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PhD Thesis

Essays in Empirical Finance

Author:

Matteo Garzoli

Thesis Committee:

Prof. Alberto Plazzi - Swiss Finance Institute, Università della Svizzera italiana
Prof. Loriano Mancini - Swiss Finance Institute, Università della Svizzera italiana
Prof. Rossen Valkanov - Rady School of Management, University of California San Diego

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ABSTRACT

I use empirical methods to forecast U.S. repeat-sales house price indices, to analyze Swiss long-run default rates and to investigate the role of country and industry effects on the downside risk of stock index returns.

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Chapter 1

Preface

This thesis is composed of three distinct articles, each of which focuses on a different area of the empirical finance. In the chapters of this dissertation I use recent empirical methods to forecast the U.S. residential real estate market prices, to analyze Swiss default rates in the long-run and to investigate how country- and industry-aggregation of stocks impact the downside risk of stock index returns.

In the following paragraphs, I present a summary of each paper.

1.1 Summary of Papers

Chapter 2, "Backcasting, Nowcasting, and Forecasting Residential Repeat-Sales Returns: Forecast Combination meets Mixed Frequency" (co-authored with Alberto Plazzi and Rossen Valkanov) proposes an innovative application of Mixed-Data Sampling methods together with a "big-data" approach to forecast Case-Shiller index returns. The Case-Shiller is the reference repeat-sales index for the U.S. residential real estate market, yet it is released with a two-month delay. We find that incorporating recent information from 71 financial and macro predictors improves backcasts, nowcasts, and short-term out-of-sample forecasts of the index returns. Combining individual forecasts delivers large improvements in forecast accuracy at all horizons. Additional gains are obtained with Mixed-

Data Sampling methods that exploit the daily frequency of financial variables, reducing the out-of-sample mean squared forecast error by as much as 11% compared to a simple autoregressive benchmark. The forecast improvements are largest during economic turmoil and throughout the 2020 COVID-19 pandemic period.

Chapter 3, "What drives corporate default rates? Evidence from a century of Swiss data" (co-authored with Alberto Plazzi) studies the long-run default rate behaviour of Swiss firms. In the paper, we construct national and macroregional time series of default rates for limited liability companies in Switzerland using a new dataset covering the full universe of firms in the country over the extensive period 1902-2015. We find that default rates are highly persistent and exhibit variation both over time as well as in the cross-section of regions. A Markov switching regime model for default rates identifies two distinct regimes with GDP growth, stock market return and inflation rate as significant predictors. In an out-of-sample experiment, we show that macroeconomic and financial variables are valuable forecasters of the term structure of default rates. At the same time, even after controlling for the principal components of such covariates, we find a significant dynamic frailty factor that is responsible for default clustering.

Chapter 4, "Downside Risk and International Diversification: The Role of Country and Industry Effects"(co-authored with Eric Ghysels, Alberto Plazzi and Rossen Valkanov) investigates the relative importance of industry and country factors in determining the downside risk of equity returns in developed markets with a large international dataset spanning the three most recent decades. Using the Heston and Rouwenhorst (1994) decomposition we find that the pure country effects and pure industry effects play an important role in explaining total skewness of country and industry indices. With a stratified bootstrap approach, we present evidence that the difference in variance reduction between investing across countries or industries has diminished dramatically over time, whereas portfolios concentrated within countries are on average more positively skewed than portfolios concentrated within industries. In the static setting the higher skewness of within-country

concentrated portfolios is accompanied by a higher Certainty Equivalent and a lower VaR compared to within-industry portfolios. Finally, we consider the benefits of exploiting time-variation in skewness in a dynamic portfolio allocation problem between countries and industries, finding sizeable certainty-equivalent gains for investors and a higher tilt towards the more positively skewed country indices.

1.2 Additional Work and Outline

Furthermore, during my PhD studies I have also worked on two other projects related to downside risk and credit risk which are still in a draft stage. In my second year sole-authored term paper *"Conditional Skewness and Momentum Profits"*, I analyze the potential of timing stock return skewness in momentum strategies. Compared to plain momentum, I find that a strategy that goes long past winners with high conditional skewness and short past losers with low conditional skewness delivers higher Sharpe ratio, higher α and a larger certainty equivalent while mitigating the adverse impact of higher moments. I document that double-sorting on momentum and skewness reduces total transaction costs and shorts a smaller amount of stocks, enhancing momentum net profitability. I finally show with international data that skewness predictability improves momentum diversification benefits across countries.

In addition, as part of the SNF project *Corporate Default Risk in the Long-Run: Evidence from Switzerland, 1883-2015*, I also wrote the paper *"If at first you don't succeed... Contagion effects of (serially) defaulting board members in Switzerland"* jointly with Virginia Gianinazzi, Eric Nowak and Alberto Plazzi. In this paper, using information from the Commercial Registry covering the universe of firms in Switzerland over 2002-2016, we identify board members that are involved in multiple bankruptcy filings. We find that the number of board members' past defaults is a strong positive out-of-sample predictor of a newly established company's default probability, even controlling for time and industry effects

as well as for the number of boards individuals serve on. Only in sectors that are more prone to innovation we also find a positive relationship between the board members' default record and upside growth - as measured by turnover, suggesting this evidence may reflect risk preferences by board members. We also show that individuals defaults are contagious, in that having been in the board together with a serial defaulter increases the likelihood that another member files for bankruptcy in the future. We document that this effect is stronger when the initial connection happens in a small board, where personal relations are easier to establish.

The thesis is structured as follows:

Chapter 2 ***Backcasting, Nowcasting, and Forecasting Residential Repeat-Sales Returns: Forecast Combination meets Mixed Frequency***, Matteo Garzoli, Alberto Plazzi, Rossen Valkanov

Chapter 3 ***What drives corporate default rates? Evidence from a century of Swiss data***, Matteo Garzoli, Alberto Plazzi

Chapter 4 ***Downside Risk and International Diversification: The Role of Country and Industry Effects***, Matteo Garzoli, Eric Ghysels, Alberto Plazzi, Rossen Valkanov.

Chapter 2

Backcasting, Nowcasting, and Forecasting Residential Repeat-Sales Returns: Forecast Combination meets Mixed Frequency

2.1 Introduction

Fluctuations in house prices have wide-ranging effects on economic variables, such as consumption (Case et al., 2005; Mian et al., 2013), employment (Mian and Sufi, 2014; Adelino et al., 2013), and economic growth (Leamer, 2007; Loutskina and Strahan, 2011). House price indices, as exemplified by the Case-Shiller repeat-sales index ("`CS`" henceforth), capture the dynamics of residential real estate values and have become central in informing the decisions of not only homeowners, buyers and sellers, but also banks, government sponsored enterprises (GSEs), and the Fed.

There are two key features the `CS` shares with most real estate indices. First, it is released with a delay of several months. For instance, on December 29th, 2020, the newest release of

the CS featured prices for October 2020 – a delay of two months. On that day, November and December 2020 values of the index were simply unavailable. Decisions based on stale October 2020 CS values would have failed to factor in the vast amount of recent and potentially relevant information about the real estate market – contained in interest rates, employment, economic activity, REITs, and other industry and aggregate market returns – that became available over the course of two months.[1] Participants seeking up-to-date information about residential prices would have had to find back-of-the-envelope ways of "backcasting" and "nowcasting" CS values (for November and December 2020, respectively).

Second, because of sizeable frictions in real estate markets, CS returns are serially correlated. These frictions imply that recent information about the state of the economy might be informative about future CS returns, after controlling for their lag....In this article, we ask whether macroeconomic and financial variables available during the lag release window improve CS return forecasts.

At the risk of oversimplifying, the answer to the question is a resounding "yes": recent macroeconomic and financial variables can lead to significant improvements in backcasting, nowcasting, and short-term forecasting of CS returns. Accurate monthly out-of-sample forecasts require combinations of individual forecasts, emphasizing the importance of using a "big-data" approach rather than focusing on one or few predictors. Additional improvements in forecasting error are obtained by using daily rather than monthly financial predictors in a mixed-frequency setting. Overall, the improvement in forecasting accuracy is economically relevant. Our estimates imply that, in annual terms, the forecast error on the out-of-sample $33'300 average annual return for a representative $1 million residential property in the U.S. improves by $3'029 in "calm" quarters, and as much as $7'038 in quarters of financial and economic turmoil. Given the $2.9 trillion one-year turnover in the 2020 U.S. residential market, these estimates translate into forecasts that are $8.8 and $20.4 billion closer to

[1] The regular release lag of two months implies that the November and December 2020 values of the CS would become available at the end of January and February 2021, respectively.

the actual (ex-post) values over calm and turbulent quarters, respectively.[2] During the March-December 2020 period, corresponding to the onset of the COVID-19 pandemic, this figure is a stunning $30.2 billion. We analyze the COVID-19 period in more detail, as it perfectly illustrates the advantages of using recent financial information after a shock that engenders rapidly changing economic conditions.

The above findings are obtained in a framework that accommodates: (i) a multitude of macroeconomic and financial predictors; (ii) predictors available at mixed, monthly and daily frequency; (iii) various ways of combining individual predictors' forecasts; (iv) backcasting, nowcasting, and forecasting at 1-month and 3-month horizons; (v) in-sample and out-of-sample performance; (vi) forecasting errors that vary with the state of the economy. We gauge the value added by the predictors against the benchmark autoregressive model, as its ability to capture the persistence of `CS` returns in a parsimonious way makes it a difficult hurdle to outperform out-of-sample.

In more detail, we first examine whether 71 predictors, sampled at the monthly frequency, yield more precise forecasts of `CS` index returns out-of-sample, in mean squared forecasting error (MSFE) sense, relative to an autoregressive model. The predictors include 38 financial variables – returns of different portfolios and yield spreads – and 33 macroeconomic series – common measures of economic activity, unemployment, wages, and housing starts. We find that several financial variables are standout predictors, relative to the autoregressive benchmark, with the best performers being the S&P500, REITs, and the construction industry portfolio returns. Relative to financial predictors, the improvement offered by macroeconomic variables is limited, with housing permits being a notable exception. Importantly, the improvements arise not only when adding the most recent release of these predictors at the time of the forecast, but also when using their lags.

We then consider forecast combination methods. In addition to the equally-weighted

[2] Yearly turnover is computed as the number of houses sold in a year times the average price of a house at the end of the period. There were 7.535 million homes sold during the year ending in the third quarter of 2020 and the average sales price in the third quarter of 2020 of houses in the U.S. was $387,000 according to Federal Reserve Bank of St. Louis data.

scheme, we aggregate forecasts based on their mean squared forecasting error (MSFE), a commonly used loss function (Rapach and Zhou, 2013). The forecasting performance improves significantly when we combine the individual predictions based on inverse MSFE and inverse rank MSFE (Elliott and Timmermann, 2013). In particular, combining the financial predictors weighted by the inverse MSFE rank yields the largest MSFE improvement out-of-sample, ranging from 1.52% for backcasting to 4.37% for the 3-month ahead forecast.

The second dimension we consider is the high-frequency availability of financial data. Given that the `CS` index is available monthly, the standard approach is to aggregate higher frequency predictors at monthly intervals. This aggregation method corresponds to imposing an arbitrary restriction on the data without exploiting the flow of available daily information within a month, which might well result in a loss of useful signals in a predictive setting (Andreou et al., 2013). Moreover, various predictors are useful at different lags. Given that our financial variables are available at daily frequency, we use a Mixed-Data Sampling (MIDAS) approach to predict the monthly values of the `CS`. MIDAS regressions represent tightly parameterized models that exploit information sampled at different frequencies by means of a parsimonious distributed lag polynomial, which avoids an excessive proliferation of parameters (Ghysels et al., 2006).

Across the financial predictors, the MIDAS specifications improve the univariate forecasts by as much as 5% and nearly all predictors deliver statistically significant improvements in MSFE relative to the benchmark for 1-month and 3-month ahead forecasts, according to the Clark and West (2007) test. The largest forecasting gains are obtained for the MIDAS specifications used jointly with the forecast combination schemes, resulting in additional 1% to 7% improvements in MSFE, compared to the forecast combinations with monthly predictors alone. For example, the inverse ranking MSFE combination of the MIDAS models with financial predictors leads to an out-of-sample improvement of 2.11% for backcasting, 7.89% for nowcasting, and an impressive 11.13% for the 3-month ahead forecasts.

The accuracy gain for the aggregate index are not unduly driven by a few local markets.

Indeed, repeating the analysis on the nineteen individual metropolitan statistical areas (MSA) series we find pervasive improvements over the autoregressive benchmark, confirming the nationwide evidence.

We further explore sources of time-series variation in forecast accuracy. To this end, we relate the difference in out-of-sample squared and absolute forecast errors between the autoregressive and inverse rank MIDAS model to periods of market turmoil, defined as periods when the VIX exceed its 90th percentile, the University of Michigan Consumer Sentiment index falls below its 10th percentile, or NBER recessions. We find that the inverse rank MIDAS model delivers more precise forecasts both outside and inside turbulent market periods, relative to the benchmark. Notably, the wedge between the two models widens significantly in bad times. The average absolute difference in the 3-month forecast error is about 3 basis points in non-volatile times, and as much as 18 basis points in particularly volatile times, when the Michigan, VIX and NBER dummies are jointly one. These differences are not only statistically, but also economically significant, as discussed above.

We next analyze the performance of our forecasts during the COVID-19 pandemic. The onset of the pandemic was characterized by great uncertainty and rapidly changing conditions in the real estate market, the stock market, and real economy, and as such provides a challenging period for forecasting models.[3] We conjecture that, despite the significant volatility, our forecasts will outperform the benchmark, because they incorporate up-to-date information that is crucially important during this period. We also note that the March to November 2020 period affords us the opportunity to gauge the forecasting performance of all models in a truly out-of-sample setting.[4]

During the admittedly short nine-month COVID-19 sample, the inverse rank models significantly outperform the benchmark. The MIDAS (non-MIDAS) model has a 19% (6%) lower MSFE than the autoregressive model, out-of-sample. In economic terms, the MIDAS

[3]In March of 2020, the S&P500 fell about 30% percent. The VIX surged to above 80% (annualized) on March 16th, 2020. Unemployment spiked to more than 14% in April 2020, GDP growth in the second quarter decreased 31% (annualized).

[4]The first version of the paper was completed in January, 2020.

model is about 60 basis points closer to the true (but observable with a two-month lag) CS than the autoregressive forecast. In other words, investors would earn a 0.6% higher return if they chose to transact during that period following the inverse rank MIDAS forecasts. The smoothness of the autoregressive model and its inability to incorporate the rapidly evolving economic conditions translate into forecasting higher CS returns (than observed ex-post) during the early months of the pandemic, and lower returns during the latter months. As the stock market and many sectors of the economy showed unexpected resilience and recovered after the onset of the pandemic, the inverse rank MIDAS models incorporate that information as soon as it becomes publicly available. Finally, the better performance of our forecasts is positively correlated with the overall uncertainty during the period, as proxied by the number of COVID-19 positive cases.

The remainder of the paper is organized as follows. This introduction concludes with an outline of our contribution to the related literature. The next section details the data we use. The third section presents the modelling framework. The fourth section describes the empirical results. The fifth section analyses the sources of variation in forecast accuracy and highlights some cross-sectional patterns. The sixth section concludes.

Related Literature

Our paper contributes to three strands of literature. A stream of research establishes a link between house prices and future macroeconomic and financial variables (Case et al., 2005; Campbell and Cocco, 2005; Leamer, 2007; Loutskina and Strahan, 2011; Mian et al., 2013; Mian and Sufi, 2014; Adelino et al., 2013). In this paper, we undertake the reverse predictability exercise by asking whether macroeconomic and financial variables forecast house prices at various horizons. Establishing a lead-lag relation between financial variables and CS is of importance as it suggests not only that we can improve decision-making by providing timely information about the real estate market, but also that there is a feedback from these variables to real estate prices.

