)	**0.37*****	(3.69)	0.18	(1.00)	0.13	(1.13)
EP	0.33	(1.30)	**0.35*****	(3.22)	0.22	(1.12)	0.24**	(2.00)
DE	0.03	(0.10)	-0.03	(-0.29)	-0.07	(-0.31)	-0.13	(-0.97)
SVAR	0.22	(1.25)	-0.08	(-1.00)	**0.14**	(0.90)	-0.17*	(-1.65)
BM	0.25	(1.22)	**0.36*****	(3.76)	0.06	(0.33)	0.17	(1.52)
NTIS	0.02	(0.09)	-0.18**	(-1.97)	0.16	(0.72)	-0.05	(-0.45)
TBL	0.12	(0.57)	0.06	(0.68)	-0.05	(-0.29)	-0.10	(-1.07)
LTY	0.14	(0.69)	0.04	(0.46)	-0.01	(-0.08)	-0.11	(-1.11)
LTR	0.31	(1.53)	**0.10**	(1.33)	0.00	(0.02)	-0.20**	(-1.98)
TMS	-0.01	(-0.04)	-0.06	(-0.62)	0.04	(0.21)	-0.02	(-0.18)
DFY	0.06	(0.19)	0.15*	(1.73)	-0.18	(-0.77)	-0.08	(-0.62)
DFR	0.39	(1.22)	-0.05	(-0.53)	**0.43***	(1.80)	-0.01	(-0.06)
INF_Lag	0.30	(1.23)	**0.20****	(2.01)	0.11	(0.48)	0.01	(0.13)
SMB	0.19	(0.90)	0.05	(0.55)	0.01	(0.06)	-0.13	(-1.10)
HML	-0.27	(-1.26)	**-0.35*****	(-3.25)	0.12	(0.65)	0.05	(0.34)
RMW	-0.34	(-1.58)	-0.07	(-0.54)	-0.29	(-1.46)	-0.02	(-0.17)
CMA	-0.38*	(-1.79)	**-0.39*****	(-3.22)	0.10	(0.54)	0.08	(0.65)
LT	-0.25	(-1.01)	**-0.45*****	(-4.65)	0.15	(0.76)	-0.06	(-0.48)
ST	0.02	(0.06)	-0.06	(-0.44)	0.08	(0.41)	0.00	(0.02)
Mom	-0.05	(-0.22)	0.12	(1.06)	-0.10	(-0.49)	0.07	(0.70)
Asset Growth	-1.82***	(-8.15)	-0.25***	(-4.83)	**-1.78*****	(-8.28)	-0.21**	(-1.99)
Gross Prof	0.79***	(3.28)	**0.45*****	(5.13)	-0.03	(-0.14)	-0.37***	(-2.69)
Inv to Assets	-1.59***	(-6.02)	-0.37***	(-6.56)	**-1.19*****	(-5.07)	0.04	(0.33)
Net Stock Issues	-1.95***	(-6.24)	-0.37 ***	(-2.53)	**-1.43*****	(-8.27)	0.14	(0.97)
NOA	0.13	(0.47)	-0.22**	(-2.02)	0.38**	(2.01)	0.03	(0.23)
Accruals	-0.42**	(-1.72)	**-0.53** ***	(-5.24)	0.03	(0.14)	-0.09	(-0.72)
O	-1.06***	(-4.00)	**-0.55*****	(-7.13)	-0.34*	(-1.66)	0.17	(1.40)
ROA	0.49**	(1.97)	**0.56** ***	(5.74)	0.32	(1.49)	0.38***	(3.34)
Distress	0.55**	(2.00)	**0.13**	(1.04)	-0.17	(-0.71)	-0.60***	(-4.43)
Comp Eq Issue	-0.23	(-1.15)	**-0.27*****	(-2.59)	0.03	(0.14)	-0.01	(-0.06)

Table 4.6: **Predictability across the Business Cycle and for positive-negative returns.** We consider the monthly out-of-sample windows 1986:1-2017:12 and 1986:1-2016:12 for univariate OLS forecasts based on the Welch and Goyal [2008] predictors and on spread returns ones. The R^2_{OS} is the Campbell and Thompson [2008] out-of-sample R^2 statistic. Statistical significance for the R^2_{OS} statistic is based on the p-value for the Clark and West [2007] out-of-sample MPSE-adjusted statistic. Exp (Rec) considers the returns conditionally on being in an Expansion (Recession) as identified by the NBER. Ret>0 and Ret<0 consider models performance when the results are subsequently positive or negative only. Average is the column mean R^2_{OS} value. For the R^2_{OS} statistic *,** and *** indicate significance level at the 10%, 5% and 1%. **Bold** indicates an R^2_{OS} above 1.00%.

	1986-2017		1986-2017	
Predictor	**Exp**	**Rec**	**Ret>0**	**Ret<0**
DP	-2.40	**2.57****	-21.39	**12.24*****
DY	-3.55	**3.79****	-27.93	**15.57*****
EP	-1.94	0.58	-26.62	**15.67*****
DE	-0.16	-1.94	**2.79****	-2.79
SVAR	0.02	**1.76**	-0.61	**1.06***
BM	-3.80	**3.33***	-28.04	**15.16*****
NTIS	0.17	-8.96	**11.10*****	-10.48
TBL	0.02	-1.07	0.01	-0.35
LTY	0.01	-0.30	-1.97	**1.23*****
LTR	-0.61	0.80	**1.96*****	-1.85
TMS	-0.69	-1.36	**6.12*****	-5.54
DFY	-0.13	-0.49	-1.19	0.46
DFR	0.39	-0.58	-1.66	**1.43**
INF_lag	0.10	-2.00	0.10	-0.65
Average	**-0.90**	**-0.28**	**-6.24**	**2.94**

	1986-2016		1986-2016	
Predictor	**Exp**	**Rec**	**Ret>0**	**Ret<0**
SMB	-0.90	**1.06**	-1.44	0.18
HML	-0.06	-0.51	**1.78****	-1.53
RMW	-1.39	**3.55*****	-1.22	0.24
CMA	-1.60	**7.53*****	**1.24****	-0.37
LT	0.05	-1.92	0.62	-1.05
ST	-0.69	-0.98	-0.88	-0.65
Mom	-0.24 9	-2.75	-0.41	-1.01
Asset Growth	**7.77*****	**35.72*****	**5.11*****	**19.63*****
Gross Prof	-1.20	**4.10***	-2.97	**1.96****
Inv to Assets	**4.68*****	**36.72*****	**4.95*****	**15.90*****
Net Stock Issues	**20.46*****	**35.24*****	**21.50*****	**24.98*****
NOA	-4.06	**2.61**	-4.49	-1.38
Accruals	-0.91	-3.96	-3.93	0.16
O	**8.22*****	-0.60	**10.06*****	**3.76****
ROA	-1.04	-12.10	-2.11	-4.22
Distress	0.12	**2.27**	**1.10**	0.19
Comp Eq Issue	-0.61	0.43	0.03	-0.70
Average	**1.68**	**6.26**	**1.70**	**3.30**

Table 4.7: **Contemporaneous Pooled Regression Analysis of the R^2_{OS} metrics**. The table reports pooled OLS estimates for the predictive regression model,

$R^2_{OS,i,t} = \alpha_i + \sum_{k=1}^{5} \beta_{i,k} F\&F_{k,t} + \sum_{s=1} \beta_{i,s} Exp_{s,t} + \epsilon_{i,t} \quad i = 1, ..., N$ where $R^2_{OS,i,t}$ is the monthly R^2_{OS} of predictor-model i, $F\&F_k$ is the monthly return of one of the 5 factors introduced by Fama and French [2015], and Exp_s is one of the following explanatory factors: Greed is the level of the Huang et al. [2015] sentiment index, Fear is the level of the Andersen and Bondarenko [2007] downside volatility risk premium, UNC is the level of the Jurado et al. [2015] financial uncertainty measure, while the other factors comes from the interaction of the Greed or Fear measure and one of the 5 Fama and French factor monthly returns. Finally, ret Greed, ret Fear, and ret UNC are the returns of the indexes previously introduced. In brackets we report the heteroskedasticity and autocorrelation robust p-values of the betas.***, ** and * indicate significance at the 10%, 5%, and 1% levels, respectively. **Bold** indicates a p-value under 10%

Pooled Betas	Predictors		Models		Predictors		Models		Predictors		Models		Predictors		Models		Predictors		Models	
Alpha	**0.03*****	(0.00)	**0.05*****	(0.01)	-0.02	(0.13)	-0.02	(0.46)	-0.11	(0.20)	-0.13	(0.45)	0.00	(0.69)	0.00	(0.94)	-0.02	(0.18)	-0.02	(0.46)
Mkt-RF	**-2.49*****	(0.00)	**-3.80*****	(0.00)	**-1.36*****	(0.00)	**-1.43****	(0.02)	**-1.36*****	(0.00)	**-1.43****	(0.02)	**-1.66*****	(0.00)	**-1.33****	(0.03)	0.25	(0.57)	0.46	(0.58)
SMB	**-1.14*****	(0.00)	**-1.15***	(0.07)	**-0.97****	(0.02)	**-1.58****	(0.05)	**-0.96****	(0.02)	**-1.58****	(0.05)	**-0.86****	(0.05)	-0.95	(0.25)	-0.30	(0.57)	0.02	(0.98)
HML	0.15	(0.72)	-3.09***	(0.00)	0.49	(0.34)	-3.87***	(0.00)	0.59	(0.26)	-3.76***	(0.00)	0.32	(0.59)	-2.79***	(0.01)	-0.68	(0.28)	**-5.27*****	(0.00)
RMW	0.35	(0.43)	-1.32	(0.11)	0.01	(0.98)	-1.71	(0.13)	-0.01	(0.99)	-1.73	(0.12)	0.20	(0.76)	**-2.30***	(0.06)	**1.92*****	(0.01)	0.17	(0.91)
CMA	**1.13***	(0.07)	**5.97*****	(0.00)	**2.49*****	(0.00)	**9.39*****	(0.00)	**2.40*****	(0.00)	**9.29*****	(0.00)	**2.50*****	(0.00)	**8.16*****	(0.00)	0.21	(0.82)	**7.19*****	(0.00)
Greed					**0.14*****	(0.00)	**0.34*****	(0.00)	0.09	(0.31)	0.11	(0.53)								
Fear					**2.32*****	(0.01)	2.28	(0.18)	**0.11****	(0.03)	**0.31*****	(0.00)								
UNC									**2.09****	(0.02)	2.02	(0.25)								
(Mkt-RF)*Greed													-1.94	(0.13)	**-12.30*****	(0.00)				
SMB*Greed													0.21	(0.85)	**-4.44****	(0.04)				
HML*Greed													1.88	(0.31)	-2.20	(0.54)				
RMW*Greed													**-3.61***	(0.08)	-5.10	(0.20)				
CMA*Greed													1.21	(0.66)	2.31	(0.66)				
(Mkt-RF)*Fear																	**-100.75*****	(0.00)	**-109.06*****	(0.01)
SMB*Fear																	-18.33	(0.56)	-61.91	(0.31)
HML*Fear																	**119.19*****	(0.00)	**153.85****	(0.03)
RMW*Fear																	-69.99	(0.19)	36.60	(0.72)
CMA*Fear																	**147.13*****	(0.01)	147.87	(0.15)

Pooled Betas	Predictors		Models		Predictors		Models		Predictors		Models		Predictors		Models		Predictors		Models	
Alpha	**0.03*****	(0.00)	**0.05*****	(0.01)	0.01	(0.50)	0.02	(0.44)	0.00	(0.84)	0.00	(0.84)	0.01	(0.37)	0.02	(0.44)	0.00	(0.99)	0.01	(0.54)
Mkt-RF	**-2.49*****	(0.00)	**-3.80*****	(0.00)	**-1.66*****	(0.00)	**-1.88*****	(0.00)	**-1.22*****	(0.00)	-0.87	(0.18)	**-1.87*****	(0.00)	**-2.10*****	(0.00)	**-1.52*****	(0.00)	**-1.74*****	(0.00)
SMB	**-1.14*****	(0.00)	**-1.15***	(0.07)	**-0.83****	(0.04)	-0.93	(0.24)	**-0.80****	(0.05)	-0.87	(0.27)	-0.53	(0.21)	-0.67	(0.40)	**-1.24*****	(0.00)	-1.26	(0.11)
HML	0.15	(0.72)	**-3.09*****	(0.00)	0.32	(0.54)	**-4.28*****	(0.00)	0.30	(0.57)	**-4.32*****	(0.00)	0.25	(0.64)	**-4.26*****	(0.00)	-0.25	(0.64)	**-4.98*****	(0.00)
RMW	0.35	(0.43)	-1.32	(0.11)	0.19	(0.73)	-0.88	(0.41)	0.28	(0.62)	-0.68	(0.53)	-0.30	(0.62)	-1.42	(0.21)	-0.14	(0.81)	-1.03	(0.34)
CMA	**1.13***	(0.07)	**5.97*****	(0.00)	**2.93*****	(0.00)	**10.38*****	(0.00)	**3.24*****	(0.00)	**11.10*****	(0.00)	**2.94*****	(0.00)	**10.21*****	(0.00)	**2.22*****	(0.00)	**9.97*****	(0.00)
ret Greed					0.00	(0.53)	0.00	(0.37)	**1.96*****	(0.00)	**4.53*****	(0.00)								
ret Fear					0.00	(0.73)	0.00	(0.31)	0.00	(0.64)	0.00	(0.48)								
ret UNC									0.00	(0.96)	0.00	(0.60)								
(Mkt-RF)*ret Greed													0.04	(0.85)	-0.27	(0.56)				
SMB*ret Greed													-0.40	(0.26)	-0.57	(0.41)				
HML*ret Greed													0.20	(0.26)	0.45	(0.18)				
RMW*ret Greed													-0.08	(0.82)	-0.43	(0.51)				
CMA* ret Greed													-0.11	(0.85)	-0.12	(0.91)				
(Mkt-RF)* ret Fear																	**-0.22*****	(0.01)	**-0.13*****	(0.39)
SMB*ret Fear																	**0.18*****	(0.01)	-0.09	(0.52)
HML*ret Fear																	**0.33****	(0.05)	**0.78****	(0.02)
RMW*ret Fear																	-0.16	(0.49)	-0.11	(0.81)
CMA*ret Fear																	**2.76*****	(0.00)	**1.60*****	(0.02)

Table 4.8: **Predictive Pooled Regression Analysis of the R^2_{OS} metrics**. The table reports pooled OLS estimates for the predictive regression model,
$R^2_{OS,i,t+1} = \alpha_i + \sum_{k=1}^{5} \beta_{i,k} F\&F_{k,t} + \sum_{s=1} \beta_{i,s} Exp_{s,t} + \epsilon_{i,t+1} \quad i = 1, ..., N$
where $R^2_{OS,i,t}$ is the monthly R^2_{OS} of predictor-model i, $F\&F_k$ is the monthly return of one of the 5 factors introduced by Fama and French [2015], and Exp_s is one of the following explanatory factors: Greed is the level of the Huang et al. [2015] sentiment index, Fear is the level of the Andersen and Bondarenko [2007] downside volatility risk premium, UNC is the level of the Jurado et al. [2015] financial uncertainty measure, while the other factors comes from the interaction of the Greed or Fear measure and one of the 5 Fama and French factor monthly returns. Finally, ret Greed, ret Fear, and ret UNC are the returns of the indexes previously introduced. In brackets we report the heteroskedasticity and autocorrelation robust p-values of the betas.***, ** and * indicate significance at the 10%, 5%, and 1% levels, respectively. **Bold** indicates a p-value under 10%

pooled Betas	Predictors		Models		Predictors		Models		Predictors		Models		Predictors		Models		Predictors		Models	
Alpha	**-1.19*****	(0.00)	**-1.90*****	(0.00)	-0.56	(0.10)	-0.94	(0.14)	-0.55	(0.10)	-0.94	(0.14)	**-0.80*****	(0.01)	**-1.39****	(0.02)	**-1.53*****	(0.00)	**-3.34*****	(0.00)
Mkt-RF	-0.26	(0.44)	-0.52	(0.42)	0.08	(0.86)	-0.08	(0.92)	0.08	(0.86)	-0.08	(0.92)	-0.46	(0.30)	-1.35	(0.11)	0.76	(0.16)	0.10	(0.92)
SMB	0.41	(0.35)	-0.97	(0.24)	**1.04****	(0.05)	0.05	(0.96)	**1.13****	(0.04)	0.10	(0.92)	0.88	(0.13)	0.52	(0.64)	**1.16***	(0.07)	0.66	(0.59)
HML	-0.16	(0.72)	**2.55*****	(0.00)	0.09	(0.87)	**2.83*****	(0.01)	0.08	(0.89)	**2.82*****	(0.01)	-0.28	(0.67)	1.26	(0.31)	-1.09	(0.17)	-0.57	(0.71)
RMW	-0.56	(0.38)	1.39	(0.25)	**-1.74****	(0.02)	-0.10	(0.94)	**-1.82*****	(0.01)	-0.14	(0.92)	**-2.23*****	(0.01)	-2.42	(0.12)	-0.08	(0.93)	**3.40***	(0.06)
CMA	**0.03*****	(0.00)	**0.03***	(0.10)	**0.19*****	(0.00)	**0.30*****	(0.00)	0.08	(0.38)	0.05	(0.79)	**-2.18***	(0.09)	**-5.59****	(0.02)	**44.63****	(0.05)	**106.38*****	(0.01)
Greed					**2.16****	(0.02)	**4.79*****	(0.01)	**0.17*****	(0.00)	**0.29*****	(0.00)								
Fear					-0.02	(0.22)	-0.05	(0.11)	**1.97****	(0.03)	**4.69*****	(0.01)								
UNC									-0.10	(0.27)	-0.09	(0.58)								
(Mkt-RF)*Greed													**6.02*****	(0.00)	**9.26*****	(0.00)				
SMB*Greed													1.67	(0.37)	-0.93	(0.80)				
HML*Greed													-0.34	(0.87)	-1.86	(0.64)				
RMW*Greed													1.14	(0.68)	**9.73***	(0.06)				
CMA*Greed													0.00	(0.97)	-0.01	(0.77)				
(Mkt-RF)*Fear																	-46.95	(0.15)	-9.61	(0.88)
SMB*Fear																	0.68	(0.99)	-34.43	(0.62)
HML*Fear																	**152.05*****	(0.01)	**336.83*****	(0.00)
RMW*Fear																	**-108.84****	(0.05)	**-237.64****	(0.02)
CMA*Fear																	0.01	(0.24)	0.03	(0.18)