We also contribute to the literature on real estate forecasting. Several authors find that real

estate market returns have a high positive serial correlation (Linneman, 1986; Guntermann and Smith, 1987; Rayburn et al., 1987; McIntosh and Henderson, 1989) and studies that use the Case-Shiller index reach the same conclusion (Case and Shiller, 1987, 1990; Hill et al., 1999; Schindler, 2013) although it is not clear whether this serial correlation can be exploited in investment strategies (Ghysels et al., 2013). Another stream of the literature focuses on the information content of economic variables in forecasting residential (Linneman, 1986; Case and Shiller, 1990; Abraham and Hendershott, 1996) and commercial (MacKinnon and Al Zaman, 2009; Plazzi et al., 2010) real estate price changes. Recent work has expanded the information set further by extracting signals from Google internet searches to predict house transactions or house prices (Wu and Brynjolfsson, 2015; Bork et al., 2020; Møller et al., 2021).[5] We add to this literature by focusing on the value of economic and financial predictors to a market participant facing a time gap from the release lag of repeat-sales indexes.

There are preciously few big data papers in the real estate forecasting literature. One notable exception is Kok et al. (2017), who use machine learning approaches to estimate appraisal values of US properties. We show that simple forecasting combination techniques often used for financial and macroeconomic variables as the ones suggested by Aiolfi and Timmermann (2006) and Elliott and Timmermann (2013) enhance real estate returns predictability. Most of the above-mentioned studies in the real estate predictability literature use uni- or multi-variate models sampled at the monthly or quarterly frequency, thus potentially losing precious information embedded in daily data. Mixed-Data Sampling (MIDAS) is a convenient econometric specification that can handle high-frequency information in a flexible way, by exploiting a distributed lag polynomial scheme for the regressors that is able to keep the number of parameters to be estimated low. MIDAS' original work focused on volatility

[5] These signals are either at quarterly frequency (Wu and Brynjolfsson, 2015; Bork et al., 2020) or monthly for a short time span (Møller et al., 2021), which complicates the comparison with our other predictors. For what it is worth, when we include the publicly available quarterly housing sentiment index of Bork et al. (2020) as a predictor, our forecasts do not improve, out-of-sample. As explained below, this is expected as lagged quarterly variables contain dated information about the real estate sector, which is precisely the issue we are trying to address by including recent daily predictors in the MIDAS specifications. Should search-based signals become available at a higher frequency or over longer samples, they would naturally be part of the list of potential predictors.

predictions (Ghysels et al., 2006) and since then MIDAS models have been succesfully used to nowcast and forecast several macroeconomic and financial variables such as GDP (Kuzin et al., 2011), employment (Armesto et al., 2009), output growth (Clements and Galvão, 2008), inflation (Monteforte and Moretti, 2013), oil prices (Baumeister et al., 2015) and asset correlations (Asgharian et al., 2016). Recently, Babii et al. (2021) combine MIDAS models with machine learning regressions to improve GDP nowcasting. Applications of MIDAS models in the real estate literature are limited to Ghysels et al. (2007), who study the relation between cap rates and future REIT returns. To our knowledge, this paper is the first to forecast repeat-sales indexes with MIDAS regressions.

Finally, we contribute to the literature that seeks to improve inference of house prices using the `CS`. Bollerslev et al. (2016) provide a high-frequency way of measuring repeat sales. Anenberg and Laufer (2017) and Wang et al. (2020) develop house price indices using final listing prices of properties instead of actual repeated transactions. Nowak and Smith (2020) argue for an explicit quality adjustment that improves upon the accuracy of the monthly `CS` to measure transactions of constant quality. Rather than measurement improvements, our focus here is on enhancing predictions of the `CS` with the goal of providing up-to-date pricing information to real estate market participants.

2.2 Data

Our dataset spans the period from January, 1987 to December, 2019. The variable to backcast, nowcast, and forecast is the return of the seasonally-adjusted S&P/Case-Shiller U.S. National Home Price Index (CSUSHPINSA), which we obtain from the Federal Reserve Bank at St. Louis. It is an aggregate repeat-sales price index from single-family homes and goes back to January 1987. Henceforth, we denote the series with `CS`. In addition to the aggregate series, we use local indexes for nineteen Metropolitan Statistical Areas (MSA) that are part

of the CS20 index.[6] We organize the predictors in two main categories depending on their type and frequency of observation. Details on the data sources are collected in Appendix Table 3A.1.

Financial Variables: We have 38 financial variables, available at daily and monthly frequency. They are: the value- and equally-weighted aggregate S&P500 return; the spread between the 30-year fixed rate mortgage and the 30-year Treasury rate; the slope of the term structure, computed as the difference between the 10-year and 3-month Treasury yield; returns to the value- and equally-weighted aggregate, mortgage, residential, equity, and hybrid REITs; the credit spread, computed as the difference between BAA- and AAA-rated corporate bond yields; the Aruoba-Diebold-Scotti Business Conditions Index[7]; and nineteen value-weighted industry stock returns aggregated at the two-digit NAICS level.

Macroeconomic Variables: We gather 33 widely-used macroeconomic indicators, which are available at monthly frequency: the Chicago Fed National Activity Index; the unemployment rate; inflation rate; non-farm payrolls; new privately owned housing units started and permits, in the U.S. as well as Northeast, Midwest, South, and West; total industrial production along with twelve disaggregated indexes; the ISM Report on Manufacturing Business Employment; average weekly hours of production and nonsupervisory employees (goods producing); average weekly overtime hours of production and nonsupervisory employees (manufacturing); average hourly earnings of production and nonsupervisory employees (goods producing, construction, and manufacturing). For all these predictors except CFNAI we use monthly growth rates. In our analysis, we take into account that these series are typically released with a one-month lag.[8]

[6] These are: Greater Boston (BOXR), Chicago metropolitan area (CHXR), Denver-Aurora metropolitan area (DNXR), Las Vegas metropolitan area (LVXR), Greater Los Angeles (LXXR), South Florida metropolitan area (MIXR), New York metropolitan area (NYXR), San Diego County (SDXR), San Francisco (SFXR) and Washington metropolitan area (WDXR), which are all part of the CS10 index; and Atlanta metropolitan area (ATXR, Greater Cleveland (CEXR), Charlotte metropolitan area (CRXR), Metro Detroit (DEXR), Minneapolis-Saint Paul (MNXR), Phoenix metropolitan area (PHXR), Portland metropolitan area (POXR), Seattle metropolitan area (SEXR) and Tampa Bay Area (TPXR) which are all part of the CS20 index only. The missing area is Dallas-Fort Worth metroplex (DAXR), whose index only starts in 2000. The areas are displayed in Appendix Figure 2A.1

[7] The index combines macro and financial variables. We list it among the latter as it is available at the daily frequency.

[8] A different issue for macroeconomic series is that they are often subject to data revisions. For the great majority of the series, we do not have access to the various vintages. For variables for whose vintages are available, we do not find major differences in forecasting performance.

2.3 Modelling Framework

In this section, we model the real estate market participants' information set. In particular, we highlight the fact that the Case-Shiller index is released with a delay of two months. Let R_{t-2} denote the simple return to the `CS` index in month $t-2$, to which investors have access at time t. We collect in vector X_t all other variables x_ts that are potentially relevant predictors at time t. The information set that is actually available at the end of month t is

$$\Phi_t \equiv (R_{t-2}, R_{t-3}, ..; X_t, X_{t-1}, X_{t-2}, ...) .$$

Note that R_{t-1} and R_t are not part of the information set at time t. The natural question is whether we can use the recent information captured by macroeconomic and financial variables in Φ_t to predict real estate market returns.

We focus on backcasts, nowcasts, and two forecast horizons. We define backcasts of the `CS` return as the conditional expectations $E(R_{t-1}|\Phi_t)$. Similarly, we define nowcasts as $E(R_t|\Phi_t)$. In standard settings, R_{t-1} and R_t would be part of Φ_t and there would be no need for backcasting or nowcasting. However, the two-month release lag in the `CS` index implies that both R_t and R_{t-1} are not available to investors at time t. Nevertheless, an agent can condition her expectation of the unobservable R_{t-1} and R_t on the predictors x_ts, and on their lags, as they are known at t. In a similar vein, we look at the more standard one-month ahead forecast of the `CS` return, $E(R_{t+1}|\Phi_t)$, and three-month ahead cumulative forecast $E(R_{t+1:t+3}|\Phi_t)$.

In section 2.3.1 we present the baseline econometric framework to forecast S&P/Case-Shiller returns and, in section 2.3.4, we outline the loss function we use to evaluate the models and carry out hypothesis testing. In section 2.3.2 we discuss forecast combinations, one aspect of our big data approach. In section 2.3.3, we exploit the high-frequency dimension of the financial variables, which is another aspect of the data-rich environment.

2.3.1 Baseline Backcasts, Nowcasts, and Forecasts: Individual Predictors

For all backcasts, nowcasts, and forecasts, we restrict our attention to linear conditional expectation functions in evaluating the benefits from adding the predictors under the simplest possible modelling assumptions.[9] The model we use is

$$R_k = c + \delta_j x_{t-j} + \phi R_{t-2} + \epsilon_k^A \,, \tag{2.1}$$

where $k = (t-1)$ for backcasting, $k = t$ for nowcasting, $k = (t+1)$ for forecasting, and $k = (t+1 : t+3)$ for 3-months forecasting. The individual predictor x_t is one of the 71 (38 financials and 33 macro) variables listed in section 2.2.[10] It is sampled at monthly frequency, which is the frequency at which we observe the `CS` index, and the index j denotes the (monthly) lag. We consider a total of 180 different specifications of the model in Eq.(3.9), which are obtained from as many predictor-j combinations. For the group of financial predictors we allow $j = \{0, 1, 2\}$, namely, we either use the contemporaneous, previous month, or two month lag with respect to month t, which yields 114 (i.e., 38 predictors $\times$ 3 lags) distinct specifications.[11] The macro variables are typically released with lag and therefore are not available at the end of month t. Hence, we only use $j = \{1, 2\}$, which implies evaluating other 66 (i.e., 33 predictors $\times$ 2 lags) specifications. The superscript 'A' denotes forecast errors from a given predictor-j specification.

We need a sensible benchmark model of `CS` returns to evaluate the backcasts, nowcasts and forecasts. Returns to the `CS` index are highly persistent (Schindler, 2013; Ghysels et al., 2013; Giannetti, 2018) due to frictions in the real estate market (Case and Shiller, 1989) and to the repeat-sales nature of the index (Ghysels et al., 2013). We model the dependence in

[9] Other papers use more sophisticated models, such as heterogeneous autoregressive (HAR) specifications (Bollerslev et al., 2016), Support Vector Regressions (Plakandaras et al., 2015), Bayesian Vector Autoregressive (BVAR) models (Gupta and Das, 2010) and regime-switching models (Crawford and Fratantoni, 2003).

[10] Since we have 71 distinct predictors, we should strictly index them by $x_{f,t}$, where $f = 1 \ldots 71$, along with all parameters in Eq.(3.9). To keep the notation simple, we omit the f-subscript.

[11] Note that, as mentioned above, in the case of backcasting, using $j = 0$ means that we are effectively exploiting information subsequent to the month we seek to predict.

returns with a parsimonious autoregressive process that uses the most recently released lag of the Case-Shiller returns and no other conditioning variables.[12] In other words, we consider $\Phi_t = (R_{t-2})$. The benchmark model thus takes the form

$$R_k = c + \phi R_{t-2} + \epsilon_k^N \,, \tag{2.2}$$

and is a nested version of the extended model in Eq.(3.9), which facilitates statistical comparison in- and out-of-sample. The superscript 'N' indicates that forecast errors come from the benchmark (null hypothesis) model. For backcasting, Eq.(3.8) is akin to estimating an AR(1) model, for nowcasting it corresponds to an AR(2), while 1-month forecasting coincides with an AR(3).[13]

We estimate all models with ordinary least squares both in-sample and out-of-sample. In-sample, we let t start on Apr87 (the first date on which we can run backcasting) and end on Sept19 (the last date on which we can run the 3-month forecasting), so that all models are estimated with $T = 390$ observations. We note that the in-sample estimation is not feasible in real time, since the return in month t that we use as dependent variable will be only known two months later. Rather, we use the wealth of historical data to gauge how well the models would fare (ex-post) at predicting actual real estate market performance, without considering the timing at which the dependent variable was released. Also, we do not consider models with multiple predictors ('kitchen-sink' approach) or with more lags simultaneously, as the forecast combinations and MIDAS extensions that we discuss next essentially tackle these two dimensions in a more efficient way.

The out-of-sample experiment, instead, mimics a real time forecasting exercise as we account for estimation uncertainty and availability of the dependent variable. To be precise, we set $t =$ Feb02 as the first date at which we form the dataset and estimate the models –

[12] In our sample period, the correlation between R_t and the most recently available R_{t-2} value is 0.88.

[13] We verified that the alternative approach of using the predictors as stand-alone variables (i.e., without the lag) diminishes their predictive value-added. This is to be expected in light of the persistence of `CS` returns, which implies that on average it is optimal to anchor the forecast to the lag term.

which implies, due to the release lag, that the Jan87 to Dec01 period represents the first burn-in sample. We use the resulting coefficients together with the most up to date and available information to compute the forecasts.[14] We then move t forward by one month in a rolling fashion, incorporate the newly released information and follow the same procedure to create the forecasts, and so on until $t =$ Sept19. The difference between the forecasts from the (benchmark or alternative) model and the realized ex-post returns yields a time series of 212 out-of-sample forecast errors (which we denote with $\widetilde{\epsilon}^N$ and $\widetilde{\epsilon}^A$, respectively) at each of the four horizons.

2.3.2 Exploiting the Large Number of Predictors: Forecast Combination

We explore an extension of the baseline, single-predictor approach that takes advantage of the large number of predictors. Namely, we construct combinations of individual forecasts. In the stock market literature, Rapach et al. (2009) provide evidence that even simple forecast average combinations consistently deliver statistically and economically significant out-of-sample gains. Let $E_i(R_k|\Phi_t)$ denote the month-t forecast of R_k for model $i \in I$, with I being the total number of combinations in each group (financials, macro, or both). Forecast averaging implies computing

$$E_{FC}(R_k|\Phi_t) = \sum_{i=1}^{I} w_{i,t} E_i(R_k|\Phi_t) \tag{2.3}$$

for suitable weights $w_{i,t}$, which add up to one and potentially vary with t.

We consider three weighting structures for the forecast combinations. The first and simplest one is equally weighting, or $w_{i,t} = 1/I$, which amounts to taking the arithmetic average of the individual forecasts. The second structure is the inverse MSFE average, defined

[14] As an example, for the 3-month forecast, we estimate the model until the last available 3-month return (from Oct01 to Dec01). We apply the coefficients on the Dec01 return and, for the alternative model, on the value of the predictor as of Feb02 (or Jan02, for predictors available at the monthly frequency) to predict the return from Mar02 to May02.

as in Elliott and Timmermann (2016) as

$$w_{i,t} = \frac{\text{MSFE}_i^{-1}}{\sum_{i=1}^{I} \text{MSFE}_i^{-1}} \,. \tag{2.4}$$

The third weighting scheme is based on the inverse rank MSFE average

$$w_{i,t} = \frac{\text{Rank}_i^{-1}}{\sum_{i=1}^{I} \text{Rank}_i^{-1}} \,, \tag{2.5}$$

where Rank_i equals 1 for the model with lowest MSFE, 2 for the model with the second lowest MSFE, and so on (Aiolfi and Timmermann, 2006). We allow the weights to vary over time in-sample by computing the MSFE as in Eq.(2.8) at each t, so that we are essentially over-weighting forecasts from models that delivered the lowest historical MSFE at a given date (although the model parameters are estimated over the entire sample). For the out-of-sample analysis, we recompute the MSFE in Eq.(2.10) until the last date of each estimation sample.

2.3.3 Exploiting High-Frequency Data: The MIDAS approach

The second extension exploits the availability of high-frequency financial data and the possibility of parsimoniously incorporating multiple lags of the predictor by means of a Mixed-Data Sampling (MIDAS) approach (see Ghysels et al., 2005, 2006; Pettenuzzo et al., 2016). Specifically, for a given financial predictor x, the MIDAS conditional expectation function of the `CS` at forecast horizon k is:

$$E\left(R_k|\Phi_t\right) = c + \phi R_{t-2} + \gamma Z_t\left(\kappa_1, \kappa_2\right) \tag{2.6}$$

$$Z_t\left(\kappa_1, \kappa_2\right) = \sum_{d=0}^{D/22} \varphi_d\left(\kappa_1, \kappa_2\right) x_{t-d} \,. \tag{2.7}$$

Compared to the expression in Eq.(3.9), this specification replaces the monthly lags (and potentially leads, in the case of backcasting) of the predictor with a variable Z_t constructed from current and lagged *daily* conditioning information until D days in the past. We set

$D = 65$, which implies that, including the last day of month t, we are using 66 trading days, or about three calendar months, to form expectations about monthly `CS` returns. The "$D/22$" notation reminds us that the information spans three months, but in the form of daily observations.[15]

The main advantage of the MIDAS approach is its mixed frequency structure, namely, it allows us to use recent, daily observation when forming expectations about monthly `CS` returns. The filtering of the daily observations x_{t-d} obtains through the weighting function φ_d, which is parameterized as a lag polynomial whose shape is captured by a low-dimensional parameter vector (κ_1, κ_2). Following Ghysels et al. (2016a), we express φ_d through a "Beta" function, which is flexible as can take many shapes such as flat, gradually declining, as well as hump-shaped, depending on the values of (κ_1, κ_2). The weights are normalized to sum to one, so that we can identify the scale parameter γ. By letting (κ_1, κ_2) vary with the forecast horizon, we are able to pinpoint the exact timing at which the information in x helps forecasting real estate returns. We thus "let the data speak" without aggregating the predictor to match the monthly frequency of the `CS`, which could potentially result in loss of information. In other words, the MIDAS specifications allows us to succinctly exploit the daily information over a three month time span while reducing the number of lag coefficients to estimate from sixty-six down to three $(\gamma, \kappa_1, \kappa_2)$.

The five parameters of the model are estimated jointly for each x and k. Given that the optimization of (κ_1, κ_2) can prove challenging, especially in small samples, we follow Ghysels and Qian (2019) and resort to OLS estimation of the slope and intercept parameters (c, ϕ, γ) combined with profiling the polynomial weighting scheme parameters.[16] In-sample and out-of-sample forecast errors and MSFE are then obtained using the same procedure as for the previous models.

[15] The framework implies that, e.g., to backcast the Feb2010 `CS` return we use a weighted average of the 66 daily observations of the financial predictor (e.g., the aggregate stock market return) spanning the period from March 31, 2010 (the last day in month t) back until December 24, 2009. The same daily information, but with a potentially different weighting scheme, is used to form the other forecasts.

[16] Namely, we discretize the parameters (κ_1, κ_2) over a comprehensive grid. Conditional on a pair of values in the grid, Eq.(2.6) becomes linear and thus OLS can be applied. We then select the pair in the grid that delivers the lowest MSFE. See Ghysels and Qian (2019) for the properties of this profile likelihood method compared to the traditional nonlinear least squares.

2.3.4 Measuring Forecast Improvements: Loss Function and Testing

To evaluate the accuracy of our models and to carry out statistical tests, we resort to the mean squared forecast error criterion, MSFE, which is widely used in studies on return predictability (see Rapach and Zhou, 2013, for a literature review). For the in-sample analysis, let

$$\text{MSFE}_{IS}^{N} = \frac{1}{T_{IS}} \sum_{t=\text{Apr87}}^{\text{Sept19}} \left(\tilde{\epsilon}_t^N\right)^2 \qquad \text{and} \qquad \text{MSFE}_{IS}^{A} = \frac{1}{T_{IS}} \sum_{t=\text{Apr87}}^{\text{Sept19}} \left(\tilde{\epsilon}_t^A\right)^2 \tag{2.8}$$

be the benchmark and the alternative model MSFE, respectively, at a given forecast horizon. We measure the in-sample improvement of model A over the benchmark N with

$$R_{IS}^2 = 1 - \left(\text{MSFE}_{IS}^{A}/\text{MSFE}_{IS}^{N}\right) , \tag{2.9}$$

which can be expressed in terms of the difference between the in-sample R-squared statistics.[17] Given that we compare nested linear models that contain a constant term, R_{IS}^2 ought to be positive and captures the marginal in-sample improvement from adding x_{t-j} to forecast R_k.

For the out-of-sample exercise, we analogously define

$$\text{MSFE}_{OS}^{N} = \frac{1}{T_{OS}} \sum_{t=\text{Feb02}}^{\text{Sept19}} \left(\tilde{\epsilon}_t^{\,N}\right)^2 \qquad \text{and} \qquad \text{MSFE}_{OS}^{A} = \frac{1}{T_{OS}} \sum_{t=\text{Feb02}}^{\text{Sept19}} \left(\tilde{\epsilon}_t^{\,A}\right)^2 , \tag{2.10}$$

and the out-of-sample R^2 is

$$R_{OS}^2 = 1 - \left(\text{MSFE}_{OS}^{A}/\text{MSFE}_{OS}^{N}\right) . \tag{2.11}$$

In an out-of-sample setting, adding x_{t-j} to the conditioning set does not necessarily improve forecast accuracy. Models with $R_{OS}^2 > 0$ are those that deliver more precise (in the MSFE

[17] From the definition, $R_{IS}^2 = (R_A^2 - R_N^2)/(1 - R_N^2)$, with R_N^2 and R_A^2 being the benchmark and alternative model R-squared, respectively.

sense) predictions than the benchmark, or $\text{MSFE}^A_{OS} < \text{MSFE}^N_{OS}$. Whenever $R^2_{OS} > 0$, we also look at whether the improvement is statistically different from zero. Since we are comparing nested models, we use the Clark and West (2007) *MSFE-adjusted* statistic, which has an asymptotic normal distribution and performs relatively well in finite samples (Rapach and Zhou, 2013).

2.4 Empirical Results

In this section, we provide empirical results for predicting `CS` returns. Section 2.4.1 discusses the performance of individual predictors, while section 2.4.2 and 2.4.3 present, respectively, the forecast combination and MIDAS approach. These sections focus on the aggregate index. In section 2.4.4, we summarize the results for the individual MSAs.

2.4.1 Individual predictors

In Figure 2.1, we present the backcasting, nowcasting, and forecasting performance of individual predictors, organized into financial (Panel A) and macroeconomic (Panel B) as in section 2.2. Due to the multitude of predictors and lags considered, the results are presented graphically. The figure plots the R^2_{OS} statistic from recursive out-of-sample estimations of the alternative model of Eq.(3.9) against the benchmark model of Eq.(3.8). A higher bar indicates better out-of-sample forecasting performance and an asterisk denotes significance at the 5% level based on the Clark and West (2007) test. In-sample results, suggesting even more predictability, are collected in Appendix Figure 2A.2.

Starting with the backcasting results in Panel A, we observe that S&P500 returns (first two variables), equity, aggregate and hybrid REITs returns (equally-weighted) and most industry returns (bottom nineteen variables) lead to significant improvement in performance relative to the autoregressive benchmark. Across the predictors, the $t-1$ and $t-2$ lags produce the largest increase in forecasting precision. As we move toward nowcasting and

forecasting, all lags of the financial variables provide statistically significant conditioning information. Given that the return predictors are not persistent, this evidence shows that the forecasting relation linking real estate returns with financial markets has a complex frequency pattern. The gains in nowcasting accuracy are of the order of about 2%, which is economically significant, given the persistent nature of the `CS` returns. At the one- and three-month forecasting horizons, the accuracy increases to about 3%, with a peak at about 6.8% for the Ziman aggregate equal-weighted index (REAEW) and 6.4 % for the construction (CONSTR) sector. The S&P500 equally-weighted portfolio (SP500EW), the Ziman equity equal-weighted index (REEEW) and several of the industry portfolios, such as arts (ARTS) and food (FOOD) also prove to be valuable predictors. Out of the 114 distinct specifications we consider, 35 (31%) are significant at backcasting, 70 (61%) at nowcasting, 72 (63%) at forecasting one period ahead, and 56 (49%) at the three-month horizon. While we do not explicitly account for multiple testing, these predictive gains appear way too large to be due to random sampling, especially since they are out-of-sample.

Turning to Panel B, the out-of-sample backcasting power of macroeconomic variables is concentrated in a few variables that are natural bellwethers of the residential real estate market: housing permits (HP) and manufacturing (MANREP). This conclusion extends to nowcast and forecasts, where national and regional housing starts (HS) and industrial production of residential utilities (IBREUT) also emerge as valuable predictors. We further notice that the gains are often concentrated in the $t-2$ lag, and not in the most recently available $t-1$ value. Compared with Panel A, however, the predictive power of individual macroeconomic variables is overall arguably weaker, which is expected as financial variables incorporate timely expectations about the future state of the economy. Given the prior evidence that real estate variables lead aggregate conditions (see, e.g., Leamer, 2007; Hong et al., 2007), our results imply a two-way Granger causality relation and a complex structural dependence between the two sets of variables.

2.4.2 Forecast Combination

The encouraging performance of individual forecasts prompts us to investigate whether combination forecasts can further enhance the predictability of `CS` returns, similarly to what is documented in predicting macroeconomic (Granger and Ramanathan, 1984; Stock and Watson, 1999, 2004; Aiolfi and Timmermann, 2006; Rapach and Strauss, 2008; Clark and McCracken, 2010) and financial variables (Rapach et al., 2009; Pettenuzzo et al., 2014; Bakshi and Panayotov, 2013; Gargano and Timmermann, 2014; Guidolin and Timmermann, 2009).

In Table 2.1, we present the in-sample (Panel A) and out-of-sample (Panel B) forecast combinations results. The four columns display the backcasting, nowcasting, and two forecasting horizons percent improvement in MSFE relative to the autoregressive benchmark model, whose MSFE is reported in the first row of each panel. For the out-of-sample results, bold numbers denote entries that are significant at the 5% level based on the Clark and West (2007) test. We combine forecasts across three combination sets: financial variables only ('Financials'); macroeconomic variables only ('Macro'); and financial and macroeconomic variables together. In the combination sets, we use the three aforementioned weighting schemes, namely equally weighted, inverse MSFE average (Eq. 3.11) and inverse rank MSFE average (Eq. 3.12).

In Panel A, we make three observations related to combination weights, performance at different horizons, and gains across combination sets. First, combinations constructed with inverse Rank weights produce by far the largest improvement in MSFE for longer horizons. For instance, at three-month horizon, the inverse weights combination with financial forecasts leads to an improvement of 4.16% relative to the benchmark, whereas the inverse rank weights yields a 4.88% improvement in MSFE. Second, the forecast improvement increases with the horizon for all weight specifications and combination sets. For financial forecasts, it is 1.13% at the backcasting horizon, increasing monotonically to 4.88% at three-month ahead horizon. Finally, the most accurate (in MSFE sense) forecasts are obtained for financial variables. Combination of macroeconomic forecasts lead to improvement relative to the benchmark,

but not nearly as significant, and indeed lead to deterioration of the MSFE when used in combination with financial forecasts.

Out-of-sample results, in Panel B, confirm and bolster the in-sample findings. Namely, forecast combinations based on individual financial variables with inverse rank weights is, in almost all cases, better than the alternatives. Importantly, the improvements in performance are statistically significant. Two differences with respect to Panel A are noteworthy. First, while the improvement in performance is, as expected, lower than in-sample, the drop is small – in the order of 0.5-1.5% for the EW and inverse MSFE weighting schemes. Moreover, for the inverse rank MSFE combination, the out-of-sample improvements are sometimes larger than their in-sample counterparts, most likely because when we weight the earliest observations of the sample, the time-varying MSFE that is responsible for the weight construction is potentially noisy, while it stabilizes as the sample increases. For instance, in backcasting, inverse rank weights combination with financial forecasts yields an improvement in performance of 1.52% out of sample compared to a 1.13% improvement in-sample. At three-month-ahead horizon, the out-of-sample improvement in MSFE is 4.37% relative to 4.828% in-sample. Second, while the relative performance increases with the horizon, if flattens at the three-month horizon, where it is quite at par with the one-month prediction accuracy.

The takeaway from the forecast combination results is that the most accurate (in MSFE sense) forecasts obtain with financial variables using inverse rank weights, and the relative improvement in forecasting performance increases with the horizon up to one-month ahead.

2.4.3 The MIDAS Touch

The evidence that several lags of monthly financial variables help to predict `CS` returns prompts us to ask whether higher frequency – daily – observations of these variables can lead to even more precise forecasts (in the MSFE sense). We explore this question by estimating the MIDAS specification of Eq.(2.6)-(2.7) on daily series of the 38 financial predictors. We

estimate all parameters on a rolling basis to produce out-of-sample forecasts. In Figure 2.2, we present the out-of-sample backcasting, nowcasting, and forecasting R^2_{OS} statistic from these recursive estimations. The figure is directly comparable to Panel A of Figure 2.1, the differences being that the predictors are daily rather than monthly and the lags are selected automatically via the estimation of the MIDAS parametric weights. Analogous in-sample results are in Appendix Figure 2A.3.

We note that a number of predictors lead to large and significant out-of-sample predictive improvements, relative to the autoregressive benchmark. This is true across all horizons, and is particularly striking for nowcasting and forecasting. At the one-month horizon, 30 variables significantly outperform the benchmark model – and of them, 19 (i.e., half of the set) by more than 5%. Only a handful of predictors have negative R^2_{OS}. Overall, by comparing these numbers with those in Panel A of Figure 2.1, the additional benefits from the MIDAS specification are in the order of 2 to 3%. In other words, the MIDAS scheme essentially doubles the gains in predictive accuracy compared to the average specification where the forecasters are sampled at monthly frequency.

Among the most robust MIDAS predictors are the returns of the S&P500, the Ziman real estate indices, and various industries, such as construction (CONSTR) and finance (FIN). For instance, the returns to FIN produce the largest nowcast improvement (10.8%) while those to CONSTR yield the best forecast at three-month-ahead horizon (16.1%). The fact that the largest gains are in sectors that are linked either directly (such as, REITs and construction) or indirectly (such as financials, through the credit channel) to the residential real estate market suggests that our statistical findings have a natural economic backbone.

We can take further advantage of the MIDAS approach by blending it with forecast combinations. Table 2.2 collects the results from combining the MIDAS forecasts from financial variables either alone, or together with the (non-MIDAS) macroeconomic forecasts. We focus the discussion on the out-of-sample outcomes in Panel B – the in-sample figures in Panel A are generally stronger. Consistent with previous findings, the largest improvements

are generated by the inverse rank MSFE weights. This is true at all horizons, and with or without macroeconomic variables. Compared to Table 2.1, we find that the use of MIDAS daily financial predictors leads to sizable betterments of 2-4% for backcasting and nowcasting, and up to 7% for forecasting. For example, for nowcasting, we report a R^2_{OS} of 7.89% (financials only), which represents a 4% increase (i.e., +107% in relative terms) with respect to the same forecast combination using monthly-sampled data. At the three-month horizon, combining the financials MIDAS forecasts delivers a large 11.13% R^2_{OS}, which is a 155% increase relative to the corresponding figure in Table 2.1 (4.37%). These gains in forecast accuracy confirm the visual message from Figure 2.2 that the use of daily information enhances predictability. Furthermore, we also note that the addition of macroeconomic variables leads to a larger deterioration in forecasting performance than in Table 2.1, which is likely due to the fact that the monthly predictors are strictly dominated by the daily ones.