Pooled Betas	Predictors		Models		Predictors		Models		Predictors		Models		Predictors		Models		Predictors		Models	
Alpha	**-1.19*****	(0.00)	**-1.90*****	(0.00)	**-0.99*****	(0.00)	**-1.72*****	(0.01)	-0.38	(0.27)	-0.98	(0.14)	**-0.86*****	(0.01)	**-2.28*****	(0.00)	**-0.79****	(0.02)	**-1.83****	(0.00)
Mkt-RF	-0.26	(0.44)	-0.52	(0.42)	0.57	(0.17)	0.55	(0.49)	0.63	(0.13)	0.62	(0.44)	0.37	(0.38)	1.29	(0.11)	0.25	(0.56)	0.40	(0.62)
SMB	0.41	(0.35)	-0.97	(0.24)	**0.96***	(0.07)	-0.05	(0.96)	**0.96***	(0.07)	-0.05	(0.96)	**1.01***	(0.06)	-0.59	(0.57)	0.42	(0.44)	-1.15	(0.27)
HML	-0.16	(0.72)	**2.55*****	(0.00)	0.54	(0.34)	**3.35*****	(0.00)	0.66	(0.24)	**3.50*****	(0.00)	0.62	(0.30)	1.49	(0.19)	0.50	(0.38)	**3.58*****	(0.00)
RMW	-0.56	(0.38)	1.39	(0.25)	**-1.52****	(0.04)	0.25	(0.86)	-1.09	(0.15)	0.78	(0.58)	**-1.52****	(0.04)	0.93	(0.51)	**-1.50****	(0.04)	0.54	(0.71)
CMA	**0.03*****	(0.00)	**0.03***	(0.10)	0.00	(0.90)	0.00	(0.68)	**2.70*****	(0.00)	**3.31*****	(0.00)	-0.15	(0.55)	-0.32	(0.49)	-0.02	(0.81)	0.03	(0.85)
ret Greed					**-0.01****	(0.05)	0.00	(0.30)	0.00	(0.73)	0.00	(0.58)								
ret Fear					0.01	(0.27)	0.02	(0.45)	0.00	(0.15)	0.00	(0.48)								
ret UNC									0.01	(0.63)	0.01	(0.72)								
(Mkt-RF)*ret Greed													0.07	(0.85)	-0.49	(0.49)				
SMB*ret Greed													0.06	(0.74)	**0.83*****	(0.01)				
HML*ret Greed													-0.12	(0.73)	0.60	(0.36)				
RMW*ret Greed													0.11	(0.85)	-0.87	(0.44)				
CMA* ret Greed													0.01	(0.43)	0.03	(0.19)				
(Mkt-RF)* ret Fear																	**-0.14****	(0.05)	**-0.34****	(0.02)
SMB*ret Fear																	**0.50*****	(0.00)	**1.45*****	(0.00)
HML*ret Fear																	0.29	(0.20)	-0.36	(0.42)
RMW*ret Fear																	0.55	(0.13)	-0.53	(0.44)
CMA*ret Fear																	0.01	(0.50)	0.02	(0.32)

Table 4.9: **Fundamental and Behavioural Adaptive Elastic Net variable selection in percentage for $R^2_{OS,t}$ and $R^2_{OS,t+1}$ returns time series.** The table reports how often a variable is selected (in percentage) by the Adaptive Elastic Net. In the left panel (Time t) results comes from Adaptive Elastic Nets which employ $R^2_{OS,t}$ as a dependent variable while for the right panel (Time t+1) results comes from Adaptive Elastic Nets which employ $R^2_{OS,t+1}$ as a dependent variable. The regressors include 5 macroeconomic (Income, Industrial Production, Labor, House and Inflation) and 4 financial (Fixed Income, Forex, Commodities, Industries) principal components extrapolated from a rich panel of time series plus the indexes of Greed (Huang et al. [2015]), Fear (Andersen and Bondarenko [2007]) and Uncertainty (Jurado et al. [2015]). All the details about the fundamental and behavioural variables considered are detailed in Section 3 and in the appendix. The columns with the label Level employ the level of the chosen variables while the columns with the label Return make use of the returns of the same variables. Observations are monthly and span the period 1986:01-2016:12.

Time t	Level	Return	Level	Return	Level	Return	Level	Return	Level	Return
Income	0.59	0.35	0.59	0.15	0.35	0.07	0.43	0.22	0.61	0.13
Industrial Production	0.52	0.13	0.50	0.00	0.43	0.00	0.26	0.00	0.37	0.00
Labor	0.59	0.09	0.57	0.02	0.52	0.00	0.37	0.00	0.61	0.02
House	0.43	0.13	0.39	0.07	0.26	0.07	0.13	0.04	0.41	0.13
Inflation	0.72	0.65	0.70	0.37	0.43	0.22	0.50	0.15	0.70	0.13
Greed			0.65	0.00	0.61	0.00	0.50	0.02	0.61	0.00
Fear			0.61	0.35	0.39	0.11	0.39	0.17	0.57	0.35
UNC			0.33	0.67	0.35	0.59	0.24	0.50	0.33	0.54
Fixed Income					0.26	0.09				
Forex					0.37	0.11				
Commodities					0.54	0.33				
Industries					0.61	0.46				
Income*ret Greed							0.11	0.11		
Industrial Production*ret Greed							0.09	0.00		
Labor*ret Greed							0.00	0.04		
House*ret Greed							0.09	0.04		
Inflation*ret Greed							0.07	0.00		
Income*ret Fera							0.24	0.15		
Industrial Production*ret Fear							0.33	0.11		
Labor*ret Fear							0.39	0.04		
House*ret Fear							0.28	0.17		
Inflation*ret Fear							0.20	0.11		
Income*ret UNC									0.52	0.37
Industrial Production*ret UNC									0.50	0.07
Labor*ret UNC									0.54	0.07
House*ret UNC									0.48	0.22
Inflation*ret UNC									0.48	0.57

Time t+1	Level	Return	Level	Return	Level	Return	Level	Return	Level	Return
Income	0.50	0.24	0.41	0.11	0.41	0.17	0.37	0.15	0.22	0.11
Industrial Production	0.54	0.07	0.46	0.00	0.48	0.02	0.39	0.04	0.22	0.00
Labor	0.48	0.33	0.43	0.20	0.52	0.09	0.30	0.07	0.48	0.07
House	0.39	0.11	0.30	0.04	0.26	0.02	0.15	0.02	0.20	0.04
Inflation	0.39	0.11	0.28	0.00	0.37	0.04	0.22	0.02	0.17	0.15
Greed			0.63	0.02	0.63	0.00	0.43	0.02	0.61	0.00
Fear			0.70	0.15	0.72	0.24	0.46	0.11	0.67	0.09
UNC			0.50	0.63	0.46	0.57	0.43	0.46	0.54	0.46
Fixed Income					0.37	0.00				
Forex					0.30	0.00				
Commodities					0.28	0.11				
Industries					0.41	0.24				
Income*ret Greed							0.24	0.13		
Industrial Production*ret Greed							0.15	0.00		
Labor*ret Greed							0.30	0.15		
House*ret Greed							0.26	0.00		
Inflation*ret Greed							0.20	0.09		
Income*ret Fera							0.13	0.02		
Industrial Production*ret Fear							0.37	0.07		
Labor*ret Fear							0.37	0.63		
House*ret Fear							0.30	0.04		
Inflation*ret Fear							0.15	0.00		
Income*ret UNC									0.43	0.37
Industrial Production*ret UNC									0.57	0.07
Labor*ret UNC									0.46	0.09
House*ret UNC									0.39	0.11
Inflation*ret UNC									0.28	0.46

Table 4.10: **Adaptive Elastic Net model selection for the contemporaneous aggregate R^2_{OS}.** The table reports adaptive elastic net net estimates of β coming from the by the Adaptive Elastic Net. In the upper panel (Time t) results comes from the contemporaneous regression model: $R^2_{OS,i,t} = \beta_{i,0} + \sum_{j=1} \beta_{i,j} X_t + \epsilon_{i,t}$. The regressors include 5 macroeconomic (Income, Industrial Production, Labor, House and Inflation) and 4 financial (Fixed Income, Forex, Commodities, Industries) first principal components extrapolated from a rich panel of time series plus the indexes of Greed (Huang et al. [2015]), Fear (Andersen and Bondarenko [2007]) and Uncertainty (Jurado et al. [2015]). All the details about the fundamental and behavioural variables considered are detailed in Section 3 and in the on-line appendix. The columns with the label Level employ the level of the chosen variables while the columns with the label Return make use of the returns of the same variables. Observations are monthly and span the period 1986:01-2016:12. Bias-corrected wild bootstrapped 90% confidence intervals are reported in brackets. Bold indicates significance at the 10% level.

Time t	**Level**		**Return**		**Level**		**Return**		**Level**		**Return**		**Level**		**Return**		**Level**		**Return**	
Greed	**3.5**	[1.54, 5.53]	0	0	**1.07**	[0.89, 2.57]	0	0	**2.49**	[0.84, 4.72]	0	0	**2.18**	[1.51, 4.40]	0	0	**2.03**	[1.71, 4.25]	0	0
Fear	**79.85**	[-20.44, 180.84]	0	0	**26.74**	[-9.92, 88.70]	0	0	**60.68**	[-22.89, 153.16]	0	0	**61.52**	[-9.43, 167.90]	0	0	**60.51**	[-2.64, 169.11]	0	0
UNC	**3.91**	[-2.31,10.05]	**41.48**	[3.50,88.43]	**1.48**	[-0.05, 4.22]	**37.40**	[4.13,85.22]	**3.21**	[-1.43,8.93]	**28.71**	[7.71,70.22]	**2.05**	[-0.47,5.98]	**36.65**	[5.62,84.88]	**1.53**	[-0.77, 4.40]	**39.26**	[6.66,87.28]
Income	**0.38**	[0.09, 0.69]	0	0	**0.10**	[0.05, 0.26]	0	0	**0.49**	[0.20, 0.95]	0	0	**0.25**	[0.13, 0.57]	0	0	**0.22**	[0.11, 0.53]	0	0
Industrial Production	**0.29**	[-0.04, 0.63]	0	0	**0.13**	[0.03, 0.39]	0	0	**0.10**	[-0.06, 0.26]	0	0	**0.21**	[0.02, 0.54]	0	0	**0.16**	[0.02, 0.40]	0	0
Labor	**0.29**	[0.04, 0.55]	0	0	**0.04**	[0.02, 0.14]	0	0	**0.27**	[0.07, 0.64]	0	0	**0.11**	[0.07, 0.31]	0	0	**0.04**	[0.01, 0.15]	0	0
House	**0.16**	[0.00, 0.34]	0	0	**0.05**	[0.03, 0.12]	0	0	**0.20**	[0.06, 0.43]	0	0	**0.10**	[0.05,0.25]	0	0	**0.08**	[0.05, 0.22]	0	0
Inflation	**0.42**	[0.08, 0.77]	0	0	**0.10**	[0.07, 0.21]	0	0	**0.25**	[0.12 ,0.41]	0	0	**0.30**	[0.17, 0.63]	0	0	**0.22**	[0.14, 0.49]	0	0
Fixed Income					0	0	0	0												
Forex					**0.04**	[-0.03, 0.12]	0	0												
Commodities					**0.11**	[0.00, 0.31]	0	0												
Industries					**-0.10**	[-0.25,-0.04]	0	0												
Income*ret UNC									**16.00**	[7.44, 30.30]	**-0.33**	[-0.94, -0.27]								
Industrial Production*ret UNC									**11.56**	[-2.72, 27.96]	0	0								
Labor*ret UNC									**-1.90**	[-9.15, 6.71]	**0.01**	[-0.93, 0.93]								
House*ret UNC									**6.60**	[2.64, 14.89]	**-2.81**	[-9.49, 1.59]								
Inflation*ret UNC									0	0	**1.32**	[-0.39, 4.01]								
Income*ret Greed													**0.026**	[0.034, 0.063]	0	0				
Industrial Production*ret Greed													0	0	0	0				
Labor*ret Greed													**-0.004**	[-0.010, -0.005]	0	0				
House*ret Greed													0	0	0	0				
Inflation*ret Greed													**0.001**	[-0.004, 0.004]	0	0				
Income*ret Fear																	0	0	0	0
Industrial Production*ret Fear																	**0.11**	[-0.01, 0.32]	0	0
Labor*ret Fear																	0	0	0	0
House*ret Fear																	0	0	**-0.07**	[-0.16, -0.08]
Inflation*ret Fear																	**0.01**	[-0.01, 0.05]	0	0

Table 4.11: **Adaptive Elastic Net model selection for the predictive aggregate R^2_{OS}.** The table reports adaptive elastic net net estimates of β coming from the by the Adaptive Elastic Net. Results comes from the predictive regression model: $R^2_{OS,i,t+1} = \beta_{i,0} + \sum_{j=1} \beta_{i,j} X_t + \epsilon_{i,t+1}$. The regressors include 5 macroeconomic (Income, Industrial Production, Labor, House and Inflation) and 4 financial (Fixed Income, Forex, Commodities, Industries) first principal components extrapolated from a rich panel of time series plus the indexes of Greed (Huang et al. [2015]), Fear (Andersen and Bondarenko [2007]) and Uncertainty (Jurado et al. [2015]). All the details about the fundamental and behavioural variables considered are detailed in Section 3 and in the appendix. The columns with the label Level employ the level of the chosen variables while the columns with the label Return make use of the returns of the same variables. Observations are monthly and span the period 1986:01-2016:12. Bias-corrected wild bootstrapped 90% confidence intervals are reported in brackets. Bold indicates significance at the 10% level.

Time t+1	Level		Return		Level		Return		Level		Return		Level		Return		Level		Return	
Greed	**0.85**	[-0.27, 2.61]	0	0	**0.73**	[-0.38, 2.33]	0	0	**0.82**	[-0.89, 2.95]	0	0	**0.81**	[-0.10, 2.38]	0	0	**1.06**	[-1.00, 3.52]	0	0
Fear	**23.94**	[16.46, 59.09]	0	0	**16.24**	[7.44, 41.48]	0	0	**22.78**	[13.82, 51.74]	0	0	**16.18**	[11.63, 43.43]	0	0	**37.07**	[17.13, 78.90]	0	0
UNC	**0.76**	[-1.06, 2.96]	**32.98**	[-3.83, 80.41]	**0.70**	[-0.81, 2.60]	**3.06**	[0.73, 10.77]	**1.04**	[-1.50, 3.78]	**9.22**	[0.79, 31.13]	**1.13**	[-0.66, 3.67]	**24.49**	[-3.40, 68.92]	**0.96**	[-2.38, 4.50]	**22.54**	[-0.71, 64.49]
Income	**0.03**	[-0.05, 0.14]	0	0	**0.01**	[-0.06, 0.08]	0	0	**0.06**	[-0.07, 0.25]	0	0	**0.05**	[-0.03, 0.21]	0	0	**0.01**	[-0.13, 0.14]	0	0
Industrial Production	**-0.27**	[-0.63,-0.08]	0	0	**-0.28**	[-0.64, -0.09]	0	0.00	**-0.09**	[-0.20, -0.03]	0	0	**-0.17**	[-0.47, -0.08]	0	0	**-0.33**	[-0.70, -0.04]	0	0
Labor	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
House	**0.07**	[0.03, 0.19]	0	0	**0.06**	[0.03, 0.17]	0	0	**0.14**	[0.03, 0.36]	0	0	**0.06**	[0.03, 0.17]	0	0	**0.08**	[-0.02, 0.22]	0	0
Inflation	**-0.02**	[-0.09, 0.00]	0	0	**-0.07**	[-0.20, -0.04]	0	0	0	0	0	0	**-0.04**	[-0.14,-0.01]	0	0	0	0	0	0
Fixed Income					-0.02	[-0.07, 0.00]	0	0												
Forex					0	0	0	0												
Commodities					0	0	0	0												
Industries					**-0.07**	[-0.17,-0.04]	**-0.01**	[-0.05, 0.01]												
Income*ret UNC									**12.69**	[6.42, 23.95]	**0.27**	[0.02, 1.00]								
Industrial Production*ret UNC									**-9.61**	[-15.36,-6.01]	0	0								
Labor*ret UNC									**-4.60**	[-10.62, -0.64]	0	0								
House*ret UNC									**7.36**	[-0.98, 21.30]	0	0								
Inflation*ret UNC									**-2.49**	[-9.07, 0.54]	0	0								
Income*ret Greed													0	0	0	0				
Industrial Production*ret Greed													0	0	0	0				
Labor*ret Greed													**-0.013**	[-0.037, -0.008]	0	0				
House*ret Greed													**0.002**	[-0.009,0.012]	0	0				
Inflation*ret Greed													0	0	0	0				
Income*ret Fear																	0	0	0	0
Industrial Production*ret Fear																	**-0.09**	[-0.20, -0.04]	0	0
Labor*ret Fear																	**0.03**	[0.02, 0.05]	0	0
House*ret Fear																	**0.03**	[0.02, 0.06]	0	0
Inflation*ret Fear																	0	0	0	0

Table 4.12: **VAR of the R^2_{OS} and the Behavioural and Fundamental variables returns.** t-statistics appear in parentheses below the coefficient estimate. The VAR system includes 5 macroeconomic (Income, Industrial Production, Labor, House and Inflation) first principal components extrapolated from a rich panel of time series plus the indexes of Greed (Huang et al. [2015]), Fear (Andersen and Bondarenko [2007]) and Uncertainty (Jurado et al. [2015]). All the details about the fundamental and behavioural variables considered are detailed in Section 3 and in the appendix. The estimates are based on monthly returns for the period 1996:01-2016:12. In brackets we report the heteroskedasticity and autocorrelation robust p-values of the betas.***, ** and * indicate significance at the 10%, 5%, and 1% levels, respectively. **Bold** indicates a p-value under 5%

Dependent Variable	**Const** (t-stat)	**(1)** (t-stat)	**(2)** (t-stat)	**(3)** (t-stat)	**(4)** (t-stat)	**(5)** (t-stat)	**(6)** (t-stat)	**(7)** (t-stat)	**(8)** (t-stat)	**(9)** (t-stat)
R^2_{OS} **(1)**	0.03	-0.42	-2.05	-0.72	**4.06****	0.15	-0.11	-0.50	0.27	7.54
	(0.93)	(-0.64)	(-0.37)	(-0.12)	(3.10)	(0.48)	(-0.31)	(-0.62)	(0.17)	(0.43)
Greed (2)	0.36	-0.36	-1.07	-11.77	-0.16	0.24	-1.90	-0.64	-2.09	2.03
	(1.06)	(-0.05)	(-0.02)	(-0.17)	(-0.01)	(0.07)	(-0.46)	(-0.07)	(-0.11)	(0.01)
Fear (3)	0.06*	0.85	-0.21	-3.33*	-2.44	0.08	0.15	-0.17	0.05	-1.75
	(1.92)	(1.17)	(-0.04)	(-0.51)	(-1.68)	(0.23)	(0.39)	(-0.20)	(0.03)	(-0.09)
UNC (4)	0.00	**-1.56*****	0.16	1.69	**7.35*****	0.05	0.11	0.16	0.02	-3.94
	(0.27)	(-6.85)	(0.09)	(0.82)	(16.06)	(0.43)	(0.92)	(0.58)	(0.03)	(-0.64)
Income (5)	-0.06	-0.12	0.55	0.48	1.44	-0.05	0.00	0.16	0.19	-3.14
	(-1.00)	(-0.09)	(0.05)	(0.04)	(0.52)	(-0.07)	(0.00)	(0.10)	(0.06)	(-0.08)
Industrial Production (6)	**0.12****	-0.75	0.54	4.21	1.88	0.16	-0.64	-0.15	0.00	-8.29
	(2.18)	(-0.63)	(0.05)	(0.39)	(0.79)	(0.29)	(-0.99)	(-0.10)	(0.00)	(-0.26)
Labor (7)	0.25	-0.27	-1.71	-11.57	-9.75	0.20	0.01	-0.67	0.09	-0.50
	(1.08)	(-0.05)	(-0.04)	(-0.24)	(-0.92)	(0.08)	(0.00)	(-0.10)	(0.01)	(0.00)
House (8)	-0.05	4.26	-0.04	-10.68	-13.10*	0.06	-0.08	-0.10	-6.44	-18.37
	(-0.28)	(1.07)	(0.00)	(-0.29)	(-1.63)	(0.03)	(-0.04)	(-0.02)	(-0.68)	(-0.17)
Inflation (9)	-0.10	0.37	1.71	4.98	-2.84	-0.04	0.67	0.10	-1.11	-13.23
	(-0.90)	(0.15)	(0.08)	(0.23)	(-0.58)	(-0.04)	(0.50)	(0.04)	(-0.19)	(-0.20)

Table 4.13: **VAR of the R^2_{OS} and the Behavioural and Fundamental variables levels.** t-statistics appear in parentheses below the coefficient estimate. The VAR system includes 5 macroeconomic (Income, Industrial Production, Labor, House and Inflation) first principal components extrapolated from a rich panel of time series plus the indexes of Greed (Huang et al. [2015]), Fear (Andersen and Bondarenko [2007]) and Uncertainty (Jurado et al. [2015]). All the details about the fundamental and behavioural variables considered are detailed in Section 3 and in the appendix. The estimates are based on monthly returns for the period 1996:01-2016:12. In brackets we report the heteroskedasticity and autocorrelation robust p-values of the betas.***, ** and * indicate significance at the 10%, 5%, and 1% levels, respectively. **Bold** indicates a p-value under 5%

Dependent Variable	**Const** (t-stat)	**(1)** (t-stat)	**(2)** (t-stat)	**(3)** (t-stat)	**(4)** (t-stat)	**(5)** (t-stat)	**(6)** (t-stat)	**(7)** (t-stat)	**(8)** (t-stat)	**(9)** (t-stat)
R^2_{OS} **(1)**	-2.84	-3.17	1.82	**48.1****	2.57	0.22	**-0.43*****	0.16	0.17*	-0.11
	(-1.11)	(-0.46)	(1.41)	(1.98)	(0.94)	(1.16)	(-3.13)	(1.06)	(1.63)	(-0.73)
Greed (2)	**-6.8****	-5.01	**99.7*****	-32.7	**7.64****	0.22	**-0.29****	**0.72*****	0.05	-0.22
	(-2.99)	(-0.82)	(86.20)	(-1.51)	(3.14)	(1.27)	(-2.39)	(5.38)	(0.57)	(-1.54)
Fear (3)	**-1.28****	3.27*	**-1.14*****	**20.7*****	**2.27*****	-0.03	-0.02	-0.07*	-0.03	**-0.29*****
	(-1.98)	(1.88)	(-3.45)	(3.35)	(3.27)	(-0.70)	(-0.48)	(-1.74)	(-1.19)	(-7.38)
UNC (4)	-0.24	-6.76*	0.28	-7.06	**100*****	0.15	**-0.2****	**0.2****	0.05	-0.09
	(-0.18)	(-1.87)	(0.41)	(-0.55)	(69.78)	(1.46)	(-2.78)	(2.54)	(0.83)	(-1.05)
Income (5)	9.42	-2.48	6.72	68.5	-10.7	-1.2*	**-1.31****	-0.69	**-1.9*****	**1.55****
	(1.00)	(-0.10)	(1.40)	(0.76)	(-1.06)	(-1.68)	(-2.57)	(-1.25)	(-4.81)	(2.68)
Industrial Production (6)	14.5	-53.7	-9.38	**417*****	-19.3	-1.08	-0.92	1.31*	0.45	-1.32*
	(1.16)	(-1.59)	(-1.47)	(3.49)	(-1.44)	(-1.14)	(-1.36)	(1.78)	(0.85)	(-1.72)
Labor (7)	**20.9****	-21.3	**-10.7****	43.9	**-21.8****	-0.6	0.07	**6.93*****	0.04	**-1.33*****
	(2.84)	(-1.08)	(-2.86)	(0.63)	(-2.77)	(-1.08)	(0.17)	(16.07)	(0.11)	(-2.96)
House (8)	0.31	11.3	-0.43	-49.1*	0.17	**-0.42****	-0.01	-0.11	**9.73*****	**-0.42****
	(0.11)	(1.51)	(-0.30)	(-1.85)	(0.06)	(-2.02)	(-0.08)	(-0.66)	(83.38)	(-2.49)
Inflation (9)	-10.1	**94.3*****	1.05	153	8.46	**2.46*****	-0.22	-0.35	0.13	**4.54*****
	(-1.00)	(3.48)	(0.21)	(1.59)	(0.78)	(3.23)	(-0.40)	(-0.59)	(0.30)	(7.34)

Table 4.14: **Regression Markov Switching models on Contemporaneous R^2_{OS} returns**. This table reports the results for the following 2 regimes Markov Switching regression:

$R^2_{OS,t} = \beta_{0,S_t} + \sum_{i=1}^{n} \beta_{i,S_t} x_t + \epsilon_t \quad \epsilon_t \sim N(0, \sigma^2_{i,S_t})$.

The intercept, all the coefficients of the independent variables and the variance of the normal errors are assumed to change across regimes. Monthly data span the period 01:1996-12:2016. In brackets we report the p-values of the betas. ***, ** and * indicate significance at the 10%, 5%, and 1% levels, respectively. **Bold** indicates that the betas are statistically significant at the 10%.

Time t	Bull	(p-val)	Bear	(p-val)	Bull	(p-val)	Bear	(p-val)	Bull	(p-val)	Bear	(p-val)	Bull	(p-val)	Bear	(p-val)
Constant	**-2.70*** **	(0.01)	2.19	(0.25)	2.37	(0.77)	-2.37	(0.80)	0.18	(0.30)	-0.18	(0.84)	**-2.01***	(0.06)	0.31	(0.98)
Greed ret	0.01	(0.98)	-0.10	(0.96)					0.00	(0.78)	0.00	(1.00)	0.01	(0.99)	-0.82	(0.97)
Fear ret	-0.10	(0.76)	**1.67*** **	(0.03)					0.02	(0.74)	-0.02	(0.95)	-0.38	(0.54)	2.75	(0.65)
UNC ret	22.46	(0.65)	-45.04	(0.35)					**39.89*** **	(0.00)	-39.89	(0.21)				
Income ret					-0.01	(1.00)	-0.01	(0.99)								
Industrial Production ret					0.03	(0.98)	-0.03	(1.00)								
Labor ret					-0.01	(0.98)	0.01	(0.99)								
House ret					-0.25	(0.93)	0.25	(0.99)								
Inflation ret					0.14	(0.74)	-0.14	(0.79)								
Income ret *UNC ret									-1.25	(0.18)	1.25	(0.75)				
Industrial Production ret *UNC ret									0.84	(0.27)	-0.84	(0.91)				
Labor ret * UNC ret									**1.38*** **	(0.05)	-1.38	(0.91)				
House ret * UNC ret									**-5.46*** **	(0.01)	5.46	(0.92)				
Inflation ret * UNC ret									**2.32*** **	(0.02)	-2.32	(0.21)				
Income ret *Fear ret													0.00	(0.96)	**-6.17***	(0.06)
retIndustrial Production ret *Fear ret													-0.19	(0.43)	**14.26*** **	(0.00)
Labor ret * Fear ret													-0.10	(0.57)	-0.47	(0.92)
House ret * Fear ret													-1.43	(0.33)	0.30	(0.99)
Inflation ret * Fear ret													-0.01	(0.91)	-1.39	(0.19)
Time t	**Bull**	**(p-value)**	**Bear**	**(p-value)**	**Bull**	**(p-value)**	**Bear**	**(p-value)**	**Bull**	**(p-value)**	**Bear**	**(p-value)**	**Bull**	**(p-value)**	**Bear**	**(p-value)**
Constant	**-0.29*** **	(0.00)	0.01	(0.46)	**-2.96*** **	(0.01)	12.85	(0.35)	-2.83	(0.78)	1.81	(0.18)	-0.08	(0.43)	0.02	(0.18)
Greed	-0.03	(0.33)	**-0.01*** **	(0.01)					3.47	(0.35)	0.10	(0.88)	**0.36*** **	(0.03)	0.07	(0.31)
Fear	0.83	(0.11)	**-0.24*** **	(0.02)					78.13	(0.11)	**-77.73*** **	(0.00)	6.51	(0.20)	**-6.28*** **	(0.00)
UNC	**0.27*** **	(0.00)	-0.01	(0.45)					4.99	(0.59)	-1.41	(0.34)				
Income					**-1.43***	(0.08)	9.04	(0.20)								
Industrial Production					-0.33	(0.50)	**10.90*** **	(0.00)								
Labor					**1.35*** **	(0.00)	-6.48	(0.28)								
House					-0.03	(0.94)	4.88	(0.40)								
Inflation					0.97	(0.48)	0.45	(0.95)								
Income*UNC									0.60	(0.28)	**-0.17***	(0.09)				
Industrial Production*UNC									**0.62*** **	(0.04)	0.01	(0.88)				
Labor*UNC									0.42	(0.20)	0.00	(0.99)				
House*UNC									**-1.21*** **	(0.02)	**-0.09***	(0.06)				
Inflation*UNC									0.04	(0.90)	0.12	(0.51)				
Income*Fear													2.16	(0.20)	-0.31	(0.58)
Industrial Production*Fear													**4.26*** **	(0.00)	**-1.10*** **	(0.00)
Labor*Fear													-0.21	(0.89)	**1.13*** **	(0.01)
House*Fear													**1.71***	(0.10)	**-1.02*** **	(0.00)
Inflation*Fear													1.95	(0.27)	-0.49	(0.57)

Table 4.15: **Pairwise Granger Causality based on Threshold Regressions**. In the upper panel we make use of monthly returns for the 5 macroeconomic (Income, Industrial Production, Labor, House and Inflation) and 3 behavioural (Greed, Fear, Uncertainty) variables. All details are in section 3 on data. For each variable we perform the following pairwise Granger causality analysis. All t-statistics are reported in brackets and are estimated following the approach introduced by Newey-West.$r_{i,t+1} = \beta_{i,0} + \beta_{i,j} r_{j,t} + \epsilon_{i,t+1} \quad i \neq j$. The lower panel repeats the same analyses employing the threshold regression approach
$r_{i,t+1} = \beta_{i,0,Bull} + \beta_{i,j,Bull} r_{j,t,Bull} + \epsilon_{i,t+1,Bull} \quad i \neq j \quad if \quad p_{t,Bull} > p_{t,Bear}$
$r_{i,t+1} = \beta_{i,0,Bear} + \beta_{i,j,Bear} r_{j,t,Bear} + \epsilon_{i,t+1,Bear} \quad i \neq j \quad if \quad p_{t,Bull} < p_{t,Bear}$.
where $p_{t,Bull}$ and $p_{t,Bear}$ are the filtered probabilities coming from a regression markov switching models which employs as predictors the 3 behavioural variables. All details are reported in Section 7. For both panels data span the period 01:1996-12:2016.

All Periods	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Greed ret (1)		-0.11	-2.34	2.23	-1.88	-0.54	-2.06	-0.62
(t-stat)		(-0.94)	(-0.20)	(0.98)	(-0.92)	(-0.86)	(-1.03)	(-0.32)
Fear Ret (2)	-0.56		-19.99	**0.68*****	0.15	-0.17	-0.11	-0.30
(t-stat)	(-1.32)		(-0.30)	(3.10)	(0.88)	(-1.25)	(-0.25)	(-0.59)
UNC ret (3)	**0.01*****	0.00		**0.01*****	0.00	0.00	0.00	0.00
(t-stat)	(4.77)	(-0.17)		(6.61)	(1.03)	(1.05)	(0.34)	(-0.43)
Income ret (4)	77.33	-0.03	1962.60		-0.25	14.89	21.66	-25.24
(t-stat)	(1.02)	(-0.03)	(1.01)		(-0.05)	(0.99)	(0.91)	(-0.93)
Ind Prod ret (5)	0.84	0.03*	24.85	**1.70*****		-0.12	0.13	-0.72
(t-stat)	(1.12)	(1.84)	(1.04)	(4.73)		(-0.42)	(0.27)	(-1.27)
Labor ret (6)	-3.19	-0.09	-135.40	1.93	0.01		0.01	-1.01
(t-stat)	(-1.21)	(-0.96)	(-1.31)	(1.23)	(0.03)		(0.01)	(-0.89)
House ret (7)	-0.20	-0.01	-8.71	0.00	-0.01	0.00		-0.24
(t-stat)	(-0.91)	(-0.78)	(-1.06)	(0.01)	(-0.29)	(-0.10)		(-0.66)
Inflation ret (8)	1.28	0.05	0.48	-0.44	0.65	0.09	-1.18	
(t-stat)	(0.88)	(0.69)	(0.02)	(-0.65)	(1.46)	(0.40)	(-0.76)	

Bull	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Greed ret (1)		-0.14	-2.22	2.91	-2.03	-0.83	-2.97	0.27
(t-stat)		(-0.93)	(-0.14)	(0.98)	(-0.92)	(-0.89)	(-1.03)	(0.17)
Fear ret (2)	-0.23		-4.92	**0.54*****	0.15	-0.06	-0.51*	-0.23
(t-stat)	(-0.78)		(-0.30)	(3.95)	(0.91)	(-0.99)	(-1.72)	(-0.58)
UNC ret (3)	**0.01*****	0.00		**0.01*****	0.00	0.00	**0.01*****	0.00
(t-stat)	(3.69)	(-0.68)		(7.27)	(1.01)	(0.34)	(3.87)	(-0.31)
Income ret (4)	98.68	0.45	1962.60		1.94	20.40	35.26	-43.42
(t-stat)	(1.01)	(0.51)	(1.01)		(0.34)	(0.98)	(0.96)	(-0.96)
Ind Prod ret (5)	0.44	0.03	24.85	**1.91*****		-0.19	-0.13	-0.40
(t-stat)	(0.48)	(1.17)	(1.04)	(4.11)		(-0.61)	(-0.21)	(-0.80)
Labor ret (6)	-4.58	-0.14	-135.40	2.71	-0.22		-0.60	-0.02
(t-stat)	(-1.33)	(-1.13)	(-1.31)	(1.34)	(-0.95)		(-0.46)	(-0.01)
House ret (7)	-0.22	0.00	-8.71	0.02	-0.01	0.00		0.00
(t-stat)	(-0.81)	(-0.54)	(-1.06)	(0.11)	(-0.38)	(-0.08)		(-0.01)
Inflation ret (8)	0.54	0.02	0.48	-0.06	0.36	-0.08	-0.28	
(t-stat)	(0.49)	(0.33)	(0.02)	(-0.15)	(1.29)	(-0.82)	(-0.72)	

Bear	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Greed ret (1)		0.00	6.98	72.95*	-0.34	-0.23	0.30	0.17
(t-stat)		(-0.09)	(1.39)	(1.79)	(-0.66)	(-1.05)	(1.57)	(0.31)
Fear ret (2)	-517.62		-51.65	**-923.46*****	2.46*	-2.28*	4.18	-7.61
(t-stat)	(-1.43)		(-1.16)	(-2.03)	(1.64)	(-1.90)	(1.02)	(-0.97)
UNC ret (3)	2.70	0.00		**2.91*****	-0.02	0.00	**-0.05*****	0.03
(t-stat)	(1.44)	(0.96)		(2.38)	(-0.86)	(0.35)	(-5.19)	(0.37)
Income ret (4)	436.04	0.62	48.54		6.66	-2.79*	1.15	2.24
(t-stat)	(0.87)	(1.01)	(0.90)		(1.08)	(-1.74)	(0.48)	(0.43)
Ind Prod ret (5)	**471.27*****	0.05	-2.29	198.42		-0.75	0.78	-1.64
(t-stat)	(8.31)	(0.43)	(-0.29)	(1.37)		(-1.00)	(1.25)	(-0.83)
Labor ret (6)	330.54*	0.79	-13.10	147.71	5.34		-0.62	1.11
(t-stat)	(1.83)	(1.30)	(-1.02)	(0.57)	(0.81)		(-0.58)	(0.41)
House ret (7)	-14.80	-0.24	-15.46	-82.50	0.03	-0.27*		-5.74
(t-stat)	(-0.50)	(-0.99)	(-1.27)	(-1.34)	(0.16)	(-1.76)		(-0.97)
Inflation ret (8)	143.10	0.74	-75.21	1839.09	14.64	0.37	-11.18	
(t-stat)	(0.44)	(1.25)	(-0.63)	(0.67)	(0.87)	(0.12)	(-0.75)	

4.10 Appendix

4.10.1 Predictive models

Basic linear models: OLS

The Kitchen Sink Regression is a simple OLS multivariate regression which includes all the predictors at once. The estimation is performed employing all observations up to time t (the last available information) to perform the parameter estimation and then to use the estimated parameters to make inference for time t+1 employing regressors values at time t. In formulas this can be summarize in a two step procedure:

$$R_{t+1} = \alpha + \beta X_t + \epsilon_t$$

where R is a t*1 vector and X is a t*N and N is the number of predictors considered in the analysis.

$$\hat{r}_{t+1} = \hat{\alpha}_t + \hat{\beta}_t x_t$$

where $\hat{r}_{t+1}$ is the univariate forecast produced by the model $\hat{\alpha}_t$ and $\hat{\beta}_t$ are the coefficient estimated in the previous step employing data up to time t and x_t is the value of predictors at time t.

Combination Forecasts: Pooled Forecast median and MDSFE

Combination forecasts are among the most common machine learning approach employed in the literature (Rapach et al. [2009], and Detzel and Strauss [2017]). This approach is based on a two-stage estimation.

1. At first for each date t, we run a separate univariate regression for each regressor on the equity premium at time t+1 using all data available up to that date

$$R_{t+1} = \alpha + \beta x_{i,t} + \epsilon_t$$

2. After that each univariate OLS model previously estimated is employed to make inference at time t+1

$$\hat{r}_{t+1} = \hat{\alpha}_t + \hat{\beta}_t x_t$$

3. Finally, we combine the forecasts generated by univariate regressions via combination forecasts methods.

$$\hat{r}_{t+1,Comb} = \sum_{i=1}^{N} w_{i,t} \hat{r}_{t+1}$$

Finally, a the Pooled-DMSPE approach computes the weights in the third step in the following way:

$$w_{i,t} = \frac{\phi_{i,t}^{-1}}{\sum_{k=1}^{K} \phi_{j,t}^{-1}}$$

where

$$\phi_{i,t} = \sum_{s=m}^{t-1} \theta^{t-1-s}(r_{s+1} - \hat{r}_{i,s+1})$$

θ is a discount factor equal to 0.5 in this study, m+1 is the start of the holdout period and K is the number of past periods considered to compute the weights (K=13 in this paper). The DMSPE method thus assigns greater weight to individual forecasts that had better forecasting performance in terms of lower mean-squared prediction errors.