2.4.4 Forecasting MSA Returns

Thus far, our analysis has focused on the aggregate `CS` index. It is well known that the real estate market is highly heterogenous (Case and Shiller, 1990; Crawford and Fratantoni, 2003; Plazzi et al., 2010; Bollerslev et al., 2016; Baldauf et al., 2020). Thus, it is interesting to explore if and how much of the evidence extends to predicting the 19 MSA real estate markets.

The set of predictors we use are nationwide (the exceptions being the four regional housing starts and permits series), and thus we might expect them to have less potential to capture the idiosyncrasies of the local real estate. To possibly ameliorate this issue, we also consider an additional local industry stock return predictor that weights each industry return by the local MSA employment share, in the spirit of Bartik (1991). That is, for a given MSA, we add to the set of predictors

$$R_t^{MSA} = \sum_{n=1}^{N} w_{n,t}^{MSA} r_{n,t}, \tag{2.12}$$

where $w_{n,t}^{MSA}$ is the fraction of employees that are active in the 2-digit NAICS industry n at time t in the given MSA and $r_{n,t}$ is the value-weighted stock return of the 2-digit NAICS industry n at time t (the same series we use in the nationwide analysis). The weights $w_{n,t}^{MSA}$ are rebalanced annually.[18] By over-weighting the performance of industries that are mostly responsible for an area's local employment, we attempt to tilt the aggregate stock return portfolio to the local economic and hence residential real estate outlook.

In Table 2.3, we report the out-of-sample MSFE for the nineteen MSAs and four horizons for the benchmark autoregressive model and the R^2_{OS} statistic for the forecast combination of the financial and macro variables plus the predictor in Eq.(2.12) based on the inverse rank MSFE. As in Table 2.1, the improvement in forecast accuracy over the benchmark increases with the horizon. As expected, we observe a great deal of heterogeneity with negative R^2_{OS}s in some regions and significant positive R^2_{OS} in the range of $8\% - 9\%$ in others, such as Charlotte and Seattle. However, MSAs returns are on average less predictable than the national index.

We next explore the benefits of timely daily financial information in predicting MSA returns through MIDAS regressions. In Table 2.4, we report the R^2_{OS} from combining the forecasts from MIDAS regressions of the financial predictors with the lags of the macro predictors, when the weights are again based on the inverse rank MSFE. We find that the MIDAS approach improves the forecast precision; at the three-month horizon, 14 of the 19 MSAs have significantly higher R^2_{OS}. Comparing the gains with those for the national index in Table 2.2, we confirm they are increasing with the horizon, but with exception of Charlotte and Seattle, are on average smaller than for the aggregate series, which underscores the heterogeneity of local real estate markets and the relevance of domestic economic conditions.

[18] We obtain data for the MSA employment by sector from the BLS census, https://www.bls.gov/cew/downloadable-data-files.htm.

2.5 Variation in Forecast Accuracy

In this section, we explore sources of variation in forecast accuracy, and quantify the economic significance of our findings.

2.5.1 Time-Series Variation and Economic Significance

We begin by asking whether the gains in forecast accuracy we document above are equally spread over time, or if they are clustered around states of the world associated with higher economic uncertainty. We investigate this question by regressing the difference in out-of-sample squared forecast errors, $\left(\widetilde{\epsilon}_t^N\right)^2 - \left(\widetilde{\epsilon}_t^A\right)^2$, which are the basis for the R^2_{OS}s, on a set of dummy variables capturing financial and economic turmoil. A positive difference indicates that the alternative model is more accurate out-of-sample. As alternative model 'A' we use the inverse rank MIDAS with financials only from Panel B of Table 2.2. We define the dummies based on the University of Michigan Consumer Sentiment index and the VIX index, which capture economic outlook and aggregate risk. The Michigan dummy equals one if the University of Michigan Consumer Sentiment index in month t is below its historical 10th percentile, and zero otherwise. The VIX dummy equals one if the VIX index in month t is above its historical 90th percentile, and zero otherwise. We also include the NBER dummy, which is a widely accepted indicator of crisis periods, even though is not defined in real time. The three variables used to construct the dummies are not part of the predictors, which rules out concerns that the relation we capture is purely mechanical.

Panel A of Table 2.5 reports the regression results focusing on the one-month and three-month forecasting settings. In the first column, the only regressor is the constant. In line with Table 2.2, its estimates are positive and significant at both horizons, meaning that alternative model improves over the benchmark throughout the whole out-of-sample period. When introducing the turmoil dummy variables in the columns 2–5, the intercept captures the average improvements during calm periods. These are significantly positive, albeit smaller

than those from the full (OoS) period. By contrast, in turbulent times the wedge between the two models widens substantially. The Michigan, VIX, and NBER dummy coefficients are all positive, large (compared to the constant term), and statistically significant. In other words, the forecasting accuracy of the alternative model is larger during periods of economic uncertainty. For example, at the three-month horizon, the difference in squared forecast errors is 0.088 basis points in months that are not marked as recessions by the NBER, but becomes 0.618 (0.530+0.088) during crisis months. When all three dummies equal one, the difference widens further to 0.057 versus 0.797.

To gauge the economic significance of these findings, we repeat the analysis on the difference in absolute out-of-sample forecast errors, $|\widetilde{\epsilon}_t^N| - |\widetilde{\epsilon}_t^A|$, which is expressed in the same units of returns. Panel B of the table reports the corresponding estimates. The positive constant terms in the first column indicate that, over the full sample, the alternative model delivers forecasts that are 1.3 (3.7) basis points closer than the benchmark model to the true index return at the one-month (three-month) horizon. As in the previous panel, this average figure has a strong countercyclical pattern. In "normal" times, the benchmark model generates forecast errors that are some 0.7 to 3.1 basis points larger than the model that incorporates conditioning information. In turbulent times, as captured by the Michigan, VIX, or NBER dummy, the difference widens considerably. When all three dummies equal one, the difference becomes 7.6 basis points for one-month forecasts and as much as 17.6 basis points at the three-month horizon. The estimates in column (5) imply that, in annual terms, the forecast error on the out-of-sample \$33'300 average annual return for a representative \$1 million residential property in the U.S. improves by \$696 (\$3'029) in "normal" months (quarters), and as much as \$2'352 (\$7'038) in crisis months (quarters).

To summarize, the improvement from incorporating financial variables in the forecasting model is largest in periods of high volatility, when it is mostly needed, i.e., in periods of high marginal utility.

2.5.2 Comparison with Stocks

We report out-of-sample forecast improvements in real estate returns that range from 4% (combining monthly predictors, Panel B of Table 2.1) to 11% (combining daily predictors, Panel B of Table 2.2). Are these figures "reasonable" and economically meaningful? We address this question by repeating the forecasting exercise on aggregate stock market returns, whose predictability has been extensively studied (see Rapach and Zhou, 2013, for a review).

Specifically, we compute out-of-sample R^2s of monthly equity returns during the same period and following the same procedure we outlined above for `CS` returns, with two nuances.[19] First, we keep the same set of macro predictors but augment the set of financial predictors by the market dividend-price ratio, as it plays a special role in stock predictability via a present-value relation (**?**). Second, we do not compute backcasts and nowcasts of stock market returns because, unlike `CS` returns, they are available without delay.

Table 2.6 collects the corresponding one-month and three-month forecasting improvements, using the same format as Table 2.1 (for the non-MIDAS specifications in Panel A) and Table 2.2 (for the MIDAS specifications in Panel B). Consistent with the findings in Welch and Goyal (2008), we observe positive R^2s statistics in-sample that turn negative out-of-sample. In other words, equity returns are hard to forecast: even combinations of forecasts with high frequency regressors yield R^2_{OS}s comparable to or smaller than the benchmark. In particular, only equal and inverse MSE weighted averages across daily (MIDAS) predictors deliver positive (albeit insignificant) R^2_{OS}s, in line with the evidence in Rapach et al. (2009). The inverse rank MSE method, which yielded the best combination of forecasts for `CS` returns, performs poorly in the case of stocks.

Comparing the real estate and stock market results, we observe that the improvement in predictive accuracy of `CS` returns is substantial. Focusing first on combinations of monthly predictors, the out-of-sample improvement in forecasting accuracy for real estate returns of about 4% (Tables 2.1, Panel B) is higher than the forecast combination results of stock

[19] Our source for equity returns is the total return index from Datastream; mnemonic: TOTMKUS.

returns, which yield either very small or negative R^2_{OS}s. This is true for one-month-ahead and three-month-ahead horizons. Turning to MIDAS daily predictors, the R^2_{OS}s for real estate returns of about 11% (inverse rank combinations) appear again much larger than those observed for equity. The best predictive setup for equity yields an R^2_{OS} of 1.13%, which is obtained by equally weighting MIDAS daily forecasts of financial variables. We also notice an encouraging stability in predictive results for real estate returns: the improvements in accuracy at the one-month and three-month horizons are comparable. For equity, the lack of stability is not surprising, as none of the improvements are statistically significant. Overall, we conclude that the out-of-sample improvements from combining forecasts and recent information in a mixed-frequency approach we document for real estate are truly large when benchmarked against the gains in other asset classes, such as equities.

2.5.3 Forecasting During Times of COVID-19

In this section, we analyze the gains in forecasting accuracy during the COVID-19 pandemic by extending the sample until November of 2020 and take March of 2020 as the arrival of the virus in the U.S.[20] The addition of the pandemic period allows us to conduct a truly out-of-sample exercise, without look-ahead biases, as we keep the models from the previous version of the paper unchanged. Moreover, the pandemic period was particularly volatile for all sectors of the economy and was characterized by rapidly changing economic conditions, illustrating well the advantage of incorporating recent financial variables into forecasts of `CS` real estate returns.

As a starting point, in Panel A of Figure 2.3, we plot the return 1-month forecasts of the two leading approaches – the inverse rank and the inverse rank MIDAS that use financial variables – as well as that of the autoregressive benchmark, and the ex-post realization of the `CS` return. Upon cursory examination of the plots, the inverse rank forecasts track the

[20] While the first officially reported case of COVID-19 on US soil was on January 20th, 2020, it was not until March 6th that the President signed the Coronavirus Preparedness and Response Supplemental Appropriations Act, releasing about 8 billion in emergency funding for federal agencies to respond to the outbreak. On March 13th, the President declared a national emergency.

realizations closely until July of 2020 and, from that point onward, the actual CS returns increase rapidly and unexpectedly.

As in the previous section, we measure increases in forecast accuracy with $\left(\widetilde{\epsilon}_t^N\right)^2 - \left(\widetilde{\epsilon}_t^A\right)^2$, where the forecasting errors under the null and alternative models are computed from January 2020 to November 2020. The model parameters are estimated with data until December 2019 and are kept constant throughout 2020, which prevents any sort of look-ahead bias. We present the cumulative sum of this difference, where positive values capture the superior forecasts of the alternative model relative to the null. The results are plotted in Panel B of Figure 2.3 for both the inverse rank and the inverse rank MIDAS models. There are two main takeaways from this graph. First, both models produce improvements over the null model. The forecasting accuracy of the models that condition on financial information is particularly clear during the most uncertain periods, during which the pandemic was in full swing, as shown by the number of COVID-19 infections in the shaded region. Second, the MIDAS model delivers more precise estimates than the non-MIDAS model in the latter part of the sample. Given that the two models feature the same variables and forecast aggregating scheme, this evidence cleanly demonstrates how using high-frequency data results in more precise estimates during volatile and fast-changing times.

To gauge the economic magnitude of the models' predictive accuracy, we plot the cumulative difference in absolute out-of-sample forecast errors, $|\widetilde{\epsilon}_t^N| - |\widetilde{\epsilon}_t^A|$, in Panel C of Figure 2.3. This measure is similar to the one above, with the exception that the difference is expressed in units of returns. Similarly to Panel B, both models produce more precise forecasts than the null model. The inverse rank MSE MIDAS model improves the accuracy over March to November 2020 by about 80 basis points in returns (i.e., an improvement of 26 basis points per quarter) whereas the inverse rank MSE leads to about 50 basis points return improvement. These forecast gains are economically large and statistically significant at the 1% level based on the Clark and West (2007) test, and are obtained over a relatively short time span of a few months.

2.6 Concluding Remarks

The CS repeat-sales index, a widely used monthly indicator of U.S. residential real estate prices, is subject to a two-month release lag. In this paper, we tackle the question whether recent information offered by 71 financial and macroeconomic predictors helps in backcasting, nowcasting and forecasting real estate returns of the aggregate and 19 MSA-specific CS indexes.

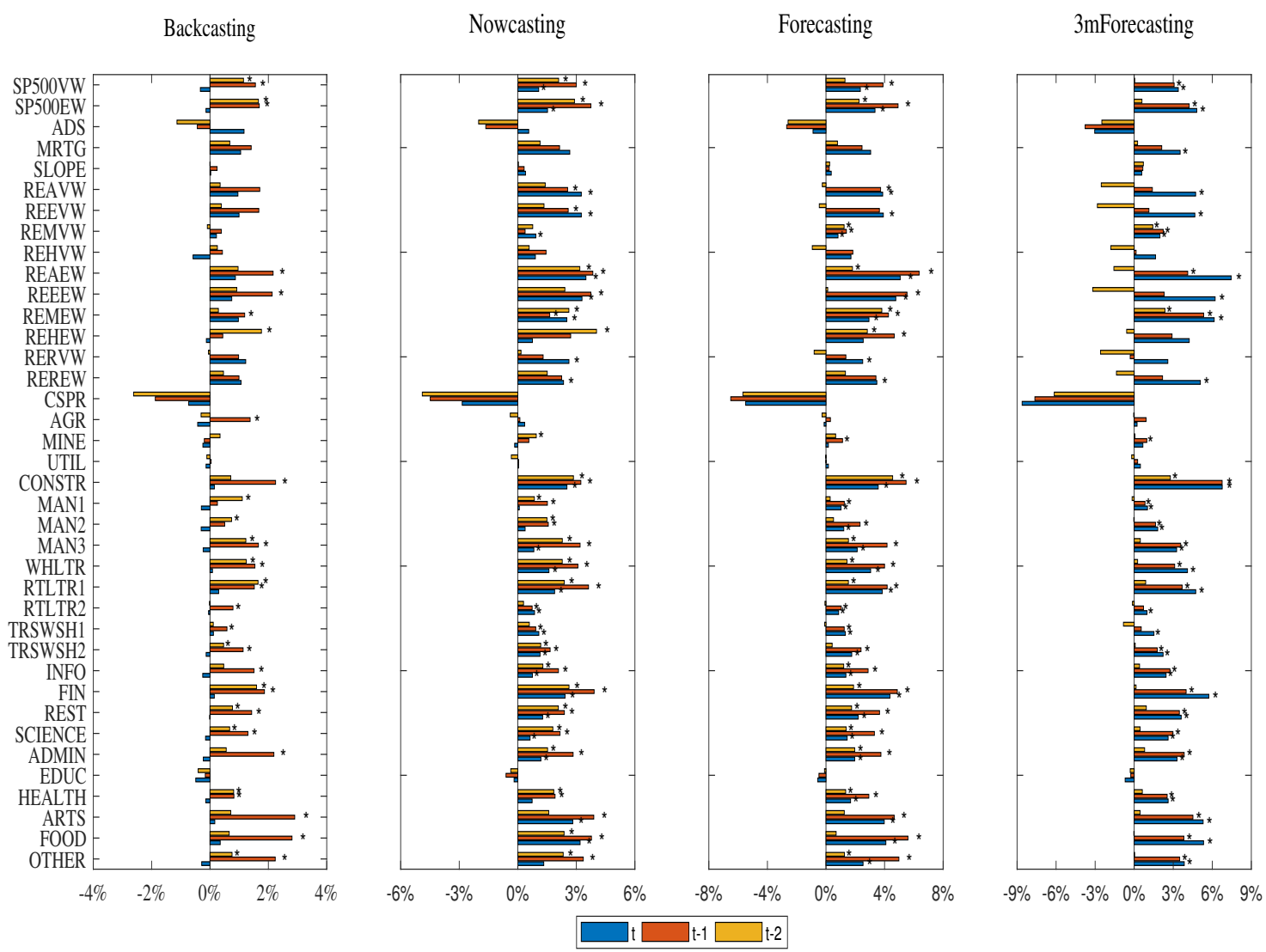
We find that, although Case-Shiller index returns are highly persistent, as documented in Schindler (2013), a big-data approach that exploits financial and macroeconomic variables together with Mixed-Data Sampling regressions adds great value to the out-of-sample returns forecasts. More accurate forecasts are obtained relative to the autoregressive benchmark, especially in tumultuous market periods, such as during the financial crisis of 2007-2009 or the onset the COVID-19 pandemic, when forecasting ability is most valuable. Finally, we show that our models consistently outperform the benchmarks also across the nineteen Metropolitan areas, with a positive and statistical significant relation between population and MIDAS forecasting gains, suggesting that MIDAS models have higher value in those areas with higher transaction volumes, which are presumably faster to incorporate economic market developments.