Sum-of-the-Parts Method

The Sum of the Parts Method has been proposed by Ferreira and Santa-Clara [2011]

$$R_{t+1} = \frac{P_{t+1} + D_{t+1}}{P_t} = CG_{t+1} + DY_{t+1}$$

where P_t is the stock price, D_t is the dividend, $CG_{t+1} = \frac{P_{t+1}}{P_t}$ is the gross capital gain, and $DY_{t+1} = \frac{D_{t+1}}{P_t}$ is the dividend yield. The gross capital gain can be expressed as

$$CG_{t+1} = \frac{\frac{P_{t+1}}{E_{t+1}}}{\frac{P_t}{E_t}} \frac{E_{t+1}}{E_t} = \frac{M_{t+1}}{M_t} \frac{E_{t+1}}{E_t} = GM_{t+1} GE_{t+1}$$

where E_t denotes earnings,$M_t = \frac{P_t}{E_t}$is the price-earnings multiple, and $GM_{t+1} = \frac{M_{t+1}}{M_t}$,$(GE_{t+1} = \frac{E_{t+1}}{E_t})$ is the gross growth rate of the price- earnings multiple (earnings). Now the dividend yield can be written as

$$DY_{t+1} = \frac{D_{t+1}}{P_{t+1}} \frac{P_{t+1}}{P_t} = DP_{t+1} GM_{t+1} GE_{t+1}$$

where $\frac{D_t}{P_t}$ is the dividend-price ratio. Based on these results the gross return becomes

$$R_{t+1} = GM_{t+1} GE_{t+1}(1 + DP_{t+1}),$$

which for the log return can be expressed as

$$log(R_{t+1}) = gm_{t+1} + ge_{t+1} + dp_{t+1}$$

Since price-earnings multiples and dividend-price ratios are highly persistent and nearly random walks, reasonable forecasts of gm_{t+1} and dp_{t+1} based on information through t are zero and dp_t, respectively. A 20-year moving average of log earnings growth through t ge_t^{20} , is employed as a forecast of ge_{t+1}Their sum-of-the-parts equity premium forecast is then given by

$$\hat{r}_{t+1}^{SOP} = \bar{ge}_t^{20} + dp_t - r_{f,t+1}$$

where is the log risk-free rate, which is known at the end of t.

Multivariate Adaptive Regression Splines and Support Vector Machines for Regression: MARS SVM

Given a set of predictors the MARS model (Friedman [1991]) selects and breaks a predictor into two groups and models linear relationships between the predictor and the outcome in each group. To determine the cut point each data point for each predictor is evaluated as a candidate cut-point by creating a linear regression model with the candidate features, and the corresponding model error is calculated. The predictor/cut point combination that achieves the smallest error is then used for the model. After the initial model is created with the first two features, the model conducts another exhaustive search to find the next set of features that, given the initial set, yield the best model fit. This process continues until a stopping point is reached. Once the full set of features has been created, the algorithm sequentially removes individual features that do not contribute significantly to the model equation. This "pruning" procedure assesses each predictor variable and estimates how much the error rate was decreased by including it in the model. MARS builds models of the form:

$$\hat{f}(x) = \sum_{i=1}^{m} c_i B_i(x) \tag{4.41}$$

where c_i is a fix coefficient and B_i can be equal to 1 or to a hinge function (a hinge function has the form max(0, x-const) or max(0, const-x)) or a product of hinge functions.

Our implementation of the algorithm builds the model in two phases: forward selection and backward deletion. In the forward phase, the algorithm starts with a model consisting of just the intercept term and iteratively adds reflected pairs of basis functions giving the largest reduction of training error (Mean Squared Error). We set the maximum number of basis functions to min(200, max(20,2d))+1, where d is the number of input variables. We do not allow for self-interaction. We impose no penalty for adding a new variable to a model in the forward phase, and we employ hinge functions only. The forward phase is executed until adding a new

basis function changes R^2 by less than 1e-4.
At the end of the forward phase we have a large model which over-fits the data, and so a backward deletion phase is engaged. In the backward phase, the model is simplified by deleting one least important basis function (i.e., deletion of which reduces training error the least) at a time until the model has only the intercept term. At the end of the backward phase, from those "best" models of each size, the one with the lowest Generalized Cross-Validation (GCV) is selected and outputted as the final one. GCV, as an estimator for Prediction Mean Squared Error, for a MARS model is calculated as follows:

$$CVG = \frac{MSE_{train}}{(1 - \frac{enp}{n})^2} \tag{4.42}$$

where MSE_{train} is the Mean Squared Error of the model in the training data, n is the number of observations in the training data, and *enp* is the effective number of parameters:

$$enp = k + c * (k+1)/2 \tag{4.43}$$

where k is the number of basis functions in the model (including the intercept term), and c=3 is the Generalized Cross-Validation (GCV) penalty. We impose no further constraints on the Maximum number of basis functions (including the intercept term) in the final pruned model[40].
Once the model is built we perform variable importance assessment. The criterion counts the number of model subsets that include the variable. Where by "subsets" we mean the subsets of terms generated by the pruning pass. There is one subset for each model size (from 1 to the size of the selected model) and the subset is the best set of terms for that model size. Obviously, only subsets that are smaller than or equal in size to the final model are used for estimating variable importance. We select only variables with a score bigger than 12. After that, we use the selected variables to estimate a machine vector regression model.
The intuition of SVM for regression is to modify the traditional simple linear regression regularized error function

$$\frac{1}{2}\sum_{n=1}^{N}(y_n - t_n)^2 + \frac{\lambda}{2}||w||^2 \tag{4.44}$$

by introducing an ϵ insensitive error function.

$$E_\epsilon(y(x) - t) = \begin{cases} 0 & if \quad |y(x) - t| < \epsilon \\ |y(x) - t| - \epsilon & otherwise \end{cases} \tag{4.45}$$

[40]To boost computational performance, and following Friedman [1991], we employ piecewise-cubic modelling for the final model only after both the forward and the backward phases.

This implies that we minimize a regularized error function given by

$$C\sum_{n=1}^{N} E_\epsilon(y(x_n) - t_n) + \frac{1}{2}||w||^2 \tag{4.46}$$

where C is a regularization parameter.
Now for each data point x_n, we now need two slack variables $\xi_n \geq 0$ and $\hat{\xi}_n > 0$, where $\xi_n > 0$ corresponds to a point for which $t_n > y(x_n)+\epsilon$ and $\hat{\xi}_n < 0$ correspond to a point for which $t_n < y(x_n) + \epsilon$. Consequently, a target point lies inside the ϵ tube whether $y_n - \epsilon \leq t_n \leq y_n + \epsilon$ where $y_n = y(x_n)$. The introduction of the two slack variables allows points to lie outside the tube provided the slack variables are different from zero:

$$t_n \leq y(x_n) + \epsilon + \xi_n \quad \textit{and} \quad t_n \geq y(x_n) - \epsilon - \hat{\xi}_n \tag{4.47}$$

This implies that the error function for support vector regression can then be written as

$$C\sum_{n=1}^{N}(\xi_n + \hat{\xi}_n) + \frac{1}{2}||w||^2 \tag{4.48}$$

which should be minimized subject to the constraints $\xi_n \geq 0$ and $\hat{\xi}_n \geq 0$ plus the conditions $t_n \leq y(x_n) + \epsilon + \xi_n$ and $t_n \geq y(x_n) - \epsilon - \hat{\xi}_n$. Consequently, the problem can be solved optimizing the Lagrangian with multipliers $a_n \geq 0$, $\hat{a}_n \geq 0$, $\mu_n \geq 0$ and $\hat{\mu}_n \geq 0$

$$\begin{aligned} L = C\sum_{n=1}^{N}(\xi_n + \hat{\xi}_n) + \frac{1}{2}||w||^2 - &\sum_{n=1}^{N}(\mu_n\xi_n + \hat{\mu}_n\hat{\xi}_n) \\ &- \sum_{n=1}^{N} a_n(\epsilon + \xi_n + y_n - t_n) - \sum_{n=1}^{N} \hat{a}_n(\epsilon + \hat{\xi}_n - y_n + t_n) \end{aligned} \tag{4.49}$$

Computing the partial derivatives and replacing gives

$$\tilde{L}(a, \hat{a}) = -\frac{1}{2}\sum_{n=1}^{N}\sum_{m=1}^{N}(a_n - \hat{a}_n)(a_m - \hat{a}_m)k(x_n, x_m) - \epsilon\sum_{n=1}^{N}(a_n + \hat{a}_n) + \sum_{n=1}^{N}(a_n - \hat{a}_n) * t_n \tag{4.50}$$

where $k(x, x') = \phi(x)^T\phi(x')$ is the kernel.
Replacing $w = \sum_{n=1}^{N}(a_n - \hat{a}_n)\phi(x_n)$ in the general case $y(x) = w^T\phi(x) + b$ where $\phi(x)$ denotes a fixed feature-space transformation, $\phi(x) * \phi(x) = k(x, x_n)$, and b is the bias parameter, we see that predictions can be made using

$$y(x) = \sum_{n=1}^{N}(a_n - \hat{a}_n)k(x, x_n) + b \tag{4.51}$$

We implement the regularized support vector machines regression presented above in the following manner. The half width of the epsilon-insensitive band is set equal to the ratio of the interquartile range of the independent variable distribution and the scalar value 1.349. The regularization Lambda is set equal to one divided the training sample size. The objective function minimization technique chosen is SpaRSA (sparse reconstruction by separable approximation optimization, Wright et al. [2009]). Initial estimates of regression coefficients are all set to zero except the bias one which is initially fixed to the weighted median of the dependent variable in the training set. The criteria for convergence during the optimization process are[41]:

- Relative tolerance on linear coefficients and bias term: 1e-4
- Absolute gradient tolerance: 1e-6
- Size of history buffer for Hessian approximation: 15
- Maximal number of optimization iterations: 1000

For each date t, the model is estimated with predictors data up to t-1. Then the values of the regressors at time t are employed to make inference for date t+1.

SIC - LASSO Support Vector Machine

The joint employment of all the available predictors is likely to give rise to severe multicollinearity and poor out-of-sample performance. Consequently, employing variable selection is likely to boost the performance of the predictive model. Following this intuition, we consider two separate model selection approaches, and subsequently, we make use of the selected variables into a Support Vector Machine regression model. The first model selection approach considered is the Schwartz Information Criterion (SIC)(Schwarz [1978]).
We employ the SIC, imposing a maximum of 2 predictors for the model selection. For each date t, we use all data available up to that moment, we consider all individual regressors and all possible combinations among two regressors, and we compute the related SIC values

$$log(SIC) = log\left(\frac{SSR}{T}\right) + k * \frac{log(T)}{T} \tag{4.52}$$

where T is the number of observations, k is the number of predictors and SSR is the sum of squared residuals. After that, for each date t, we pick the model

[41]Further details on the optimization procedure can be found looking at the details of the Matlab function "fitrlinear"

with the lowest SIC. Subsequently, we use the predictors of the chosen model to estimate a support vector machine regression model. Finally, we employ it to make inference using the values of predictors at time t to forecast the S&P500 returns at time t+1.
The alternative approach which we employ for model selection is Lasso. At each time t, we run a 10-fold Cross-validated Lasso.

$$\min_{\beta} RSS + \lambda \sum_{j=1}^{N} |\beta_j| \tag{4.53}$$

where N is the number of regressors, λ is the Lagrange multiplier, RSS is the sum of squared residuals. The value of lambda selected is the 95^{th} higher from a default geometric sequence of 100 values, with only the largest able to produce a model which exclude all predictors.
After that, the predictors selected by Lasso are employed to estimate the Linear Support Vector Machine. Finally, we employ it to make inference using the values of predictors at time t to forecast the S&P500 returns at time t+1.

Diffusion Indices

The diffusion index approach assumes a latent factor model structure for the potential predictors:

$$x_{i,t} = \lambda_i' f_t + e_{i,t} \tag{4.54}$$

with (i=1,..., K) and f_t is a q-vector of latent factors, λ_i is a q-vector of factor loadings, and $e_{i,t}$ is a zero-mean disturbance term. Co-movements in the predictors are primarily governed by movements in the small number of factors (the number of factors is much smaller than the number of predictors). The latent factors can be consistently estimated by principal components. To implement this approach we started standardizing all the predictors (standard deviation of 1 and zero mean). After that for each date t, we compute the first principal component employing all data available up to t-1. The first principal component is then employed as a regressor to estimate a support vector machine regression. Finally, the support vector machine regression previously estimated with data up to t-1 and the value f_t of the first principal component are used to make inference for time t+1.

4.10.2 Data

4.10.3 Sentiment index data

The data on sentiment are used in this paper are employed for the estimation of the Greed proxy (called Sentiment index in the original paper of Huang et al.

[2015]). The monthly time series span the period from 07-1965 to 12-2017. The indexes are built using the following monthly data[42]:

- Close-end fund discount rate (cefd): value-weighted average difference between the net asset values of closed-end stock mutual fund shares and their market prices.
- Share turnover (turn): log of the raw turnover ratio detrended by the past 5-year average. Here the raw turnover ratio is the ratio of reported share volume to average shares listed from the NYSE Fact Book.
- Number of IPOs (nipo): number of monthly initial public offerings
- First-day returns of IPOs (ripo): monthly average first-day returns of initial public offerings.
- Dividend premium (pdnd): log difference of the value-weighted average market-to-book ratios of dividend payers and nonpayers.
- Equity share in new issues (s): gross monthly equity issuance divided by gross monthly equity plus debt issuance.

Macro Data

Table A1-A4 lists the short name of each series, its mnemonic (the series label used in the source database), the transformation applied to the series, a brief data description and their economic cluster. All series are from the Federal Reserve of St. Louis Fed with the exception of stock industry indexes which come from the French website. In the transformation column, ln denotes logarithm, Δ ln and Δ^2 ln denote the first and second difference of the logarithm, lv denotes the level of the series, Δ lv denotes the first difference of the series, and % implies a division by 100. In Tables A5-A6 we test the out-of-sample predictive power of each variable in terms of R^2_{OS}. Finally, in Table A7 we test the out-of-sample predictive power of each variable Utility gains.

[42] Professor Guofu Zhou website, http://apps.olin.wustl.edu/faculty/zhou/

Table A1: See above for details

Series Number	mnemonic	Description	Tran	Cluster
1	DSPIC96	Real Disposable Personal Income, Billions of Chained 2012 Dollars, Monthly, Seasonally Adjusted Annual Rate	Delta ln	Income
2	PCEPILFE	Personal Consumption Expenditures Excluding Food and Energy (Chain-Type Price Index), Index 2012=100, Monthly, Seasonally Adjusted	Delta ln	Income
3	PCE	Personal Consumption Expenditures, Billions of Dollars, Monthly, Seasonally Adjusted Annual Rate	Delta ln	Income
4	CMRMTSPL	Real Manufacturing and Trade Industries Sales, Millions of Chained 2012 Dollars, Monthly, Seasonally Adjusted	Delta ln	Income
5	RSXFS	Advance Retail Sales: Retail (Excluding Food Services), Millions of Dollars, Monthly, Seasonally Adjusted	Delta ln	Income
6	TOTALSA	Total Vehicle Sales, Millions of Units, Monthly, Seasonally Adjusted Annual Rate	Delta ln	Income
7	MARTSMPCSM44000USS	Advance Retail Sales: Retail (Excluding Food Services), Percent Change from Preceding Period, Monthly, Seasonally Adjusted	lv	Income
8	UMCSENT	University of Michigan: Consumer Sentiment, Index 1966:Q1=100, Monthly, Not Seasonally Adjusted	lv	Income
9	MICH	University of Michigan: Inflation Expectation, Percent, Monthly, Not Seasonally Adjusted	lv	Income
10	CSCICP03USM665S	Consumer Opinion Surveys: Confidence Indicators: Composite Indicators: OECD Indicator for the United States, Normalised (Normal=100), Monthly, Seasonally Adjusted	lv	Income
11	MVGFD027MNFRBDAL	Market Value of Gross Federal Debt, Billions of Dollars, Monthly, Not Seasonally Adjusted	Delta2 ln	Income
12	INDPRO	Industrial Production Index, Index 2012=100, Monthly, Seasonally Adjusted	Delta ln	Industrial Production
13	IPMAN	Industrial Production: Manufacturing (NAICS), Index 2012=100, Monthly, Seasonally Adjusted	Delta ln	Industrial Production
14	IPDCONGD	Industrial Production: Durable Consumer Goods, Index 2012=100, Monthly, Seasonally Adjusted	Delta ln	Industrial Production
15	IPMAT	Industrial Production: Materials, Index 2012=100, Monthly, Seasonally Adjusted	Delta ln	Industrial Production
16	IPBUSEQ	Industrial Production: Business Equipment, Index 2012=100, Monthly, Seasonally Adjusted	Delta ln	Industrial Production
17	IPFUELS	Industrial Production: Fuels, Index 2012=100, Monthly, Seasonally Adjusted	Delta ln	Industrial Production
18	IPB51222S	Industrial Production: Residential utilities, Index 2012=100, Monthly, Seasonally Adjusted	Delta ln	Industrial Production
19	IPFINAL	Industrial Production: Final Products (Market Group), Index 2012=100, Monthly, Seasonally Adjusted	Delta ln	Industrial Production
20	TCU	Capacity Utilization: Total Industry, Percent of Capacity, Monthly, Seasonally Adjusted	Delta ln	Industrial Production
21	IPG211111CS	Industrial Production: Mining: Crude oil, Index 2012=100, Monthly, Seasonally Adjusted	Delta ln	Industrial Production
22	DGORDER	Manufacturers' New Orders: Durable Goods, Millions of Dollars, Monthly, Seasonally Adjusted	Delta2 ln	Industrial Production
23	ACDGNO	Value of Manufacturers' New Orders for Consumer Goods: Consumer Durable Goods Industries, Million of Dollars, Monthly, Seasonally Adjusted	Delta2 ln	Industrial Production
24	NEWORDER	Manufacturers' New Orders: Nondefense Capital Goods Excluding Aircraft, Millions of Dollars, Monthly, Seasonally Adjusted	Delta2 ln	Industrial Production
25	INVCMRMTSPL	Real Manufacturing and Trade Inventories, Chained 2012 Dollars, Monthly, Seasonally Adjusted	Delta2 ln	Industrial Production
26	BUSLOANS	Commercial and Industrial Loans, All Commercial Banks, Billions of U.S. Dollars, Monthly, Seasonally Adjusted	Delta2 ln	Industrial Production
27	TOTALSL	Total Consumer Credit Owned and Securitized, Outstanding, Billions of Dollars, Monthly, Seasonally Adjusted	Delta2 ln	Industrial Production
28	AHETPI	Average Hourly Earnings of Production and Nonsupervisory Employees: Total Private, Dollars per Hour, Monthly, Seasonally Adjusted	Delta2 ln	Industrial Production
29	CES2000000008	Average Hourly Earnings of Production and Nonsupervisory Employees: Construction, Dollars per Hour, Monthly, Seasonally Adjusted	Delta2 ln	Industrial Production
30	CES3000000008	Average Hourly Earnings of Production and Nonsupervisory Employees: Manufacturing, Dollars per Hour, Monthly, Seasonally Adjusted	Delta2 ln	Industrial Production
31	CES0600000008	Average Hourly Earnings of Production and Nonsupervisory Employees: Goods-Producing, Dollars per Hour, Monthly, Seasonally Adjusted	Delta2 ln	Industrial Production
32	CIVPART	Civilian Labor Force Participation Rate, Percent, Monthly, Seasonally Adjusted	Delta ln	Labor
33	UNRATE	Civilian Unemployment Rate, Percent, Monthly, Seasonally Adjusted	Delta ln	Labor
34	UEMPMEAN	Average (Mean) Duration of Unemployment, Weeks, Monthly, Seasonally Adjusted	Delta lv	Labor
35	UEMPLT5	Number of Civilians Unemployed for Less Than 5 Weeks, Thousands of Persons, Monthly, Seasonally Adjusted	Delta ln	Labor
36	UEMP5TO14	Number of Civilians Unemployed for 5 to 14 Weeks, Thousands of Persons, Monthly, Seasonally Adjusted	Delta ln	Labor
37	UEMP15OV	Number of Civilians Unemployed for 15 Weeks and Over, Thousands of Persons, Monthly, Seasonally Adjusted	Delta ln	Labor
38	UEMP15T26	Number of Civilians Unemployed for 15 to 26 Weeks, Thousands of Persons, Monthly, Seasonally Adjusted	Delta ln	Labor
39	UEMP27OV	Number of Civilians Unemployed for 27 Weeks and Over, Thousands of Persons, Monthly, Seasonally Adjusted	Delta ln	Labor
40	PAYEMS	All Employees: Total Nonfarm Payrolls, Thousands of Persons, Monthly, Seasonally Adjusted	Delta ln	Labor