A timely release of the Case-Shiller index is unarguably the most efficient way of capturing the dynamics of residential real estate values. To the extent that is not operationally feasible, the methods proposed above lead to precise returns forecasts and have the potential to significantly improve the decision-making of participants in the real estate market.

Figure 2.1: Out-of-sample performance of baseline model

This figure plots the R^2_{OS} statistic from recursive out-of-sample estimations of the alternative model of Eq.(3.9) against the benchmark model of Eq.(3.8). For the alternative model, panel A uses the 38 financial predictors (at lags $j = \{0, 1, 2\}$) while Panel B is for the 33 macro predictors (at lags $j = \{1, 2\}$). Variables are defined in Appendix Table 3A.1. An asterisk denotes specifications that are significant at the 5% level based on the Clark and West (2007) test. The full sample period is Jan87 to Dec19, with first burn-in period ending in Dec01.

Panel A: Financial predictors



Panel B: Macro predictors

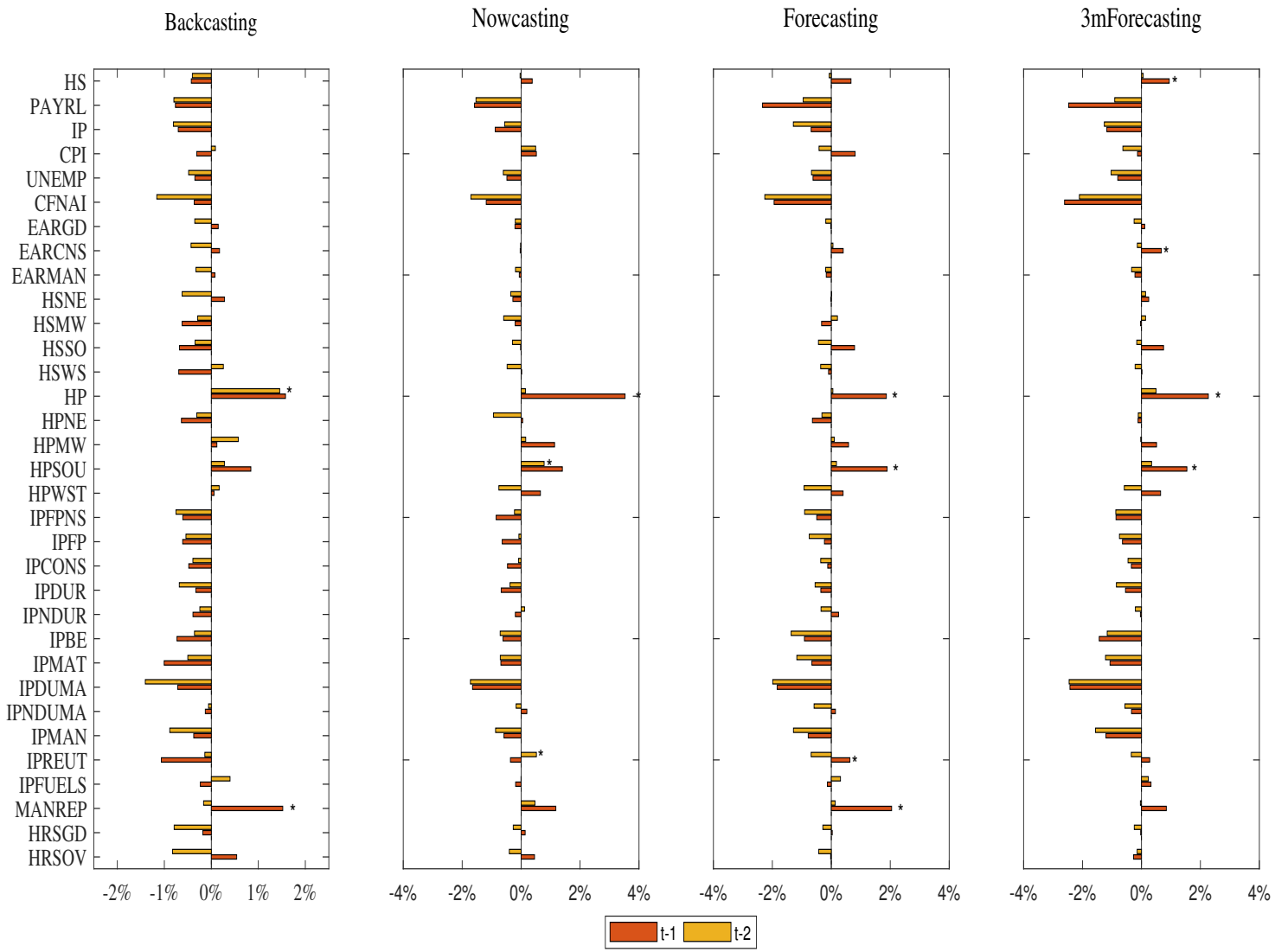


Figure 2.2: Out-of-sample performance of MIDAS model

This figure plots the R^2_{OS} statistic from recursive out-of-sample estimations of the alternative MIDAS model of Eq.(2.6)–(2.7) for each financial predictor against the benchmark model of Eq.(3.8). Variables are defined in Panel A of Appendix Table 3A.1. An asterisk denotes specifications that are significant at the 5% level based on the Clark and West (2007) test. The full sample period is Jan87 to Dec19, with first burn-in period ending in Dec01.

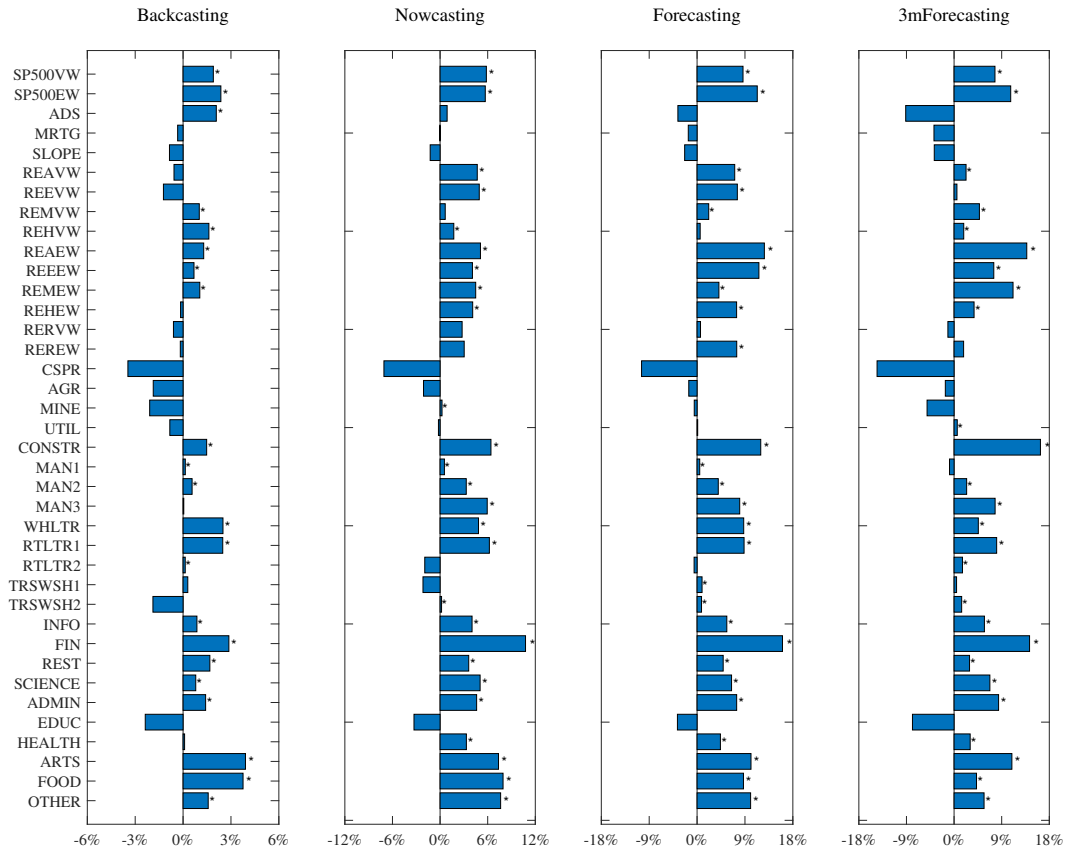
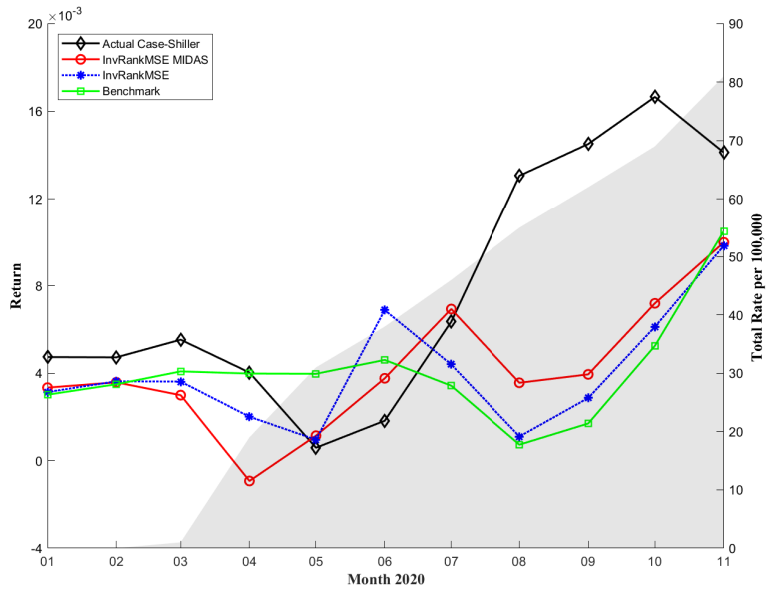


Figure 2.3: Forecasting performance during the COVID-19 period

We compute 1-month forecasts of the CS index using either the autoregressive model or the Inverse Rank MSE Forecast Combination of financial variables with or without MIDAS for the January to November 2020 COVID-19 sample. The models are estimated until December, 2019 and the parameters are then kept constant throughout the 2020 sample to generate eleven out-of-sample forecasts. Panel A of this figure plots the time series of the realized aggregate CS index return and the forecasts. Panel B and C display, respectively, the cumulative differences in squared and absolute forecast errors between the autoregressive model and the Inverse Rank models. Returns and cumulative differences are measured on the left Y-axis. In the grey area (measured on the right Y-axis), we display the total rate of COVID-19 infections in the US per 100,000 inhabitants.

Panel A: Forecast returns



Panel B: Relative Cumulative SSE

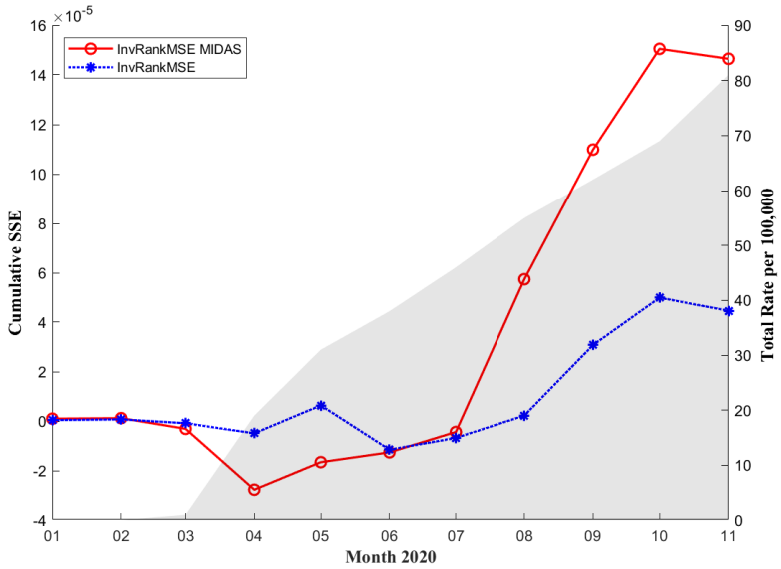


Figure continues on next page →

Panel C: Relative Cumulative SAE

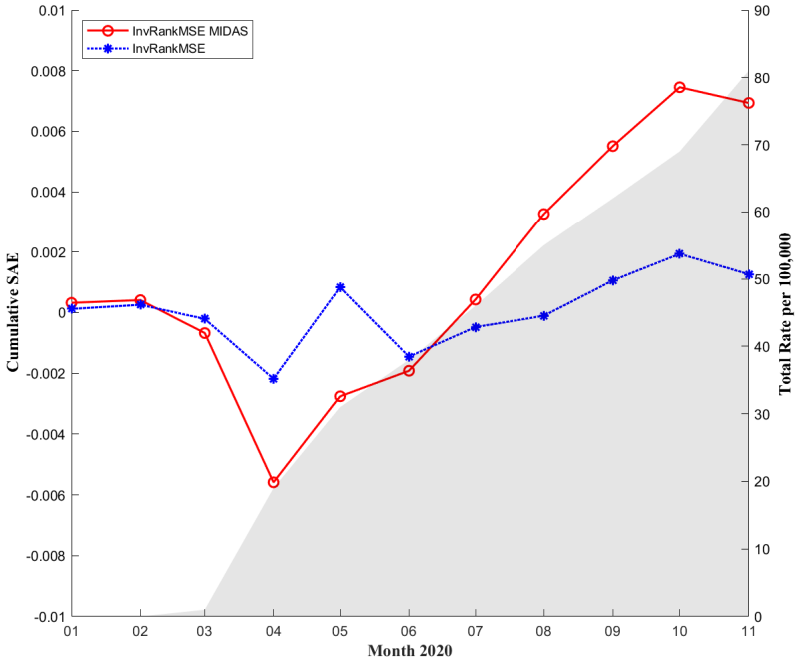


Table 2.1: Forecast combination

This table reports in-sample (Jan87 to Dec19, Panel A) and out-of-sample (with first burn-in period ending in Dec01, Panel B) results from predicting returns to the S&P/Case-Shiller index using forecast combination. The first row in each panel reports the MSFE from the benchmark model, as defined in Eq.(2.8) (for Panel A) and Eq.(2.10) (for Panel B). The other rows report the R^2_{IS} (for Panel A, see Eq.(2.9)) and R^2_{OS} (for Panel B, see Eq.(3.13)) from a forecast combination of either the financial predictors and their lags, or the macro predictors and their lags, or both. The combinations are either based on equal weights, on weights relative to the inverse of MSFE, or on weights relative to the inverse of rank MSFE. For the out-of-sample results, boldface denotes entries that are significant at the 5% level based on the Clark and West (2007) test.