Table A2: Continues from above

41	USGOOD	All Employees: Goods-Producing Industries, Thousands of Persons, Monthly, Seasonally Adjusted	Delta ln	Labor
42	USMINE	All Employees: Mining and logging, Thousands of Persons, Monthly, Seasonally Adjusted	Delta ln	Labor
43	USCONS	All Employees: Construction, Thousands of Persons, Monthly, Seasonally Adjusted	Delta ln	Labor
44	MANEMP	All Employees: Manufacturing, Thousands of Persons, Monthly, Seasonally Adjusted	Delta ln	Labor
45	DMANEMP	All Employees: Durable Goods, Thousands of Persons, Monthly, Seasonally Adjusted	Delta ln	Labor
46	NDMANEMP	All Employees: Nondurable goods, Thousands of Persons, Monthly, Seasonally Adjusted	Delta ln	Labor
47	USFIRE	All Employees: Financial Activities, Thousands of Persons, Monthly, Seasonally Adjusted	Delta ln	Labor
48	CES9091000001	All Employees: Government: Federal, Thousands of Persons, Monthly, Seasonally Adjusted	Delta ln	Labor
49	USTRADE	All Employees: Retail Trade, Thousands of Persons, Monthly, Seasonally Adjusted	Delta ln	Labor
50	USTPU	All Employees: Trade, Transportation and Utilities, Thousands of Persons, Monthly, Seasonally Adjusted	Delta ln	Labor
51	HOUST	Housing Starts: Total: New Privately Owned Housing Units Started, Thousands of Units, Monthly, Seasonally Adjusted Annual Rate	lv	House
52	HOUSTNE	Housing Starts in Northeast Census Region, Thousands of Units, Monthly, Seasonally Adjusted Annual Rate	lv	House
53	HOUSTS	Housing Starts in South Census Region, Thousands of Units, Monthly, Seasonally Adjusted Annual Rate	lv	House
54	HOUSTW	Housing Starts in West Census Region, Thousands of Units, Monthly, Seasonally Adjusted Annual Rate	lv	House
55	PERMIT	New Private Housing Units Authorized by Building Permits, Thousands of Units, Monthly, Seasonally Adjusted Annual Rate	lv	House
56	PERMITNE	New Private Housing Units Authorized by Building Permits in the Northeast Census Region, Thousands of Units, Monthly, Seasonally Adjusted Annual Rate	lv	House
57	PERMITMW	New Private Housing Units Authorized by Building Permits in the Midwest Census Region, Thousands of Units, Monthly, Seasonally Adjusted Annual Rate	lv	House
58	PERMITS	New Private Housing Units Authorized by Building Permits in the South Census Region, Thousands of Units, Monthly, Seasonally Adjusted Annual Rate	lv	House
59	PERMITW	New Private Housing Units Authorized by Building Permits in the West Census Region, Thousands of Units, Monthly, Seasonally Adjusted Annual Rate	lv	House
60	MNFCTRIRSA	Manufacturers: Inventories to Sales Ratio, Ratio, Monthly, Seasonally Adjusted	Delta2 ln	Inflation
61	M1SL	M1 Money Stock, Billions of Dollars, Monthly, Seasonally Adjusted	Delta2 ln	Inflation
62	M2SL	M2 Money Stock, Billions of Dollars, Monthly, Seasonally Adjusted	Delta2 ln	Inflation
63	MABMM301USM189S	M3 for the United States, National Currency, Monthly, Seasonally Adjusted	Delta2 ln	Inflation
64	M2REAL	Real M2 Money Stock, Billions of 1982-84 Dollars, Monthly, Seasonally Adjusted	Delta2 ln	Inflation
65	AMBSL	St. Louis Adjusted Monetary Base, Billions of Dollars, Monthly, Seasonally Adjusted	Delta2 ln	Inflation
66	CPIAPPSL	Consumer Price Index for All Urban Consumers: Apparel, Index 1982-1984=100, Monthly, Seasonally Adjusted	Delta2 ln	Inflation
67	CPITRNSL	Consumer Price Index for All Urban Consumers: Transportation, Index 1982-1984=100, Monthly, Seasonally Adjusted	Delta2 ln	Inflation
68	CPIMEDSL	Consumer Price Index for All Urban Consumers: Medical Care, Index 1982-1984=100, Monthly, Seasonally Adjusted	Delta2 ln	Inflation
69	CUSR0000SAC	Consumer Price Index for All Urban Consumers: Commodities, Index 1982-1984=100, Monthly, Seasonally Adjusted	Delta2 ln	Inflation
70	CUSR0000SAD	Consumer Price Index for All Urban Consumers: Durables, Index 1982-1984=100, Monthly, Seasonally Adjusted	Delta2 ln	Inflation
71	CPILFESL	Consumer Price Index for All Urban Consumers: All Items Less Food and Energy, Index 1982-1984=100, Monthly, Seasonally Adjusted	Delta2 ln	Inflation
72	CPIAUCSL	Consumer Price Index for All Urban Consumers: All Items, Index 1982-1984=100, Monthly, Seasonally Adjusted	Delta2 ln	Inflation
73	FEDFUNDS	Effective Federal Funds Rate, Percent, Monthly, Not Seasonally Adjusted	Delta lv	Fixed Income
74	TB3MS	3-Month Treasury Bill: Secondary Market Rate, Percent, Monthly, Not Seasonally Adjusted	Delta lv	Fixed Income
75	TB6MS	6-Month Treasury Bill: Secondary Market Rate, Percent, Monthly, Not Seasonally Adjusted	Delta lv	Fixed Income
76	GS1	1-Year Treasury Constant Maturity Rate, Percent, Monthly, Not Seasonally Adjusted	Delta lv	Fixed Income
77	GS2	2-Year Treasury Constant Maturity Rate, Percent, Monthly, Not Seasonally Adjusted	Delta lv	Fixed Income
78	GS3	3-Year Treasury Constant Maturity Rate, Percent, Monthly, Not Seasonally Adjusted	Delta lv	Fixed Income
79	GS5	5-Year Treasury Constant Maturity Rate, Percent, Monthly, Not Seasonally Adjusted	Delta lv	Fixed Income
80	GS7	7-Year Treasury Constant Maturity Rate, Percent, Monthly, Not Seasonally Adjusted	Delta lv	Fixed Income

Table A3: Continues from above

81	GS10	10-Year Treasury Constant Maturity Rate, Percent, Monthly, Not Seasonally Adjusted	Delta lv	Fixed Income
82	T10Y3MM	10-Year Treasury Constant Maturity Minus 3-Month Treasury Constant Maturity, Percent, Monthly, Not Seasonally Adjusted	Delta lv	Fixed Income
83	T1YFFM	1-Year Treasury Constant Maturity Minus Federal Funds Rate, Percent, Monthly, Not Seasonally Adjusted	Delta lv	Fixed Income
84	T6MFFM	6-Month Treasury Constant Maturity Minus Federal Funds Rate, Percent, Monthly, Not Seasonally Adjusted	Delta lv	Fixed Income
85	T10Y2YM	10-Year Treasury Constant Maturity Minus 2-Year Treasury Constant Maturity, Percent, Monthly, Not Seasonally Adjusted	Delta lv	Fixed Income
86	BAA10YM	Moody's Seasoned Baa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity, Percent, Monthly, Not Seasonally Adjusted	Delta lv	Fixed Income
87	IRLTLT01USM156N	Long-Term Government Bond Yields: 10-year: Main (Including Benchmark) for the United States, Percent, Monthly, Not Seasonally Adjusted	Delta lv	Fixed Income
88	AAA	Moody's Seasoned Aaa Corporate Bond Yield, Percent, Monthly, Not Seasonally Adjusted	Delta lv	Fixed Income
89	BAA	Moody's Seasoned Baa Corporate Bond Yield, Percent, Monthly, Not Seasonally Adjusted	Delta lv	Fixed Income
90	AAA10YM	Moody's Seasoned Aaa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity, Percent, Monthly, Not Seasonally Adjusted	Delta lv	Fixed Income
91	AAAFFM	Moody's Seasoned Aaa Corporate Bond Minus Federal Funds Rate, Percent, Monthly, Not Seasonally Adjusted	Delta lv	Fixed Income
92	T5YFFM	5-Year Treasury Constant Maturity Minus Federal Funds Rate, Percent, Monthly, Not Seasonally Adjusted	Delta lv	Fixed Income
93	T3MFFM	3-Month Treasury Constant Maturity Minus Federal Funds Rate, Percent, Monthly, Not Seasonally Adjusted	Delta lv	Fixed Income
94	EXBZUS	Brazil / U.S. Foreign Exchange Rate, Brazilian Reals to One U.S. Dollar, Monthly, Not Seasonally Adjusted	Delta ln	Forex
95	EXMXUS	Mexico / U.S. Foreign Exchange Rate, Mexican New Pesos to One U.S. Dollar, Monthly, Not Seasonally Adjusted	Delta ln	Forex
96	EXINUS	India / U.S. Foreign Exchange Rate, Indian Rupees to One U.S. Dollar, Monthly, Not Seasonally Adjusted	Delta ln	Forex
97	RBUSBIS	Real Broad Effective Exchange Rate for United States, Index 2010=100, Monthly, Not Seasonally Adjusted	Delta ln	Forex
98	NBUSBIS	Broad Effective Exchange Rate for United States, Index 2010=100, Monthly, Not Seasonally Adjusted	Delta ln	Forex
99	TWEXBMTH	Trade Weighted U.S. Dollar Index: Broad, Goods, Index Jan 1997=100, Monthly, Not Seasonally Adjusted	Delta ln	Forex
100	EXSZUS	Switzerland / U.S. Foreign Exchange Rate, Swiss Francs to One U.S. Dollar, Monthly, Not Seasonally Adjusted	Delta ln	Forex
101	EXJPUS	Japan / U.S. Foreign Exchange Rate, Japanese Yen to One U.S. Dollar, Monthly, Not Seasonally Adjusted	Delta ln	Forex
102	EXUSUK	U.S. / U.K. Foreign Exchange Rate, U.S. Dollars to One British Pound, Monthly, Not Seasonally Adjusted	Delta ln	Forex
103	EXCAUS	Canada / U.S. Foreign Exchange Rate, Canadian Dollars to One U.S. Dollar, Monthly, Not Seasonally Adjusted	Delta ln	Forex
104	MCOILWTICO	Crude Oil Prices: West Texas Intermediate (WTI) - Cushing, Oklahoma, Dollars per Barrel, Monthly, Not Seasonally Adjusted	Delta2 ln	Commodities
105	PCU2122221222	Producer Price Index by Industry: Gold Ore and Silver Ore Mining, Index Dec 1984=100, Monthly, Not Seasonally Adjusted	Delta2 ln	Commodities
106	WPUSI019011	Producer Price Index by Commodity for Special Indexes: Copper and Copper Products, Index 1982=100, Monthly, Not Seasonally Adjusted	Delta2 ln	Commodities
107	PPIACO	Producer Price Index for All Commodities, Index 1982=100, Monthly, Not Seasonally Adjusted	Delta2 ln	Commodities
108	WPSFD49207	Producer Price Index by Commodity for Final Demand: Finished Goods, Index 1982=100, Monthly, Seasonally Adjusted	Delta2 ln	Commodities
109	WPSFD4111	Producer Price Index by Commodity for Final Demand: Finished Consumer Foods, Index 1982=100, Monthly, Seasonally Adjusted	Delta2 ln	Commodities
110	WPSID612	Producer Price Index by Commodity for Intermediate Demand by Commodity Type: Materials and Components for Construction, Index 1982=100, Monthly, Seasonally Adjusted	Delta2 ln	Commodities
111	IQ00200	Export Price Index (End Use): Corn, Index 2000=100, Monthly, Not Seasonally Adjusted	Delta2 ln	Commodities
112	WPU01830131	Producer Price Index by Commodity for Farm Products: Soybeans, Index 1982=100, Monthly, Not Seasonally Adjusted	Delta2 ln	Commodities
113	WPU0121	Producer Price Index by Commodity for Farm Products: Wheat, Index 1982=100, Monthly, Not Seasonally Adjusted	Delta2 ln	Commodities
114	Agric	French Industry, Agriculture, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
115	Food	French Industry, Food Products, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
116	Soda	French Industry, Candy & Soda, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
117	Beer	French Industry, Beer and Liquor , Monthly, Not Seasonally Adjusted	%	Stock Industry Index
118	Smoke	French Industry, Tobacco Products, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
119	Toys	French Industry, Recreation, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
120	Fun	French Industry, Entertainment, Monthly, Not Seasonally Adjusted	%	Stock Industry Index

Table A4: Continues from above

121	Books	French Industry, Printing and Publishing, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
122	Hshld	French Industry, Consumer Goods, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
123	Clths	French Industry, Apparel, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
124	Hlth	French Industry, Healthcare, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
125	MedEq	French Industry, Medical Equipment, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
126	Drugs	French Industry, Pharmaceutical Products, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
127	Chems	French Industry, Chemicals, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
128	Rubbr	French Industry, Rubber and Plastic Products, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
129	Txtls	French Industry, Textiles, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
130	BldMt	French Industry, Construction Materials, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
131	Cnstr	French Industry, Construction, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
132	Steel	French Industry, Steel Work Etc, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
133	FabPr	French Industry, Fabricated Products, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
134	Mach	French Industry, Machinery, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
135	ElcEq	French Industry, Electrical Equipment, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
136	Autos	French Industry, Automobiles and Trucks, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
137	Aero	French Industry, Aircraft, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
138	Ships	French Industry, Shipbuilding and Railroad Equipment, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
139	Guns	French Industry, Defense, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
140	Gold	French Industry, Precious Metals, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
141	Mines	French Industry, Non-Metallic and Industrial Metal Mining, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
142	Coal	French Industry, Coal, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
143	Oil	French Industry, Petroleum and Natural Gas, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
144	Util	French Industry, Utilities, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
145	Telcm	French Industry, Communication, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
146	PerSv	French Industry, Personal Services, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
147	BusSv	French Industry, Business Services, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
148	Comps	French Industry, Computers, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
149	Chips	French Industry, Electronical Equipment, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
150	LabEq	French Industry, Measuring and Control Equipment, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
151	Paper	French Industry, Business Supplies, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
152	Boxes	French Industry, Shipping Containers, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
153	Trans	French Industry, Transportation, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
154	Whlsl	French Industry, Wholesale, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
155	Rtail	French Industry, Retail, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
156	Meals	French Industry, Resturants, Hotels, Motels, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
157	Banks	French Industry, Banking , Monthly, Not Seasonally Adjusted	%	Stock Industry Index
158	Insur	French Industry, Insurance, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
159	RlEst	French Industry, Real Estate, Monthly, Not Seasonally Adjusted	%	Stock Industry Index
160	Fin	French Industry, Trading, Monthly, Not Seasonally Adjusted	%	Stock Industry Index

Table A5: **Out-of-sample predictability using macro predictors:** R^2_{OS}. The R^2_{OS} is the Campbell and Thompson [2008] out-of-sample R^2 statistic. Statistical significance for the R^2_{OS} statistic is based on the p-value for the Clark and West [2007] out-of-sample MPSE-adjusted statistic; Base employs the predicted returns without constraints while Restricted replace the negative forcasts with zero. The results refer to monthly forecasts for the out-of-sample period 2000-2017. Results in **Bold** imply a positive R^2_{OS} matched by a p-value under 0.05.

Base	R^2_{OS}	p-val	Base	R^2_{OS}	p-val	Restricted	R^2_{OS}	p-val	Restricted	R^2_{OS}	p-val
DSPIC96	**0.80**	**0.01**	GS10	-1.40	0.89	DSPIC96	**0.42**	**0.02**	GS10	-1.42	0.90
PCEPILFE	-2.22	0.55	T10Y3MM	-1.71	0.89	PCEPILFE	-1.02	0.29	T10Y3MM	-1.66	0.91
PCE	0.63	0.14	T1YFFM	-0.48	0.36	PCE	**1.06**	**0.05**	T1YFFM	-1.26	0.64
CMRMTSPL	-0.97	0.49	T6MFFM	0.17	0.28	CMRMTSPL	-0.30	0.44	T6MFFM	-0.54	0.53
RSXFS	**1.98**	**0.05**	T10Y2YM	-3.31	0.80	RSXFS	**1.70**	**0.04**	T10Y2YM	-3.02	0.87
TOTALSA	-0.04	0.09	BAA10YM	-3.55	0.76	TOTALSA	0.65	0.14	BAA10YM	-3.34	0.79
MARTSMPCSM44000USS	0.04	0.01	IRLTLT01USM156N	-1.40	0.89	MARTSMPCSM44000USS	-3.43	0.00	IRLTLT01USM156N	-1.42	0.90
UMCSENT	-2.67	0.67	AAA	-1.38	0.82	UMCSENT	-0.34	0.55	AAA	-1.59	0.87
MICH	**0.66**	**0.03**	BAA	-1.24	0.84	MICH	-0.30	0.08	BAA	-1.25	0.89
CSCICP03USM665S	-2.86	0.34	AAA10YM	-1.64	0.92	CSCICP03USM665S	**1.17**	**0.07**	AAA10YM	-1.47	0.90
MVGFD027MNFRBDAL	-0.25	0.13	AAAFFM	-0.40	0.25	MVGFD027MNFRBDAL	**0.87**	**0.07**	AAAFFM	-0.42	0.40
INDPRO	**3.67**	**0.09**	T5YFFM	-1.11	0.55	INDPRO	-0.50	0.23	T5YFFM	-1.15	0.67
IPMAN	**3.99**	**0.05**	T3MFFM	0.29	0.29	IPMAN	0.23	0.12	T3MFFM	-0.83	0.52
IPDCONGD	**1.45**	**0.08**	EXBZUS	0.27	0.26	IPDCONGD	-0.54	0.18	EXBZUS	**0.81**	**0.08**
IPMAT	2.90	0.12	EXMXUS	-0.05	0.22	IPMAT	-1.05	0.32	EXMXUS	0.16	0.18
IPBUSEQ	**4.11**	**0.06**	EXINUS	-1.29	0.37	IPBUSEQ	**0.35**	**0.07**	EXINUS	0.22	0.18
IPFUELS	-3.44	0.91	RBUSBIS	-0.93	0.57	IPFUELS	-3.26	0.90	RBUSBIS	-0.76	0.62
IPB51222S	-3.66	0.89	NBUSBIS	-1.00	0.61	IPB51222S	-2.96	0.86	NBUSBIS	-0.59	0.60
IPFINAL	1.73	0.12	TWEXBMTH	-0.98	0.61	IPFINAL	-0.61	0.26	TWEXBMTH	-0.54	0.58
TCU	2.79	0.11	EXSZUS	-2.04	0.95	TCU	-1.17	0.30	EXSZUS	-1.94	0.94
IPG211111CS	-8.65	0.65	EXJPUS	-1.77	0.91	IPG211111CS	-8.39	0.74	EXJPUS	-1.70	0.91
DGORDER	-1.14	0.61	EXUSUK	-0.80	0.38	DGORDER	-0.56	0.81	EXUSUK	-0.28	0.35
ACDGNO	0.21	0.05	EXCAUS	-0.02	0.28	ACDGNO	0.66	0.13	EXCAUS	0.24	0.19
NEWORDER	-4.50	0.78	MCOILWTICO	-2.00	0.53	NEWORDER	-4.52	0.79	MCOILWTICO	-1.29	0.46
INVCMRMTSPL	**3.08**	**0.01**	PCU2122221222	-0.20	0.40	INVCMRMTSPL	**3.71**	**0.00**	PCU2122221222	-0.06	0.26
BUSLOANS	-3.39	0.52	WPUSI019011	-0.53	0.22	BUSLOANS	-2.99	0.48	WPUSI019011	**0.34**	**0.06**
TOTALSL	-2.48	0.46	PPIACO	-7.69	0.77	TOTALSL	-0.47	0.56	PPIACO	-4.88	0.89
AHETPI	-1.16	0.53	WPSFD49207	-6.15	0.67	AHETPI	-0.31	0.35	WPSFD49207	-4.48	0.56
CES2000000008	-0.72	0.84	WPSFD4111	-0.56	0.45	CES2000000008	-0.06	0.51	WPSFD4111	-0.47	0.72
CES3000000008	-0.07	0.61	WPSID612	-0.96	0.23	CES3000000008	-0.07	0.61	WPSID612	0.71	0.09
CES0600000008	-0.21	0.60	IQ00200	-1.09	0.55	CES0600000008	-0.22	0.61	IQ00200	-1.34	0.65
CIVPART	-1.39	0.51	WPU01830131	-8.96	0.21	CIVPART	-0.51	0.39	WPU01830131	-8.84	0.18
UNRATE	-0.08	0.31	WPU0121	-2.00	0.77	UNRATE	-0.26	0.35	WPU0121	0.27	0.25
UEMPMEAN	-0.61	0.47	Agric	-1.65	0.51	UEMPMEAN	0.55	0.13	Agric	-1.53	0.59
UEMPLT5	-1.19	0.52	Food	-0.80	0.78	UEMPLT5	-1.89	0.73	Food	-0.49	0.72
UEMP5TO14	-1.49	0.58	Soda	-0.54	0.61	UEMP5TO14	-1.57	0.65	Soda	-0.28	0.50
UEMP15OV	0.36	0.20	Beer	-0.62	0.83	UEMP15OV	**1.17**	**0.03**	Beer	-0.62	0.83
UEMP15T26	-0.76	0.85	Smoke	-0.15	0.27	UEMP15T26	-0.49	0.80	Smoke	0.53	0.22
UEMP27OV	0.95	0.11	Toys	-0.70	0.64	UEMP27OV	**1.27**	**0.02**	Toys	-0.39	0.52

PAYEMS	-2.57	0.31	Fun	-2.50	0.70	PAYEMS	**1.67**	**0.04**	Fun	-1.74	0.64
USGOOD	-4.81	0.11	Books	-1.07	0.46	USGOOD	**2.17**	**0.01**	Books	-0.44	0.35
USMINE	-1.12	0.46	Hshld	-1.19	0.84	USMINE	-0.17	0.30	Hshld	-0.91	0.76
USCONS	-2.23	0.56	Clths	-0.65	0.69	USCONS	-0.24	0.46	Clths	-0.42	0.60
MANEMP	-4.48	0.06	Hlth	-0.95	0.64	MANEMP	**2.24**	**0.01**	Hlth	-0.96	0.66
DMANEMP	-3.84	0.07	MedEq	-0.91	0.66	DMANEMP	**2.97**	**0.00**	MedEq	-0.33	0.62
NDMANEMP	-1.83	0.10	Drugs	-0.28	0.38	NDMANEMP	0.12	0.12	Drugs	0.05	0.29
USFIRE	-2.53	0.51	Chems	-1.20	0.58	USFIRE	-0.78	0.60	Chems	-0.23	0.39
CES9091000001	-3.65	0.86	Rubbr	-1.59	0.76	CES9091000001	-0.84	0.78	Rubbr	-0.68	0.63
USTRADE	0.05	0.19	Txtls	-1.89	0.90	USTRADE	**0.49**	**0.10**	Txtls	-1.45	0.84
USTPU	-1.28	0.37	BldMt	-1.33	0.71	USTPU	-0.04	0.32	BldMt	-0.48	0.52
HOUST	-3.48	0.51	Cnstr	-1.09	0.79	HOUST	0.52	0.20	Cnstr	-0.61	0.74
HOUSTNE	-1.68	0.61	Steel	-2.93	0.83	HOUSTNE	-0.27	0.35	Steel	-2.82	0.88
HOUSTS	-2.65	0.46	FabPr	-1.42	0.79	HOUSTS	**1.09**	**0.06**	FabPr	-1.24	0.77
HOUSTW	-3.33	0.60	Mach	-1.13	0.64	HOUSTW	-0.34	0.50	Mach	-0.58	0.56
PERMIT	-2.88	0.47	ElcEq	-1.88	0.82	PERMIT	**0.97**	**0.09**	ElcEq	-1.48	0.83
PERMITNE	-2.04	0.63	Autos	-1.83	0.45	PERMITNE	-0.16	0.48	Autos	-1.41	0.45
PERMITMW	-3.02	0.51	Aero	-1.24	0.79	PERMITMW	-0.62	0.62	Aero	-1.11	0.76
PERMITS	-2.41	0.48	Ships	-1.83	0.78	PERMITS	**0.71**	**0.11**	Ships	-1.35	0.71
PERMITW	-3.76	0.39	Guns	-0.91	0.92	PERMITW	**1.49**	**0.05**	Guns	-0.88	0.91
MNFCTRIRSA	-0.44	0.60	Gold	-0.69	0.83	MNFCTRIRSA	-0.12	0.54	Gold	-0.71	0.83
M1SL	-14.66	0.30	Mines	-3.39	0.59	M1SL	-16.31	0.54	Mines	-2.01	0.56
M2SL	0.05	0.23	Coal	-2.25	0.61	M2SL	-1.56	0.72	Coal	-1.82	0.65
MABMM301USM189S	0.11	0.22	Oil	-1.19	0.82	MABMM301USM189S	-1.51	0.71	Oil	-0.52	0.71
M2REAL	-5.83	0.62	Util	-1.57	0.82	M2REAL	-6.89	0.83	Util	-1.04	0.83
AMBSL	-268.64	0.18	Telcm	-1.15	0.72	AMBSL	-3.48	0.88	Telcm	-1.09	0.74
CPIAPPSL	-1.01	0.46	PerSv	-0.79	0.87	CPIAPPSL	-0.94	0.45	PerSv	-0.61	0.81
CPITRNSL	-5.84	0.25	BusSv	-0.32	0.50	CPITRNSL	-0.29	0.42	BusSv	-0.24	0.49
CPIMEDSL	-1.56	0.09	Comps	-1.76	0.84	CPIMEDSL	0.03	0.20	Comps	-1.33	0.79
CUSR0000SAC	-3.16	0.73	Chips	-1.61	0.76	CUSR0000SAC	-0.22	0.43	Chips	-0.82	0.63
CUSR0000SAD	-1.09	0.72	LabEq	-0.88	0.57	CUSR0000SAD	-0.98	0.70	LabEq	-0.42	0.49
CPILFESL	**1.29**	**0.03**	Paper	-1.06	0.73	CPILFESL	**1.44**	**0.04**	Paper	-0.90	0.69
CPIAUCSL	-2.78	0.16	Boxes	-1.17	0.87	CPIAUCSL	-0.33	0.41	Boxes	-0.99	0.85
FEDFUNDS	-3.58	0.76	Trans	-0.65	0.57	FEDFUNDS	-1.64	0.78	Trans	-0.10	0.38
TB3MS	-3.70	0.69	Whlsl	-1.08	0.87	TB3MS	-2.02	0.67	Whlsl	-0.79	0.86
TB6MS	-3.51	0.71	Rtail	-0.24	0.40	TB6MS	-1.66	0.65	Rtail	0.00	0.33
GS1	-1.72	0.86	Meals	-1.21	0.88	GS1	-1.76	0.87	Meals	-0.99	0.84
GS2	-0.41	0.36	Banks	-1.68	0.71	GS2	-0.13	0.31	Banks	-0.76	0.53
GS3	-1.05	0.93	Insur	-0.58	0.41	GS3	-1.07	0.93	Insur	-0.38	0.43
GS5	-1.17	0.93	RlEst	-1.80	0.90	GS5	-1.21	0.95	RlEst	-1.36	0.85
GS7	-1.16	0.91	Fin	-1.76	0.75	GS7	-1.25	0.94	Fin	-1.39	0.72

Table A6: **Out-of-sample predictability using macro predictors: Δ Utility%**. The utility gain (Δ Utility) is the portfolio management fee (in annualized percentage return) that an investor with mean-variance preferences and risk aversion coefficient of three would be willing to pay to have access to the forecasting model considered relative to the historical average benchmark forecasting model; the weight on stocks in the investor's portfolio is restricted to lie between 0 and 1.5 (inclusive). Base employs the predicted returns without constraints while Restricted replace the negative forcasts with zero. The results refer to monthly forecasts for the out-of-sample period 2000-2017. Results in **Bold** imply an annual utility gain higher than 1%.

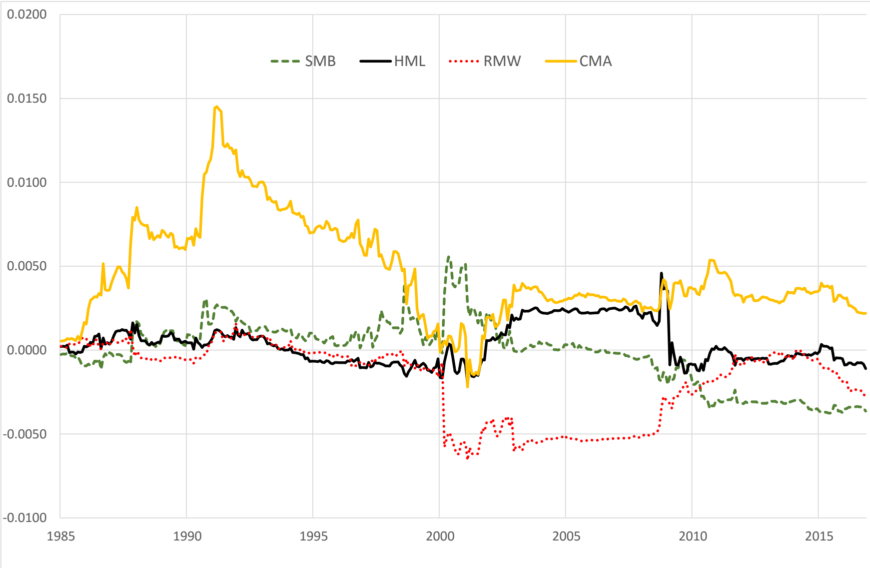
Δ Utility	**Base**	**Restricted**	**Δ Utility**	**Base**	**Restricted**	**Δ Utility**	**Base**	**Restricted**	**Δ Utility**	**Base**	**Restricted**
DSPIC96	**2.34**	**2.15**	USGOOD	**5.78**	**5.97**	GS10	-1.54	-1.54	Books	-0.80	-0.28
PCEPILFE	0.26	0.15	USMINE	-0.31	0.36	T10Y3MM	-1.23	-1.17	Hshld	-0.83	-0.43
PCE	**2.10**	**2.79**	USCONS	**1.38**	**1.42**	T1YFFM	-0.40	-0.82	Clths	-0.52	-0.19
CMRMTSPL	**1.27**	**1.46**	MANEMP	**5.19**	**4.76**	T6MFFM	-0.39	-0.74	Hlth	-1.94	-1.91
RSXFS	**2.03**	**1.75**	DMANEMP	**6.22**	**5.95**	T10Y2YM	-0.70	-0.35	MedEq	-0.29	0.12
TOTALSA	**1.36**	0.93	NDMANEMP	**4.24**	**4.18**	BAA10YM	-0.84	-0.97	Drugs	0.79	0.65
MARTSMPCSM44000USS	**6.85**	**5.29**	USFIRE	**1.22**	**1.35**	IRLTLT01USM156N	-1.54	-1.54	Chems	-1.61	-1.06
UMCSENT	-0.01	0.90	CES9091000001	-0.38	-0.27	AAA	-0.74	-0.88	Rubbr	-1.07	-0.73
MICH	**2.96**	**2.35**	USTRADE	**2.99**	**2.98**	BAA	-1.19	-1.06	Txtls	-2.40	-1.91
CSCICP03USM665S	**1.30**	**2.59**	USTPU	**2.65**	**2.60**	AAA10YM	-2.06	-1.78	BldMt	-1.86	-1.53
MVGFD027MNFRBDAL	**1.68**	**1.61**	HOUST	**1.72**	**2.54**	AAAFFM	2.12	2.07	Cnstr	-1.64	-1.32
INDPRO	**1.95**	**2.27**	HOUSTNE	-1.03	-0.53	T5YFFM	-0.13	-0.21	Steel	-1.62	-1.43
IPMAN	**2.24**	**2.32**	HOUSTS	**1.68**	**2.28**	T3MFFM	**1.40**	0.63	FabPr	-1.16	-0.92
IPDCONGD	**2.62**	**2.69**	HOUSTW	**1.27**	**2.02**	EXBZUS	**1.23**	1.81	Mach	-1.66	-1.32
IPMAT	**2.19**	**2.59**	PERMIT	**1.58**	**2.38**	EXMXUS	0.90	0.57	ElcEq	-1.21	-0.95
IPBUSEQ	**2.38**	**3.07**	PERMITNE	0.27	0.95	EXINUS	**1.34**	**1.85**	Autos	-1.37	-1.23
IPFUELS	-1.78	-1.50	PERMITMW	**1.29**	**1.77**	RBUSBIS	0.12	0.33	Aero	-2.31	-2.04
IPB51222S	-2.20	-1.39	PERMITS	**1.13**	**2.00**	NBUSBIS	-1.10	-0.63	Ships	-1.90	-1.59
IPFINAL	**1.79**	**2.38**	PERMITW	**1.97**	**2.60**	TWEXBMTH	-1.13	-0.65	Guns	-1.08	-0.94
TCU	**1.69**	**1.81**	MNFCTRIRSA	0.32	0.30	EXSZUS	-1.54	-1.33	Gold	-2.02	-2.00
IPG211111CS	-1.55	-1.55	M1SL	-1.86	-1.78	EXJPUS	-1.67	-1.55	Mines	-0.35	0.33
DGORDER	-1.53	-1.40	M2SL	0.15	-0.18	EXUSUK	-0.82	-0.27	Coal	0.39	0.35
ACDGNO	**2.40**	**1.86**	MABMM301USM189S	0.19	-0.14	EXCAUS	0.25	0.66	Oil	-0.60	-0.23
NEWORDER	-1.65	-1.55	M2REAL	-1.33	-1.42	MCOILWTICO	-0.61	-0.11	Util	-0.02	-0.27
INVCMRMTSPL	0.73	1.70	AMBSL	-2.13	-1.96	PCU2122221222	-0.15	0.00	Telcm	-0.81	-0.76
BUSLOANS	0.83	1.38	CPIAPPSL	-0.44	-0.28	WPUSI019011	0.39	0.45	PerSv	-1.07	-0.75
TOTALSL	-0.57	-0.52	CPITRNSL	-0.31	-0.27	PPIACO	-1.18	-0.99	BusSv	0.19	0.40
AHETPI	0.04	0.79	CPIMEDSL	-0.44	-0.46	WPSFD49207	-1.08	-0.67	Comps	-0.18	0.34
CES2000000008	-0.02	0.39	CUSR0000SAC	-0.61	-0.34	WPSFD4111	-0.25	-0.26	Chips	0.48	0.93
CES3000000008	0.15	0.14	CUSR0000SAD	-1.62	-1.48	WPSID612	**1.80**	**1.76**	LabEq	-0.01	0.42
CES0600000008	-0.56	-0.52	CPILFESL	0.36	0.19	IQ00200	**1.53**	**1.21**	Paper	-1.51	-1.20
CIVPART	-0.59	0.09	CPIAUCSL	-0.12	-0.62	WPU01830131	0.31	0.38	Boxes	-2.18	-2.11
UNRATE	**1.18**	**1.18**	FEDFUNDS	0.13	0.94	WPU0121	0.61	0.99	Trans	-0.68	-0.29
UEMPMEAN	-0.33	0.78	TB3MS	0.24	0.87	Agric	-0.32	-0.26	Whlsl	-1.62	-1.26
UEMPLT5	-0.77	-0.97	TB6MS	-0.04	0.73	Food	0.43	0.49	Rtail	-0.12	0.15
UEMP5TO14	-1.64	-1.58	GS1	-0.71	-0.85	Soda	0.06	0.27	Meals	-1.08	-0.84
UEMP15OV	**3.61**	**3.46**	GS2	-0.18	-0.11	Beer	-0.52	-0.45	Banks	-1.00	-0.28
UEMP15T26	-0.90	-0.73	GS3	-1.09	-1.22	Smoke	-0.31	-0.23	Insur	0.33	0.25
UEMP27OV	**3.99**	**3.75**	GS5	-1.12	-1.13	Toys	-1.02	-0.55	RlEst	-1.31	-0.84
PAYEMS	**3.39**	**3.45**	GS7	-1.16	-1.17	Fun	-1.90	-1.56	Fin	-0.52	-0.19

Table A7: **Unit Root and Cointegration Tests**. The upper part of the table reports the p-value for the Augmented Dickey Fuller and Phillips-Perron Test for the existence of a unit root in the time series employed when a maximum of 4 lags are considered. In the lower table we report the Results for the Engle-Granger cointegration test and for the Johansen cointegration test. The pairwise p-values are reported for the Engle-Granger test. For the Johansen test we report the results coming from our test with the 10^{th}, 5^{th} and 1^{st} critical values tabulated by Johansen for the identification of the presence of different unit roots.