		Backcasting	Nowcasting	Forecasting	3m Forecasting
		Panel A: In sample			
Benchmark		2.87E-06	5.11E-06	7.25E-06	6.64E-05
Financials					
	Equal weight	1.51%	3.16%	3.94%	4.03%
	Inverse MSE	1.51%	3.09%	3.96%	4.16%
	Inverse Rank MSE	1.13%	2.00%	2.69%	4.88%
Macro					
	Equal weight	0.72%	0.80%	0.69%	0.78%
	Inverse MSE	0.72%	0.79%	0.70%	0.76%
	Inverse Rank MSE	1.07%	1.23%	0.81%	0.91%
Combining Financials & Macro					
	Equal weight	1.25%	2.36%	2.83%	2.92%
	Inverse MSE	1.25%	2.30%	2.85%	3.04%
	Inverse Rank MSE	1.22%	2.02%	2.36%	4.43%
		Panel B: Out-of-sample			
Benchmark		4.85E-06	8.80E-06	1.26E-05	1.19E-04
Financials					
	Equal weight	**1.06%**	**2.55%**	**3.02%**	**2.54%**
	Inverse MSE	**1.07%**	**2.57%**	**3.06%**	**2.58%**
	Inverse Rank MSE	1.52%	**3.81%**	**4.27%**	**4.37%**
Macro					
	Equal weight	-0.22%	-0.07%	-0.31%	-0.61%
	Inverse MSE	-0.23%	-0.07%	-0.31%	-0.63%
	Inverse Rank MSE	-1.63%	0.39%	-0.73%	-2.88%
Combining Financials & Macro					
	Equal weight	**0.61%**	**1.63%**	**1.85%**	**1.44%**
	Inverse MSE	**0.62%**	**1.65%**	**1.89%**	**1.47%**
	Inverse Rank MSE	0.22%	**3.24%**	**3.90%**	**3.57%**

Table 2.2: Forecast combination and MIDAS regressions

This table reports in-sample (Jan87 to Dec19, Panel A) and out-of-sample (with first burn-in period ending in Dec01, Panel B) results from predicting returns to the S&P/Case-Shiller index using forecast combination combined with MIDAS regressions. The first row in each panel reports the MSFE from the benchmark model, as defined in Eq.(2.8) (for Panel A) and Eq.(2.10) (for Panel B). The other rows report the R^2_{IS} (for Panel A, see Eq.(2.9)) and R^2_{OS} (for Panel B, see Eq.(3.13)) from combining the forecasts from MIDAS regressions of the financial predictors alone or together with the lags of the macro predictors. The combinations are either based on equal weights, on weights relative to the inverse of MSFE, or on weights relative to the inverse of rank MSFE. For the out-of-sample results, boldface denotes entries that are significant at the 5% level based on the Clark and West (2007) test.

		Backcasting	Nowcasting	Forecasting	3m Forecasting
		Panel A: In sample			
Benchmark		2.87E-06	5.11E-06	7.25E-06	6.64E-05
Financials					
	Equal weight	4.85%	8.54%	11.28%	11.27%
	Inverse MSE	4.84%	8.57%	11.57%	11.56%
	Inverse Rank MSE	4.29%	9.73%	13.29%	14.00%
Macro					
	Equal weight	2.46%	4.17%	5.31%	5.34%
	Inverse MSE	2.45%	4.14%	5.49%	5.52%
	Inverse Rank MSE	3.27%	7.63%	10.81%	11.68%
		Panel B: Out-of-sample			
Benchmark		4.85E-06	8.80E-06	1.26E-05	1.19E-04
Financials					
	Equal weight	**2.68%**	**5.89%**	**8.44%**	**6.99%**
	Inverse MSE	**2.69%**	**5.98%**	**8.57%**	**7.14%**
	Inverse Rank MSE	**2.11%**	**7.89%**	**11.26%**	**11.13%**
Combining Financials & Macro					
	Equal weight	**1.02%**	**2.45%**	**3.35%**	**2.60%**
	Inverse MSE	**1.05%**	**2.60%**	**3.60%**	**2.80%**
	Inverse Rank MSE	**1.81%**	**6.83%**	**9.70%**	**9.42%**

Table 2.3: Forecast combination, out-of-sample MSA analysis

This table reports the out-of-sample (with first burn-in period ending in Dec01) results from predicting returns to the nineteen individual S&P/Case-Shiller MSA-level indices. At each of the four forecast horizons, the first column reports the MSFE from the benchmark model MSFE_{OS}^{N} (see Eq.(2.10)), while the second column reports the R_{OS}^2 (see Eq.(3.13)) from using forecast combination of the financial and macro predictors and their lags when weights are based on the inverse rank MSFE (see Eq.(3.12)). Boldface denotes entries that are significant at the 5% level based on the Clark and West (2007) test.

	Backcasting		Nowcasting		Forecasting		3mForecasting	
MSA	MSFE_{OS}^{N}	R_{OS}^2	MSFE_{OS}^{N}	R_{OS}^2	MSFE_{OS}^{N}	R_{OS}^2	MSFE_{OS}^{N}	R_{OS}^2
Boston	2.29E-05	0.66%	2.96E-05	**1.51%**	3.65E-05	**1.39%**	2.13E-04	**3.80%**
Chicago	3.17E-05	0.65%	4.39E-05	1.79%	5.71E-05	2.76%	4.12E-04	1.07%
Denver	1.23E-05	-0.10%	1.47E-05	-0.36%	2.03E-05	-1.85%	1.47E-04	-4.74%
Las Vegas	5.74E-05	-1.13%	8.84E-05	0.24%	1.27E-04	0.87%	1.09E-03	-0.01%
Los Angeles	1.66E-05	0.39%	2.96E-05	0.19%	4.07E-05	**3.97%**	3.99E-04	**3.61%**
South Florida	2.32E-05	**2.04%**	3.71E-05	**2.27%**	6.01E-05	**3.40%**	4.79E-04	2.83%
New York	1.43E-05	0.85%	1.71E-05	0.63%	2.32E-05	**2.15%**	1.69E-04	**6.59%**
San Diego	2.69E-05	-4.90%	3.51E-05	-1.21%	5.36E-05	-2.00%	4.61E-04	-0.82%
San Francisco	3.87E-05	1.26%	5.78E-05	-0.07%	9.02E-05	0.51%	7.89E-04	-0.42%
Washington	1.79E-05	0.11%	2.52E-05	**1.83%**	3.74E-05	**1.39%**	3.23E-04	1.11%
Atlanta	2.57E-05	0.81%	4.59E-05	1.86%	6.18E-05	2.08%	5.07E-04	1.95%
Cleveland	4.58E-05	0.88%	4.65E-05	**2.28%**	5.39E-05	**3.51%**	2.89E-04	**3.69%**
Charlotte	1.96E-05	**8.29%**	1.87E-05	**7.54%**	2.52E-05	**9.83%**	1.34E-04	**9.82%**
Detroit	5.48E-05	**3.22%**	8.52E-05	**4.91%**	1.01E-04	**5.36%**	6.51E-04	**3.85%**
Minneapolis	5.34E-05	1.45%	6.52E-05	1.66%	8.53E-05	2.14%	6.44E-04	0.47%
Phoenix	1.69E-05	0.65%	3.62E-05	2.04%	6.82E-05	1.71%	8.16E-04	2.39%
Portland	2.37E-05	**1.88%**	2.96E-05	**3.65%**	4.30E-05	**4.04%**	2.86E-04	**4.69%**
Seattle	1.76E-05	**2.77%**	1.76E-05	6.47%	3.29E-05	**8.57%**	2.83E-04	8.37%
Tampa Bay	3.48E-05	**2.20%**	4.59E-05	**2.57%**	6.90E-05	0.03%	4.66E-04	-0.38%

Table 2.4: Forecast combination and MIDAS regressions, out-of-sample MSA analysis

This table reports the out-of-sample (with first burn-in period ending in Dec01) results from predicting returns to the nineteen individual S&P/Case-Shiller MSA-level indices. At each of the four forecast horizons, the first column reports the MSFE from the benchmark model MSFE_{OS}^{N} (see Eq.(2.10)), while the second column reports the R_{OS}^2 (see Eq.(3.13)) from combining the forecasts from MIDAS regressions of the financial predictors with the lags of the macro predictors, when weights are based on the inverse rank MSFE (see Eq.(3.12)). Boldface denotes entries that are significant at the 5% level based on the Clark and West (2007) test.

	Backcasting		Nowcasting		Forecasting		3mForecasting	
MSA	MSFE_{OS}^{N}	R_{OS}^2	MSFE_{OS}^{N}	R_{OS}^2	MSFE_{OS}^{N}	R_{OS}^2	MSFE_{OS}^{N}	R_{OS}^2
Boston	2.38E-05	-3.44%	2.97E-05	1.26%	3.66E-05	0.91%	2.09E-04	**5.44%**
Chicago	3.26E-05	-2.01%	4.41E-05	1.43%	5.80E-05	1.24%	4.24E-04	-1.63%
Denver	1.27E-05	-3.57%	1.51E-05	-3.45%	1.97E-05	1.07%	1.39E-04	1.12%
Las Vegas	5.71E-05	-0.72%	8.92E-05	-0.68%	1.27E-04	0.47%	1.09E-03	0.42%
Los Angeles	1.65E-05	0.64%	2.94E-05	0.67%	4.04E-05	**4.89%**	3.87E-04	**6.46%**
South Florida	2.32E-05	**1.84%**	3.85E-05	-1.61%	6.14E-05	1.46%	4.69E-04	**4.90%**
New York	1.43E-05	0.45%	1.79E-05	-3.49%	2.40E-05	-1.40%	1.72E-04	**5.00%**
San Diego	2.70E-05	-5.21%	3.51E-05	-1.10%	5.23E-05	0.40%	4.46E-04	**2.56%**
San Francisco	3.98E-05	-1.79%	5.76E-05	0.27%	8.78E-05	**3.14%**	7.40E-04	**5.88%**
Washington	1.78E-05	0.49%	2.53E-05	1.35%	3.72E-05	**1.90%**	3.13E-04	**4.35%**
Atlanta	3.24E-05	-0.55%	5.75E-05	2.67%	7.73E-05	**3.50%**	6.31E-04	**4.31%**
Cleveland	4.61E-05	0.16%	4.64E-05	2.41%	5.47E-05	2.04%	2.85E-04	5.19%
Charlotte	1.98E-05	**7.69%**	1.88E-05	**7.02%**	2.52E-05	**9.61%**	1.34E-04	**10.41%**
Detroit	6.78E-05	**2.68%**	1.05E-04	**5.78%**	1.27E-04	**4.95%**	7.93E-04	**6.17%**
Minneapolis	5.93E-05	1.21%	7.26E-05	1.78%	9.46E-05	2.48%	6.98E-04	3.34%
Phoenix	1.88E-05	0.24%	4.04E-05	1.40%	7.48E-05	3.06%	8.98E-04	**3.79%**
Portland	2.40E-05	0.56%	3.00E-05	2.35%	4.38E-05	2.11%	2.85E-04	**5.12%**
Seattle	1.96E-05	**3.52%**	1.90E-05	**8.03%**	3.56E-05	**10.29%**	3.00E-04	**10.97%**
Tampa Bay	3.58E-05	-0.65%	4.70E-05	0.11%	6.99E-05	-1.28%	4.63E-04	0.40%

Table 2.5: Time-variation in forecast errors

This table reports estimates from regressing the difference in either squared (Panel A) or absolute (Panel B) out-of-sample forecast errors between the null and alternative model on the Michigan, VIX and NBER dummies at each of the four forecast horizons. The Michigan dummy equals one if the University of Michigan Consumer Sentiment index in month t is below its historical 10th percentile, and zero otherwise. The VIX dummy equals one if the VIX index in month t is above its historical 90th percentile, and zero otherwise. The NBER dummy equals one if month t is in a recessionary period as defined by the NBER, and zero otherwise. The alternative model 'A' is inverse rank MIDAS with financials only from Panel B of Table 2.2. In parentheses are t-statistics. Statistical significance at the 1% and 5% c.l. are denoted respectively with *** and **.

Panel A: LHS is $\left(\widetilde{\epsilon}_t^N\right)^2 - \left(\widetilde{\epsilon}_t^A\right)^2$

	Forecast					3mForecast				
Var.	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Michigan		0.039***			-0.013		0.351***			-0.123
		(2.938)			(-0.758)		(2.804)			(-0.788)
VIX			0.060***		0.049***			0.580***		0.493***
			(5.243)		(3.747)			(5.383)		(4.011)
NBER				0.060***	0.044***				0.530***	0.370**
				(4.527)	(2.654)				(4.230)	(2.353)
Constant	0.014***	0.011***	0.007*	0.009**	0.006	0.133***	0.101***	0.067*	0.088**	0.057
	(3.679)	(2.693)	(1.911)	(2.359)	(1.557)	(3.654)	(2.704)	(1.851)	(2.400)	(1.550)
Obs.	212	212	212	212	212	212	212	212	212	212
R-squared	0.000	0.039	0.116	0.089	0.147	0.000	0.036	0.121	0.079	0.145

Panel B: LHS is $|\widetilde{\epsilon}_t^N| - |\widetilde{\epsilon}_t^A|$

	Forecast					3mForecast				
Var.	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Michigan		4.468***			1.597		7.934*			-0.085
		(3.089)			(0.850)		(1.727)			(-0.014)
VIX			5.276***		4.145***			15.855***		15.992***
			(4.114)		(2.811)			(3.939)		(3.436)
NBER				4.260***	1.250				7.406	-0.271
				(2.866)	(0.662)				(1.571)	(-0.045)
Constant	1.298***	0.898**	0.701	0.936**	0.580	3.740***	3.029**	1.945	3.111**	1.960
	(3.080)	(2.073)	(1.624)	(2.162)	(1.323)	(2.837)	(2.202)	(1.436)	(2.265)	(1.417)
Obs.	212	212	212	212	212	212	212	212	212	212
R-squared	0.000	0.043	0.075	0.038	0.085	0.000	0.014	0.069	0.012	0.069

Table 2.6: Stock return predictability

Panel A reports in-sample (Jan87 to Dec19) and out-of-sample (with first burn-in period ending in Dec01) results from predicting returns to the aggregate CRSP stock index using forecast combination. The first row in each panel reports the MSFE from the benchmark model, as defined in Eq.(2.8) (for in-sample) and Eq.(2.10) (for out-of-sample). The other rows report the R^2_{IS} (for in-sample, see Eq.(2.9)) and R^2_{OS} (for out-of-sample, see Eq.(3.13)) from a forecast combination of either the financial predictors and their lags, or the macro predictors and their lags, or both. The combinations are either based on equal weights, on weights relative to the inverse of MSFE, or on weights relative to the inverse of rank MSFE. Panel B reports analogous estimates from combining the forecasts from MIDAS regressions of the financial predictors alone or together with the lags of the macro predictors. Compared to the Case-Shiller analysis, the set of financial predictors is augmented with the log dividend-price ratio. For the out-of-sample results, boldface denotes entries that are significant at the 5% level based on the Clark and West (2007) test.