Unit Root	ADF test	PP test	Unit Root	ADF test	PP test
TOT	0.01	0.01			
Sentiment	0.46	0.62	**Sen ret**	0.01	0.01
DVRP	0.01	0.01	**DVRP ret**	0.01	0.01
FU	0.14	0.48	**FU ret**	0.01	0.01
Income	0.01	0.01	**Inc ret**	0.01	0.01
Industrial Production	0.01	0.01	**Ind Pr ret**	0.01	0.01
Labor	0.34	0.03	**Labor ret**	0.01	0.01
House	0.88	0.90	**House ret**	0.01	0.01
Inflation	0.01	0.01	**Inf ret**	0.01	0.01

Engle-Granger	Sent	Unc	Labor	House
Sent		0.05	0.10	0.05
Unc	0.05		0.09	0.10
Labor	0.09	0.06		0.10
House	0.10	0.10	0.10	
Johansen	**test**	**10pct**	**5pct**	**1pct**
r<= 3	1.33	6.5	8.18	11.65
r<= 2	7.92	15.66	17.95	23.52
r<= 1	17.26	28.71	31.52	37.22
0	46.65	45.23	48.28	55.43

Figure 4.5: **Historical average benchmark forecast model cumulative square prediction error minus individual predictive regression forecast model cumulative square prediction error (times 100)**. In the upper plot we draw results for the SMB, HML, RMW, and CMA factors. In the lower plot we draw results for the LT, ST and Momentum (Mom) factors.



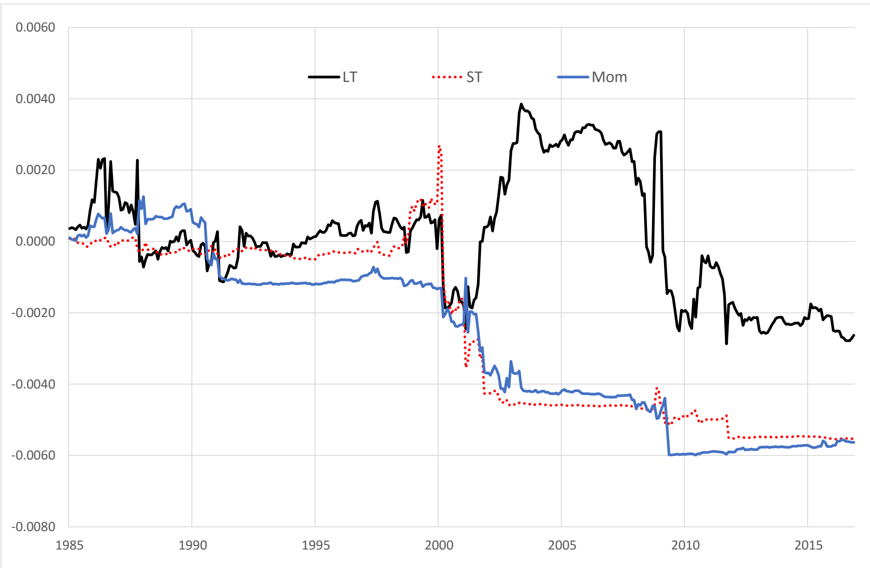
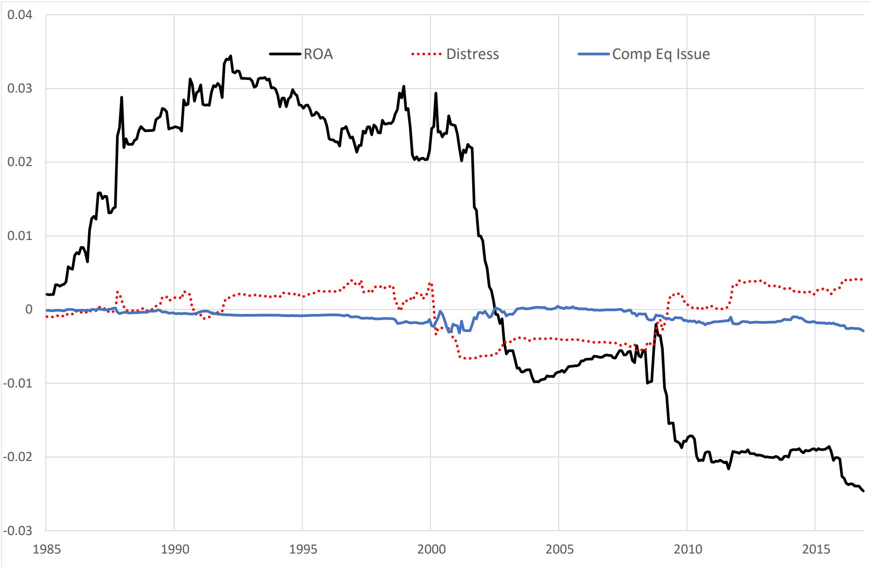


Figure 4.6: **Historical average benchmark forecast model cumulative square prediction error minus individual predictive regression forecast model cumulative square prediction error (times 100)**. In the upper plot we draw results for the ROA, Distress, and Composite Eq Issue anomalies. In the lower plot we draw results for the NOA, Accruals and O anomalies.



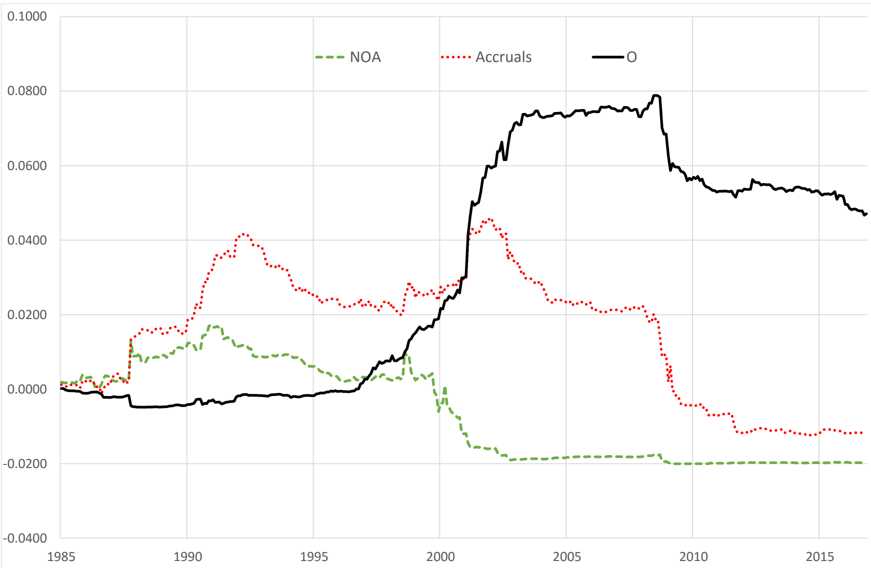
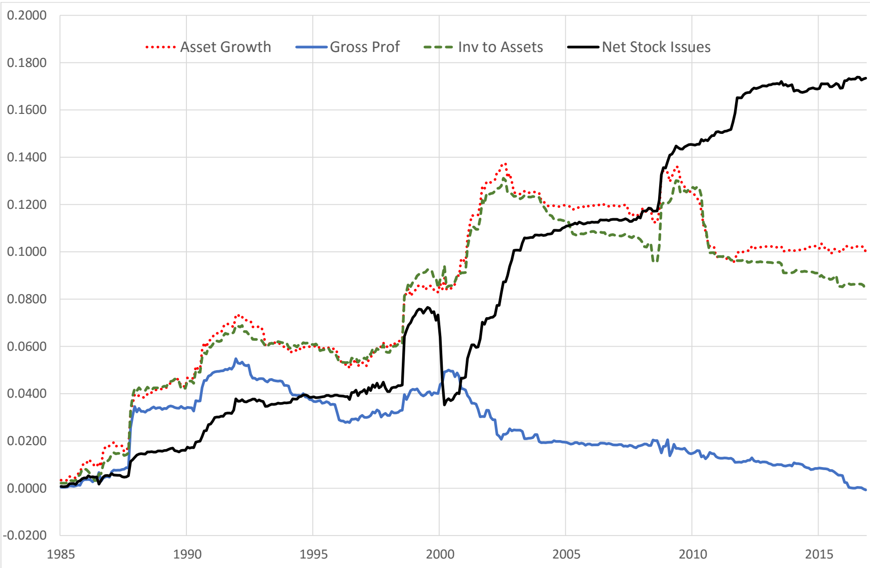


Figure 4.7: **Historical average benchmark forecast model cumulative square prediction error minus individual predictive regression forecast model cumulative square prediction error (times 100)**. In the upper plot we draw results for the Asset Growth, Gross Prof, Inv to Assets and, Net Stock Issues. In lower plot we draw results for OLS, Pooled Forecast median, Pooled Forecast MDSFE, and Diffusion Index which employ as inputs the 17 factors-anomalies spread-returns.



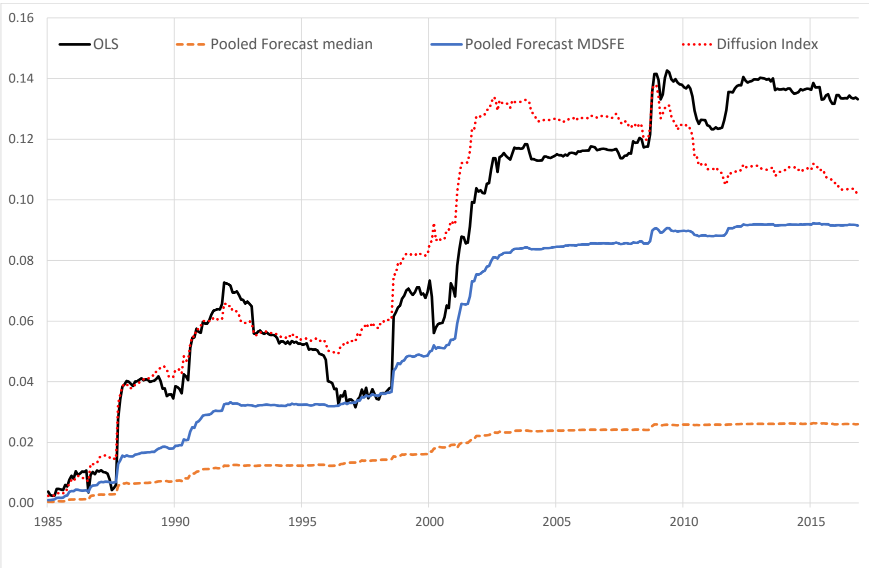


Figure 4.8: **Historical average benchmark forecast model cumulative square prediction error minus individual predictive regression forecast model cumulative square prediction error (times 100)**. In this plot we draw results for MARS SVM, SIC SVM, and, LASSO SVM which employ as inputs the 17 factors-anomalies spread-returns

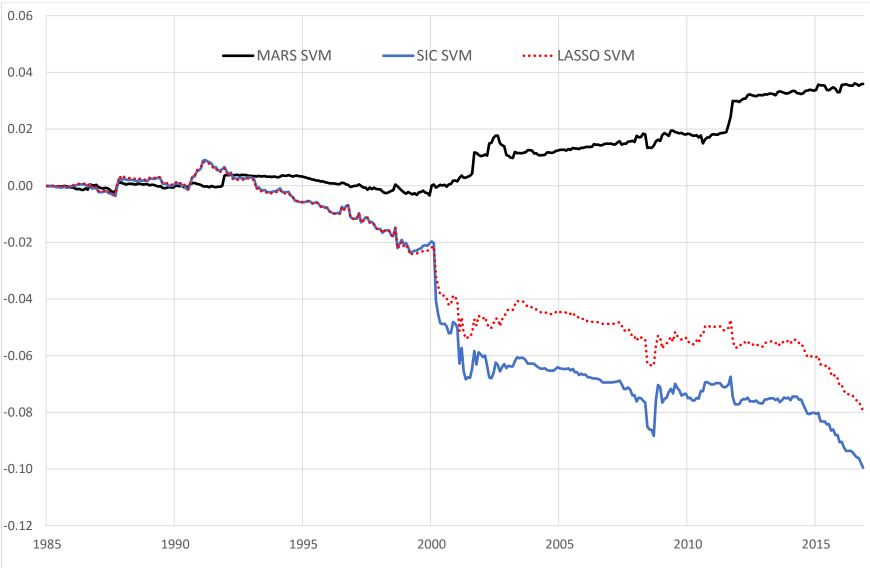
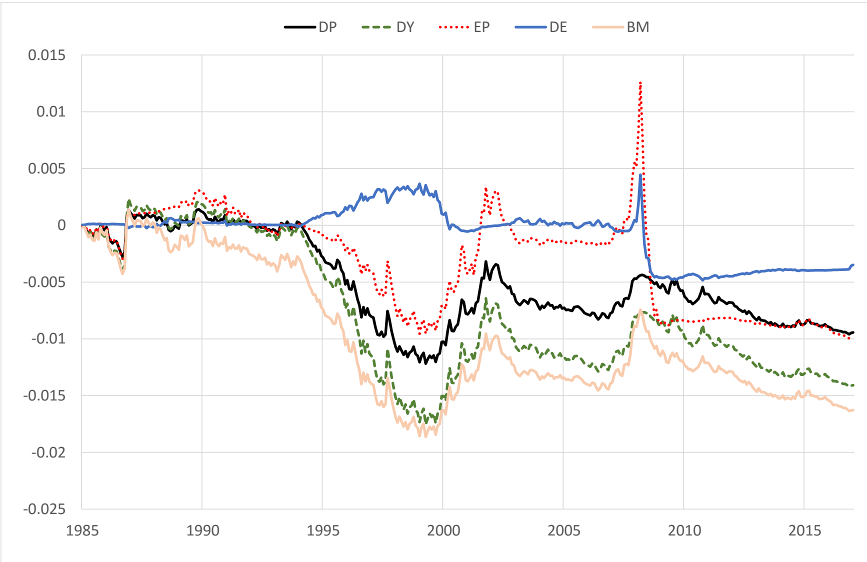


Figure 4.9: **Historical average benchmark forecast model cumulative square prediction error minus individual predictive regression forecast model cumulative square prediction error (times 100)**. In the upper plot we draw results for the Asset Growth, Gross Prof, Inv to Assets and, Net Stock Issues. In the lower plot we draw results for OLS, Pooled Forecast median, Pooled Forecast MDSFE, and Diffusion Index which employ as inputs the 17 factors-anomalies spread-returns.



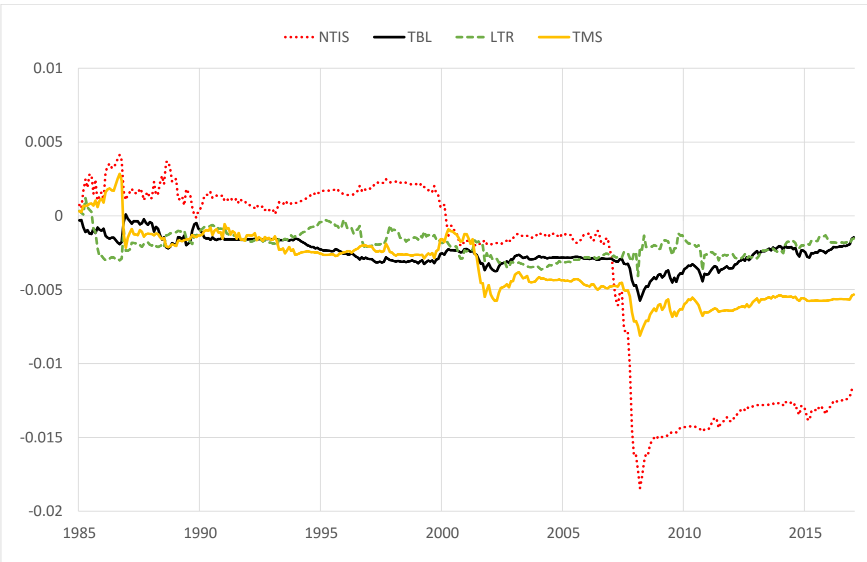
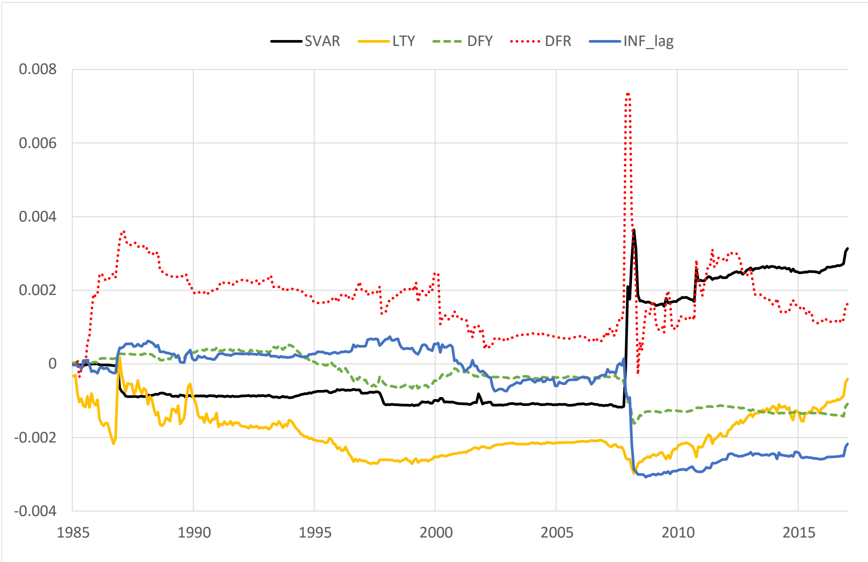


Figure 4.10: **Historical average benchmark forecast model cumulative square prediction error minus individual predictive regression forecast model cumulative square prediction error (times 100)**. In the upper plot we draw results for the Asset Growth, Gross Prof, Inv to Assets and, Net Stock Issues. In the lower plot we draw results for OLS, Pooled Forecast median, Pooled Forecast MDSFE, and Diffusion Index which employ as inputs the 17 factors-anomalies spread-returns.