Panel A: Non-MIDAS

	In-sample		Out-of-sample	
	Forecasting	3m Forecasting	Forecasting	3m Forecasting
Benchmark	1.74E-03	5.51E-03	1.62E-03	5.53E-03
Financials				
Equal weight	0.70%	0.99%	-0.21%	-0.66%
Inverse MSE	0.69%	0.99%	-0.25%	-0.87%
Inverse Rank MSE	0.48%	2.01%	-5.86%	-10.02%
Macro				
Equal weight	0.70%	0.44%	0.09%	-1.24%
Inverse MSE	0.68%	0.44%	0.07%	-1.45%
Inverse Rank MSE	0.89%	0.40%	0.54%	-8.23%
Combining Financials & Macro				
Equal weight	0.71%	0.80%	-0.06%	-0.79%
Inverse MSE	0.70%	0.80%	-0.09%	-1.01%
Inverse Rank MSE	0.71%	1.81%	-5.00%	-12.98%

Panel B: MIDAS

	In-sample		Out-of-sample	
	Forecasting	3m Forecasting	Forecasting	3m Forecasting
Benchmark	1.74E-03	5.51E-03	1.60E-03	5.50E-03
Financials				
Equal weight	4.35%	5.88%	-0.99%	1.13%
Inverse MSE	4.34%	5.89%	-1.08%	0.79%
Inverse Rank MSE	3.80%	6.47%	-6.71%	-11.99%
Combining Financials & Macro				
Equal weight	2.19%	2.74%	0.00%	0.00%
Inverse MSE	2.19%	2.77%	-0.06%	-0.23%
Inverse Rank MSE	3.26%	5.34%	-5.59%	-15.16%

Appendix 2.A Additional Tables and Figures

Figure 2A.1: S&P/Case-Shiller MSAs

This figure displays the 19 MSAs for which a Case-Shiller index is available. In blue are the ones that are present in both the 10 and 20 Composite index. In green the ones present in the Composite 20 index only.

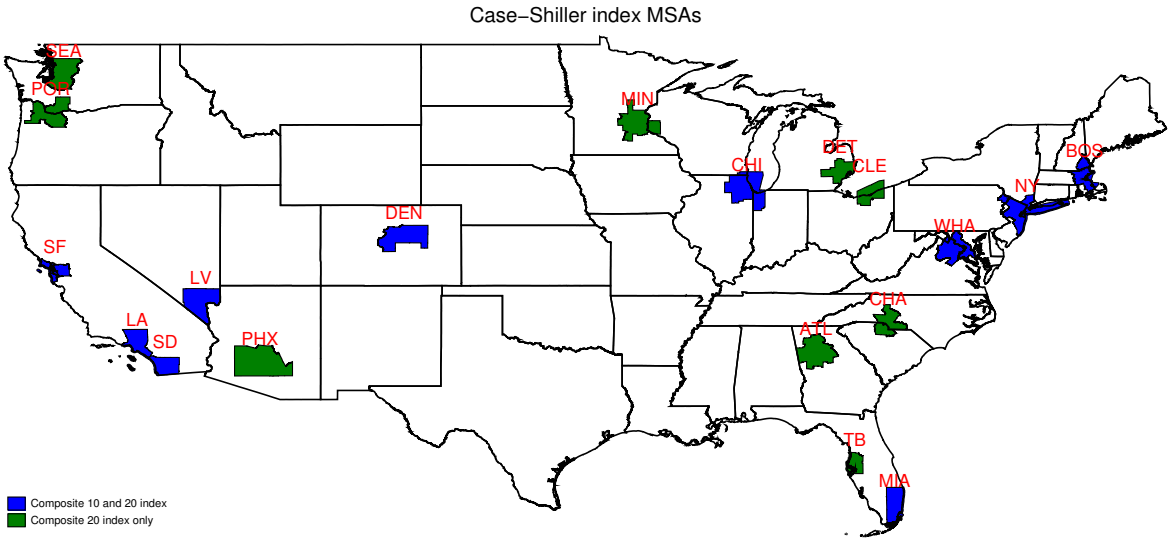
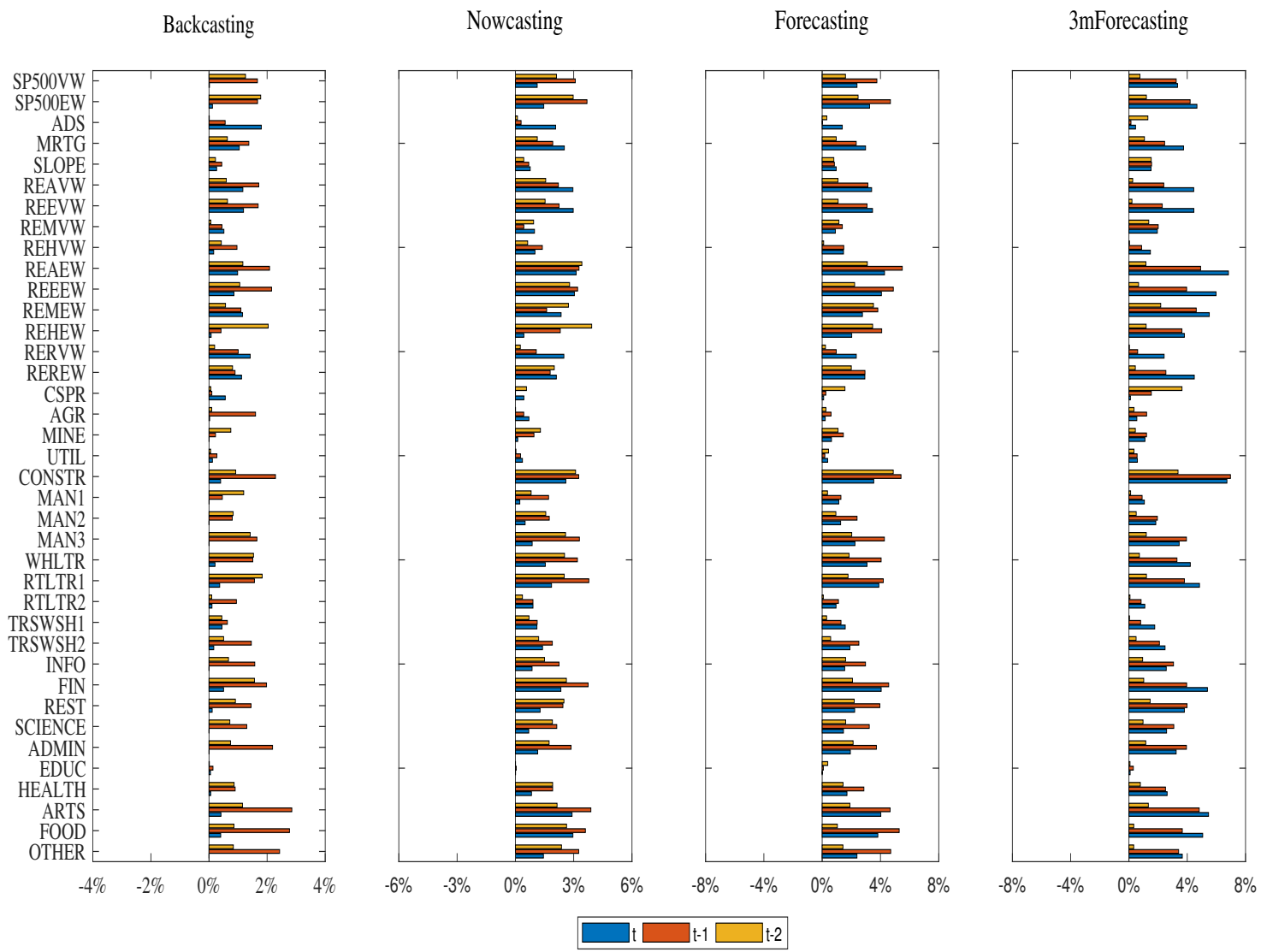


Figure 2A.2: In-sample performance of baseline model

This figure plots the R^2_{IS} statistic from the in-sample estimation of the alternative model of Eq.(3.9) against the benchmark model of Eq.(3.8). For the alternative model, Panel A uses the 38 financial predictors (at lags $j = \{0, 1, 2\}$) while Panel B is for the 33 macro predictors (at lags $j = \{1, 2\}$). Variables are defined in Appendix Table 3A.1. The full sample period is Jan87 to Dec19.

Panel A: Financial predictors



Panel B: Macro predictors

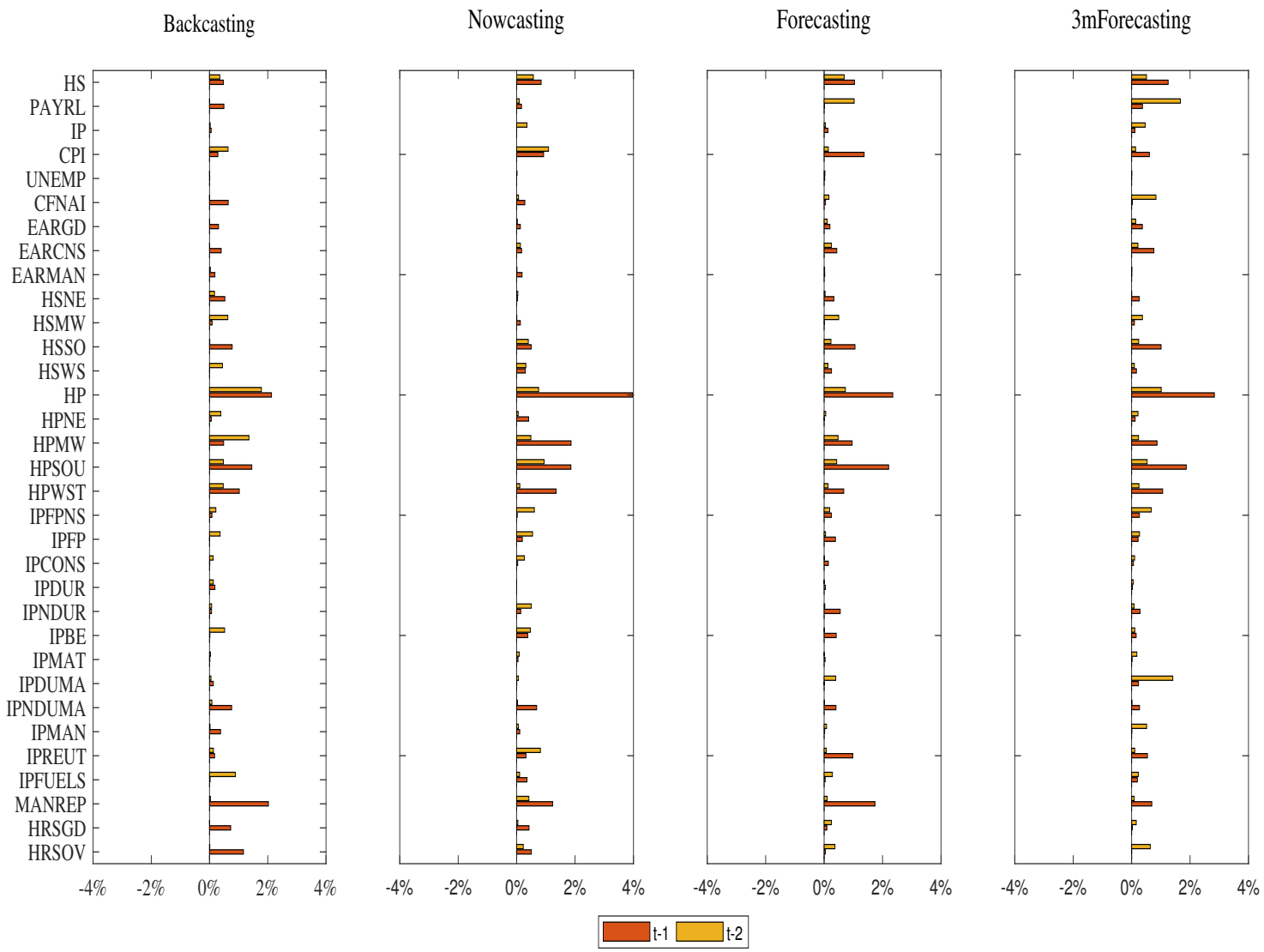


Figure 2A.3: In-sample performance of MIDAS model

This figure plots the R^2_{IS} statistic from the in-sample estimation of the alternative MIDAS model of Eq.(2.6)–(2.7) for each financial predictor against the benchmark model of Eq.(3.8). Variables are defined in Panel A of Appendix Table 3A.1. The full sample period is Jan87 to Dec19.

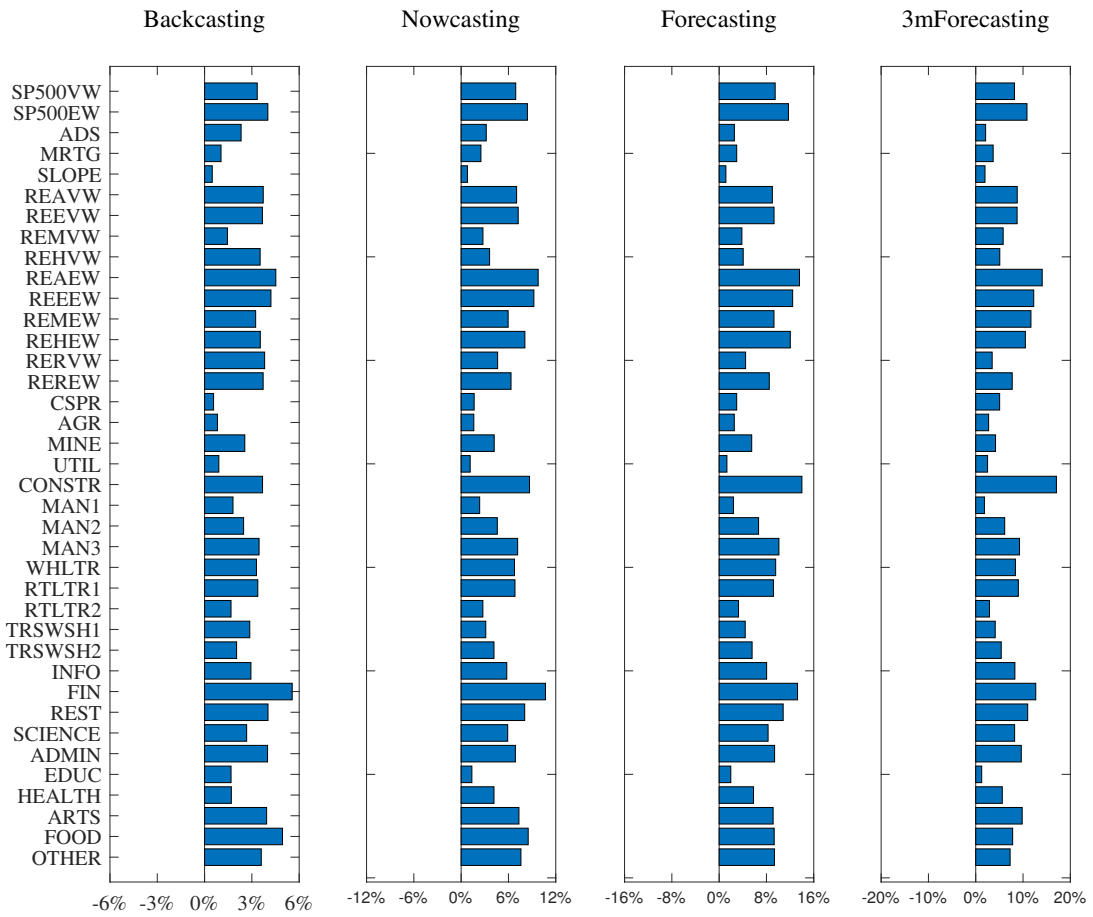


Table 2A.1: List of predictors

This table reports the description of the 38 financial predictors (available at the daily frequency) and 33 macro predictors (available at the monthly frequency) used in our study, along with their data source. For the industry portfolios returns (in Panel A, from AGR onward), we report in parentheses the corresponding NAICS code. For all macro predictors except CFNAI we use monthly growth rates.