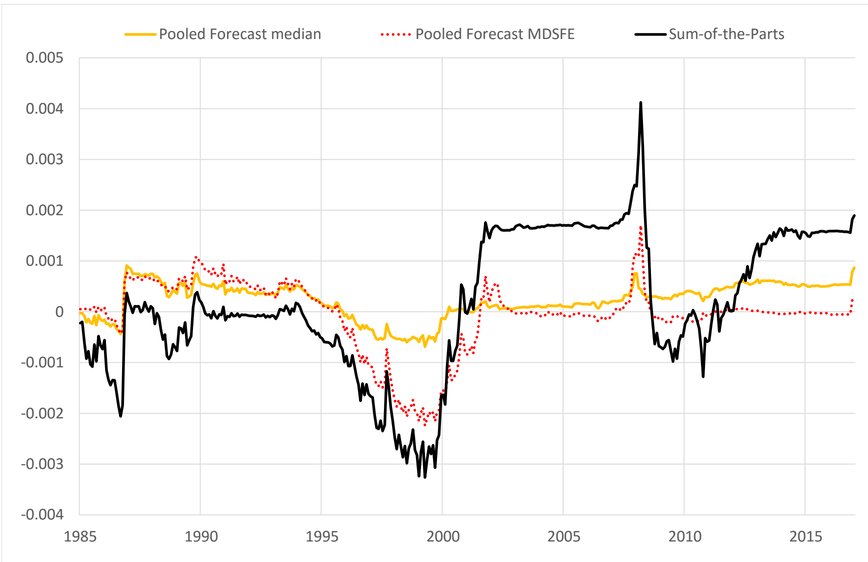
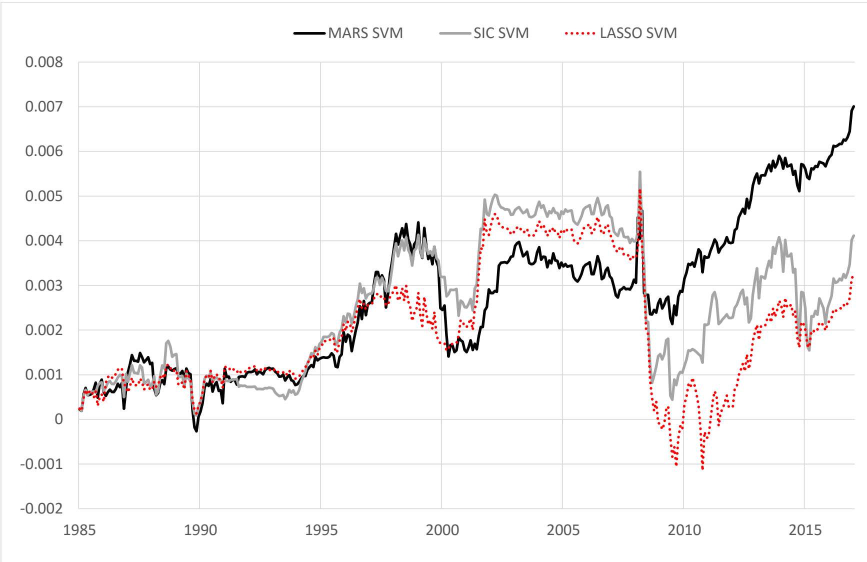
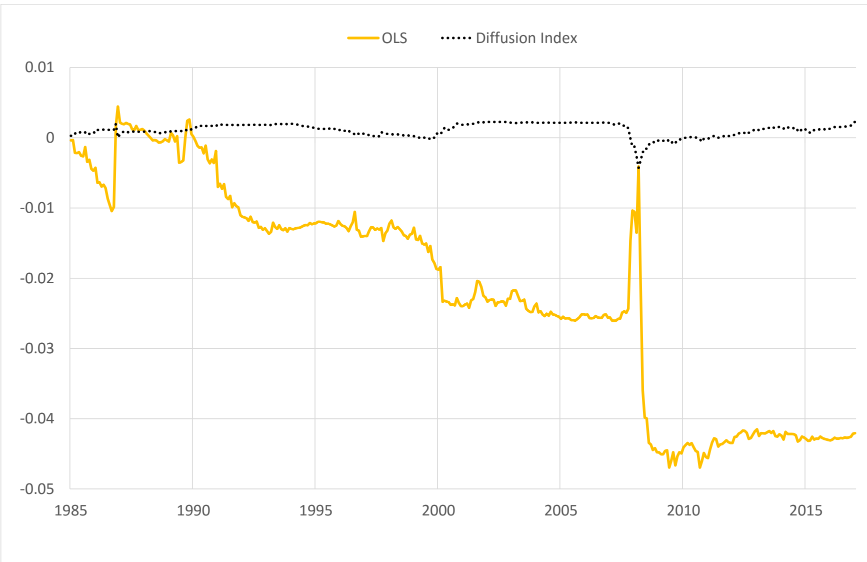


Figure 4.11: **Historical average benchmark forecast model cumulative square prediction error minus individual predictive regression forecast model cumulative square prediction error (times 100)**. In the upper plot we draw results for the Asset Growth, Gross Prof, Inv to Assets and, Net Stock Issues. In the lower plot we draw results for OLS, Pooled Forecast median, Pooled Forecast MDSFE, and Diffusion Index which employ as inputs the 17 factors-anomalies spread-returns.





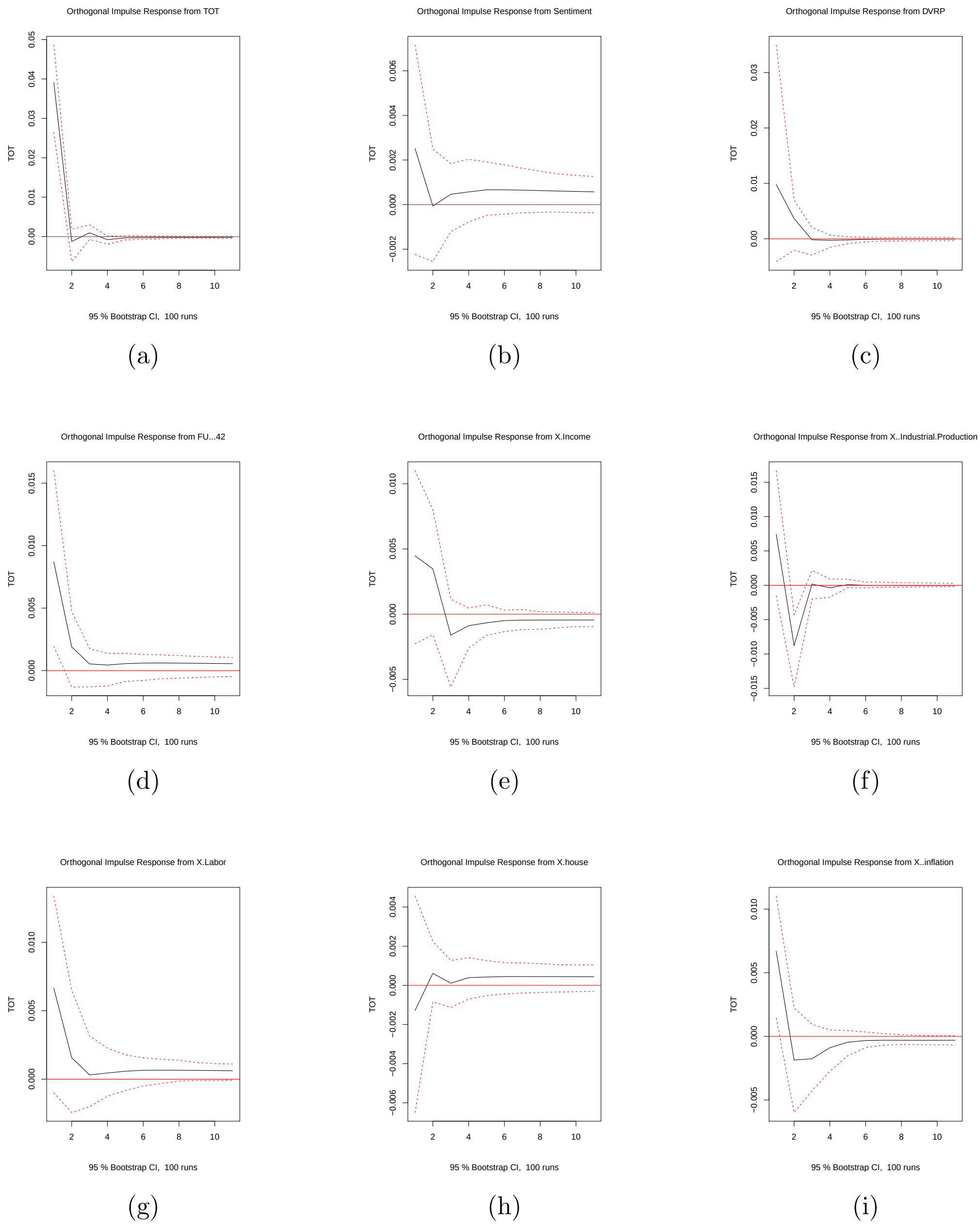


Figure 4.12: **Impulse Response Function R^2_{OS} levels**. This Figure shows the response of the Total R^2_{OS} to the following impulses: (a) R^2_{OS}, (b) Greed, (c) Fear, (d) Uncertainty, (e) Income, (f) Industrial Production, (g) Labor, (h) House, (i) Inflation

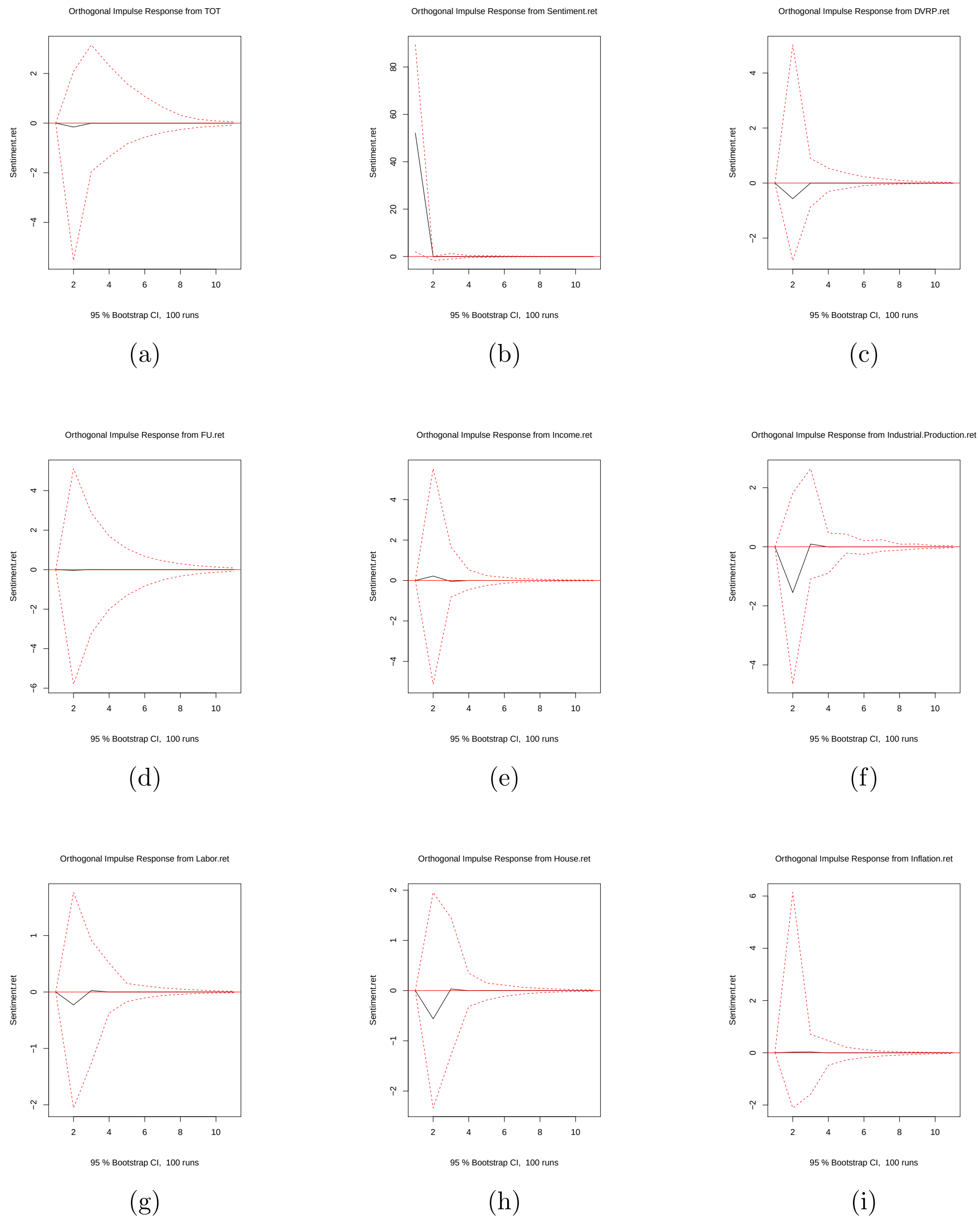


Figure 4.13: **Impulse Response Function Greed returns**. This Figure shows the response of the Gread return to the following impulses: (a) R^2_{OS}, (b) Greed, (c) Fear, (d) Uncertainty, (e) Income, (f) Industrial Production, (g) Labor, (h) House, (i) Inflation

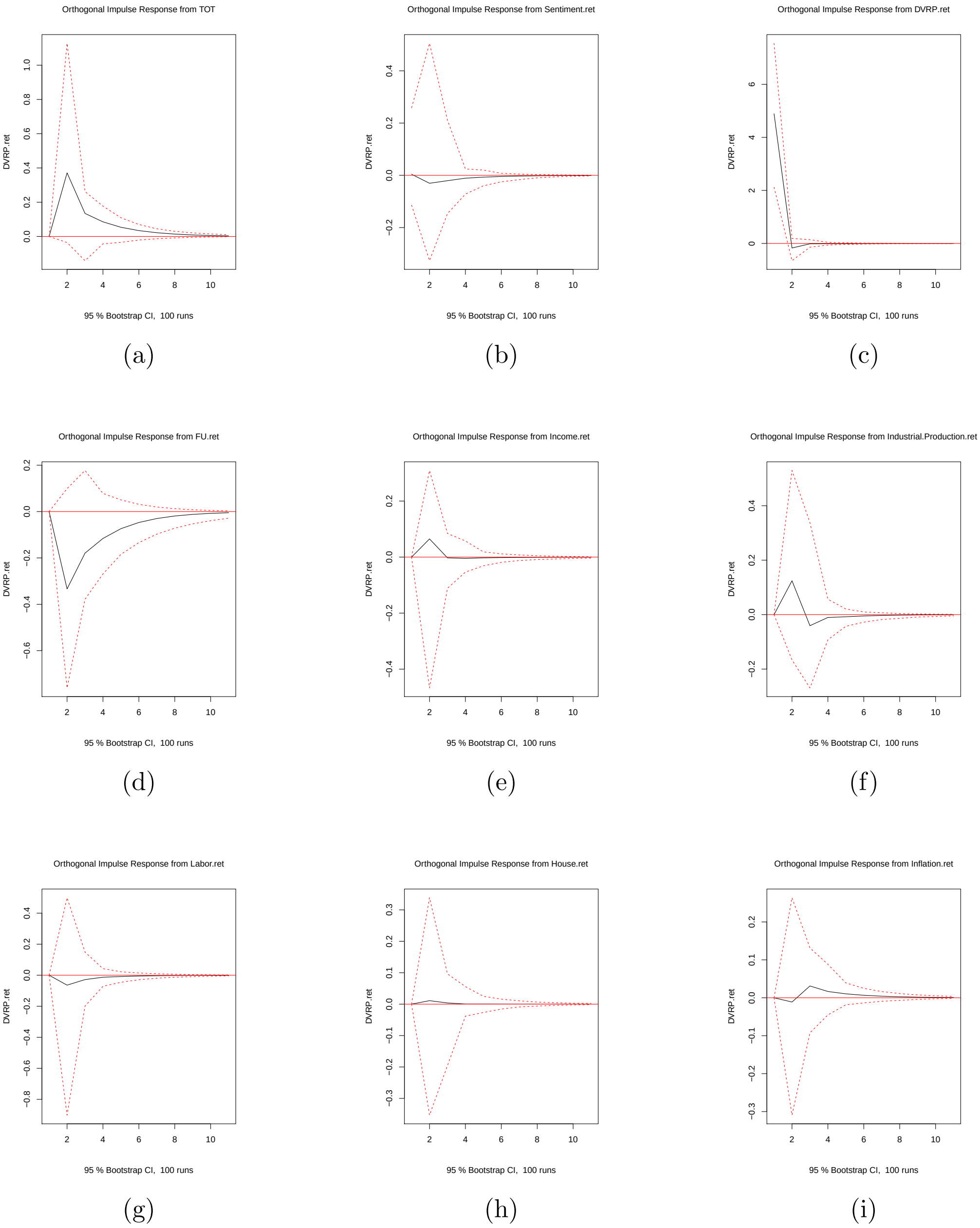


Figure 4.14: **Impulse Response Function Fear returns**. This Figure shows the response of the Fear return to the following impulses: (a) R^2_{OS}, (b) Greed, (c) Fear, (d) Uncertainty, (e) Income, (f) Industrial Production, (g) Labor, (h) House, (i) Inflation

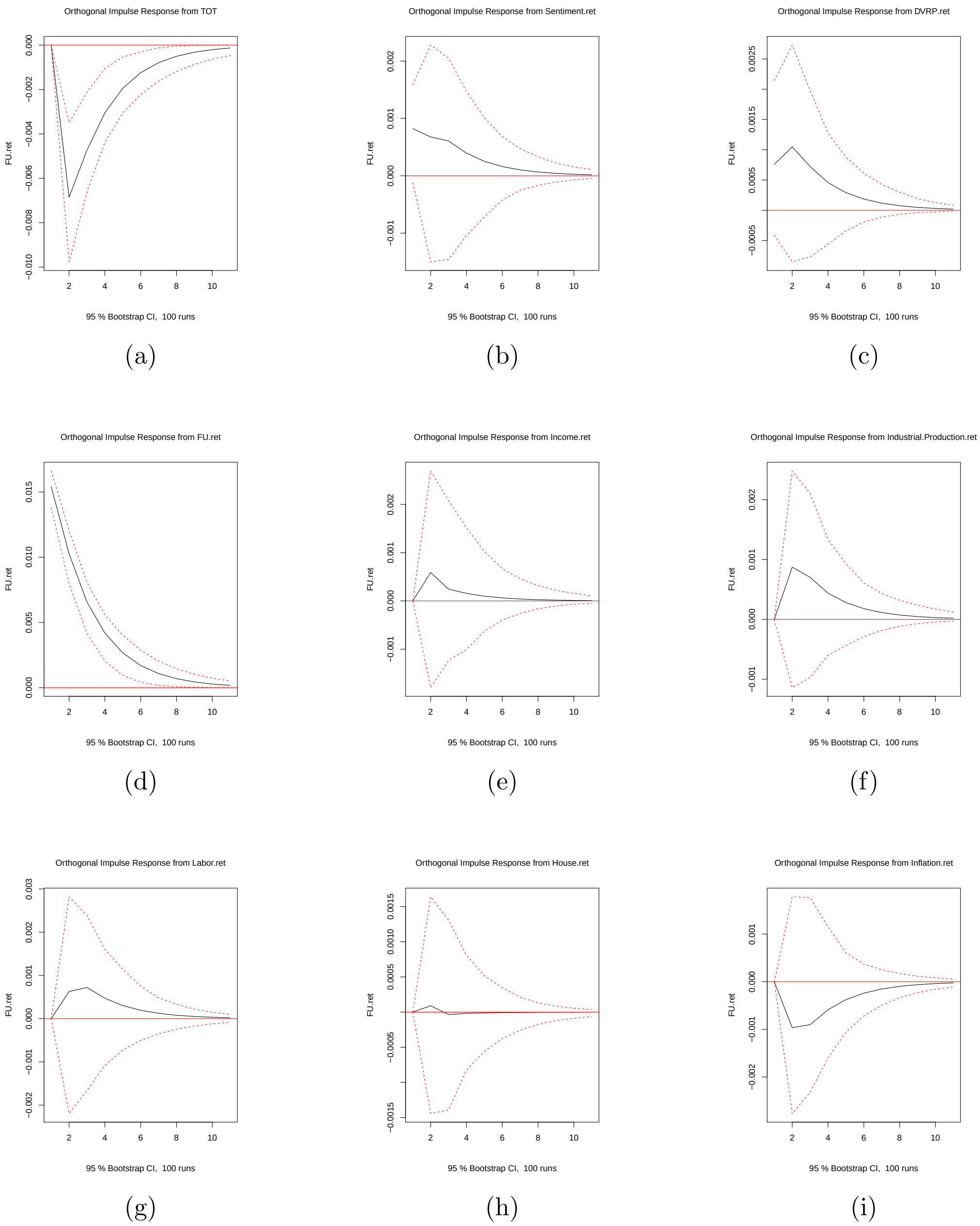


Figure 4.15: **Impulse Response Function Uncertainty returns**. This Figure shows the response of the Uncertainty return to the following impulses: (a) R^2_{OS}, (b) Greed, (c) Fear, (d) Uncertainty, (e) Income, (f) Industrial Production, (g) Labor, (h) House, (i) Inflation