Code	Description	Source
	Panel A: Financial predictors	
SP500	S&P 500 (VW & EW) return	CRSP
MRTG	30-Year Fixed Mortgage less 30-Year Treasury Rate	St. Louis FRED
SLOPE	10-Year less 3-Month Treasury Constant Maturity Rate	St. Louis FRED
REA	Ziman Aggregate REITS (VW & EW) return	CRSP Ziman
REM	Ziman Mortgage REITS (VW & EW) return	CRSP Ziman
RER	Ziman Residential REITS (VW & EW) return	CRSP Ziman
REE	Ziman Equity REITS (VW & EW) return	CRSP Ziman
REH	Ziman Hybrid REITS (VW & EW) return	CRSP Ziman
CSPR	Moody's Seasoned BAA less AAA rated corporate bonds	St. Louis FRED
ADS	Aruoba-Diebold-Scotti Business Conditions Index	FED Philadelphia
AGR	Agriculture, Forestry, Fishing and Hunting (11)	CRSP + Compustat
MINE	Mining, Quarrying, and Oil and Gas Extraction (21)	CRSP + Compustat
UTIL	Utilities (22)	CRSP + Compustat
CONSTR	Construction (23)	CRSP + Compustat
MAN1	Manufacturing (31)	CRSP + Compustat
MAN2	Manufacturing (32)	CRSP + Compustat
MAN3	Manufacturing (33)	CRSP + Compustat
WHLTR	Wholesale Trade (42)	CRSP + Compustat
RTLTR1	Retail Trade (44)	CRSP + Compustat
RTLTR2	Retail Trade (45)	CRSP + Compustat
TRSWH1	Transportation and Warehousing (48)	CRSP + Compustat
TRSWH2	Transportation and Warehousing (49)	CRSP + Compustat
INFO	Information (51)	CRSP + Compustat
FIN	Finance and Insurance (52)	CRSP + Compustat
REST	Real Estate and Rental and Leasing (53)	CRSP + Compustat
SCIENCE	Professional, Scientific, and Technical Services (54)	CRSP + Compustat
ADMIN	Admin. and Support and Waste Mgmt and Remediation Services (56)	CRSP + Compustat
EDUC	Educational Services (61)	CRSP + Compustat
HEALTH	Health Care and Social Assistance (62)	CRSP + Compustat
ARTS	Arts, Entertainment, and Recreation (71)	CRSP + Compustat
FOOD	Accommodation and Food Services (72)	CRSP + Compustat
OTHER	Other Services (except Public Administration) (81)	CRSP + Compustat
	Panel B: Macro predictors	
CFNAI	Chicago Fed National Activity Index	FED Chicago
UNEMP	Unemployment rate	St. Louis FRED
CPI	Inflation rate	St. Louis FRED
PAYRL	Non-farm payrolls	St. Louis FRED
HS	New Privately Owned Housing Units Started, SAAR	St. Louis FRED
HSNE	New Privately Owned Housing Units Started, Northeast, SAAR	Global Insight
HSMW	New Privately Owned Housing Units Started, Midwest, SAAR	Global Insight
HSSOU	New Privately Owned Housing Units Started, South, SAAR	Global Insight
HSWST	New Privately Owned Housing Units Started, West, SAAR	Global Insight
HP	New Privately Owned Housing Units Permits, SAAR	Global Insight
HPNE	New Privately Owned Housing Units Permits, Northeast, SAAR	Global Insight
HPMW	New Privately Owned Housing Units Permits, Midwest, SAAR	Global Insight
HPSOU	New Privately Owned Housing Units Permits, South, SAAR	Global Insight
HPWST	New Privately Owned Housing Units Permits, West, SAAR	Global Insight
IP	Industrial Production Index	St. Louis FRED
IPFPNS	Industrial Production Index, Final Products and Nonindustrial Supplies, SA	Global Insight
IPFP	Industrial Production Index, Final Products, SA	Global Insight
IPCONS	Industrial Production Index, Consumer Goods, SA	Global Insight
IPDUR	Industrial Production Index, Durable Consumer Goods, SA	Global Insight
IPNDUR	Industrial Production Index, Nondurable Consumer Goods, SA	Global Insight
IPBE	Industrial Production Index, Business Equipment, SA	Global Insight
IPMAT	Industrial Production Index, Materials, SA	Global Insight
IPDUMA	Industrial Production Index, Durable Goods Materials, SA	Global Insight
IPNDUMA	Industrial Production Index, Nondurable Goods Materials, SA	Global Insight
IPMAN	Industrial Production Index, Manufacturing (SIC), SA	Global Insight
IPREUT	Industrial Production Index, Residential Utilities, SA	Global Insight
IPFUELS	Industrial Production Index, Fuels, SA	Global Insight
MANREP	Manufacturing ISM Report on Business, Employment, Index, SA	Global Insight
HRSGD	Avg Weekly Hours of Production and Nonsupervisory Employees, Goods Producing, SA	Global Insight
HRSOV	Avg Weekly Overtime Hours of Production and Nonsupervisory Employees, Manufacturing, SA	Global Insight
EARGD	Avg Hourly Earnings of Production and Nonsupervisory Employees, Goods Producing, SA	Global Insight
EARCNS	Avg Hourly Earnings of Production and Nonsupervisory Employees, Construction, SA	Global Insight
EARMAN	Avg Hourly Earnings of Production and Nonsupervisory Employees, Manufacturing, SA	Global Insight

Chapter 3

What drives corporate default rates? Evidence from a century of Swiss data

3.1 Introduction

The importance of properly managing and quantifying corporate default risk, and more generally credit risk cannot be understated as the great majority of the risk faced by banks and large financial institutions comes in the form of credit risk exposures. Understanding the determinants of bankruptcy rates over time and in the cross section is of first-order importance for regulators and policy makers that are concerned about the well-functioning of the financial system, and ultimately economic growth.

Much of the extant evidence on default risk comes from probabilities of default that are extracted from either equity valuations or fixed income instruments such as corporate bonds or credit default swaps. Since the price of contingent claims contains a risk compensation, the conclusions one can draw about the determinants of bankruptcy rates are indirect and to some extent model-dependent.

In contrast, studies that directly analyze *realized* bankruptcy rates are quite limited, mainly because of the lack of available data. Bankruptcy is intimately an infrequent event

that necessitates a large sample in order to be properly measured and captured by realized default rates (Bhamra et al., 2009; Feldhütter and Schaefer, 2018). Existing datasets on company information contain sparse default episodes, and are quite limited in the time series spanning at best a few decades. In addition, only aggregate (national) series are available and mainly based on mature and publicly listed companies. These data limitations hamper our understanding of the effect that macroeconomic shocks and policy decisions may have on the default rate of small and medium enterprises (SMEs), which represent the large bulk of the exposure of financial institutions and the backbone of the economic landscape. In the wake of the recent Great Financial Crisis and the COVID-19 pandemic, the need for long and comprehensive time series of bankruptcies is therefore more compelling than ever.

In this paper, we make use of recently digitalized publications of the Swiss Official Gazette of Commerce (*Schweizerisches Handelsamtsblatt*) to analyze national and regional default rate indices based on *all* limited liability companies bankruptcy events in Switzerland over the century-long period spanning 1902 to 2015, and determine their economic drivers.

We employ a laborious data collection process to extract all limited liability companies that have filed bankruptcy in Switzerland starting as early as 1902. By merging these data with the Statistical Yearbook of Switzerland, we are able to construct time series of default rates indices aggregated at the national level for *AG* companies, starting from 1902, and *GmbH* companies starting in 1938[1]. We show that Swiss AG default rates are on average around 0.420% per year, present highly persistence and have moved considerably over time, peaking up right after known historic events like the Great Deperession of the 30s or the Real Estate Bubble of the early 90s. On the other hand, GmbH default rates are on average larger and are more noisy. We also construct regional default rate indices starting from 1928 for the seven macroregions defined by the Swiss Federal Statistical Office finding substantial heterogeneity across regions.

[1]There is no single official translation in English for AG and GmbH. In most textbooks they are referred to *limited companies* (or *corporations* in the U.S.) and *private limited companies* (*LLC* in the U.S., *Ltd.* in the UK) respectively. In this paper we'll stick to the German notation for convenience.

As a first step in our analysis, we estimate a Markov regime-switching model affine to Giesecke et al. (2011) on our dataset of AG companies to investigate the economic drivers of default rates in Switzerland. Interestingly, we replicate their conclusions that lagged GDP growth and equity returns are strong predictors of default rates in the subsequent year, with the addition of the inflation rate. Thus, our results are not driven by the country choice or the slighly shorter sample period. We also find that the low-default state is more persistent, with a probability of staying in the low-default state higher than 90%, and is on average five times longer than the high-default regime. However, we note that the predicted values of the regime-switching model have poor fit in high-default states where we observe excessive default clustering in the data.

We next exploit the panel structure of the dataset more forcefully by implementing an adapted version of the econometric framework presented in Koopman et al. (2011), which allows us to investigate the presence of a dynamic frailty component in Switzerland. More precisely, we let the cross-section of defaults to be dependent on the principal components of a large panel of macroeconomic and financial indicators, that collectively explain almost 90% of the variation in the risk factors, as well as on a latent autoregressive frailty factor. We study the frailty-correlated defaults across various specifications and time spans, considering also variation in the cross-section of macroregions and of legal forms. We find evidence that limited liability companies in Switzerland are commonly positively exposed to a dynamic frailty component, which is not captured by the business cycle indicators. This frailty factor is time-varying and particularly intense during well-known economic crises in the history of the country. Moreover, the latent variable helps to explain the excessive default clustering that have occurred over the sample period where the credit risk faced by banks is higher. The more severe impact of the frailty factor is observed on GmbH firms, which are on average smaller and less structured than AG companies. This result suggests that the factor might be on account of the financial fragility and tougher access to credit faced by small companies.

In the last part of the paper, we examine the out-of-sample forecastability of the term

structure of default rates in Switzerland using a large set of annual financial and macroeconomic variables combined in different forecast combinations. Our framework is feasible in real-time to an econometrician and allows us to quantify the incremental value of the information offered by the set of predictors compared to the simple nested autoregressive benchmark, which does quite well on its own given the high persistence of default rates. We perform the analysis both for the national as well as for the macroregional indices, for an horizon up to 3 years. We find out-of-sample forecasting gains of the order up to 12.69% at the one-year horizon which decline monotonically to 5.74% at the three-year horizon for the inverse MSE ranking combination, a weighting scheme that is consistently the best also across macroregions.

Our paper relates to several strands of the literature. A stream of research establishes a link between credit risk and aggregate risk factors by regressing failure rates on macroeconomic and financial variables. This literature assumes that macro-economic risk and other systematic risk factors are correlated with credit risk metrics of firms such as the probability of default and the loss given default (see, for example, the literature review by Allen and Saunders (2004)). Altman (1983), Hudson (1986) and Ilmakunnas and Topi (1999) find that GDP growth and other common business cycle measures are inversely related to default rates. Dewaelheyns and Van Hulle (2007) model and forecast aggregated bankruptcy rates for companies in Belgium based on macro-economic factors such as GDP. Altman et al. (2005) look at the relation between default rates and recovery rates. Using U.S. data from 1982-2002, they find a significant negative relation between them using uni/variate and multivariate analyses. Notably, they show that the supply of defaulted bonds explains a significant fraction of the variance of bond recovery rates across a wide spectrum of seniority and collateral levels. Interestingly, they find that macroeconomic variables have limited role in explaining fluctuations in recovery rates, in contrast with the evidence in other studies such as Jonsson and Fridson (1996) and Helwege and Kleiman (1996). This difference is likely due to the fact that macro factors move at low frequencies, and therefore sufficiently long time series are

needed to be properly identify their impact. In these respects, as noted by Altman et al. (2005), the alternative of sampling the data at higher, say, quarterly frequency does not represent a solution as quarterly default rates and recovery rates tend to be very volatile due to quarters with only very few defaults.

Despite the theoretical advances on the modeling of credit risk, comparably little is known on the determinants of *realized* bankruptcies since most of the academic publications are based on data covering rather short periods of time, ranging from six years up to a maximum of a few decades. A notable exception is Giesecke et al. (2011), who construct a dataset of corporate defaults for the U.S. going back to 1866 by merging several distinct data sources. Based on such an extensive set of historical data, they uncover several episodes of clustering in corporate default rates in the U.S. that they calibrate through a regime-switching model. They find that stock returns, stock return volatility, and changes in GDP, are indeed strong predictors of default rates. However, despite its unprecedented length, their dataset is based solely on the U.S. non-financial corporate bond market, which gives only a partial view of the bankruptcies events within a country. We contribute to this literature by constructing a unique dataset of Swiss bankruptcies that covers the full universe of firms within the country, including SMEs which correspond to 99% of economic activities and to 2/3 of the jobs in Switzerland[2]. To our knowledge, this dataset is unprecedented both in terms of length and completeness, as well as being one of the fews that is not based on U.S. data. Moreover, with Switzerland being a Federal country similarly to the U.S., our data also possibly allow one to investigate cross-sectional cantonal/regional differences within a common institutional setting. Finally, Switzerland constitutes a unique case, with a relatively stable monetary environment through the last century (Kaufmann, 2019) as well as without substantial changes to the Federal bankruptcy law, which dates back to 1889, making the country an ideal setting to study corporate defaults in the long-run.

Another strand of existing academic research indicates that the sources of default correla-

[2]https://www.kmu.admin.ch/kmu/en/home/facts-and-trends/facts-and-figures/figures-smes/companies-and-jobs.html

tions points at the fact that univariate models, or models based on macro factors, may miss relevant dynamics. For example, Duffie et al. (2009) find that an unobserved, time-varying factor is responsible for predicting individual firm defaults over and above observable firm specific and aggregate financial and macroeconomic variables. They refer to this missing risk factor as to a "frailty" covariate. Their estimates rely on a sample of 176 bankruptcy events for US public nonfinancial firms between 1979 and 2004. Koopman et al. (2011) propose an interesting econometric framework to model frailty-correlated defaults. In a set of U.S. corporate defaults they discover a substantial contrubution by an unobserved latent frailty factor even after controlling for a large set of macroeconomic covariates. Jorion and Zhang (2009) find that standard models based on the Gaussian copula cannot adequately explain clustering in defaults. They identify significant clustering in shocks to creditworthiness arising from counterparty exposures from a supplier–customer relationship. Other important publications that study excessive default clustering and contagion include Das et al. (2007), Koopman et al. (2012) and Azizpour et al. (2018). We add to this literature by studying default clustering in a dataset that considers all active firms within an economy. To our knowledge, this is also the first time that a frailty factor has been modelled over more than one century of data.

Finally, a substantial literature aims to forecasts defaults using structural models Merton (1974); Black and Cox (1976); Geske (1977) or reduced-form models (Jarrow and Turnbull, 1995; Jarrow et al., 1997; Lando, 1998; Duffie, 1998; Duffie and Singleton, 1999). However, these approaches are usually focused on (or tailored to) the case of a single reference entity, being this a corporation or a sovereign. In recent years, the regulatory framework of the Basel Accords and the development of complex credit derivatives and securitization has increased the interest toward portfolio credit risk. For regulatory purposes, banks are required to compute credit Value-at-Risk figures for the overall portfolio consisting of loans and other credit exposures to a variety of counterparts. In the context of such large and potentially diversified (and diverse) portfolios, default correlation is the key ingredient driving the distribution

of future losses, as recent research has shown in the context of credit risk products such as Collateralized Debt Obligations, see Hull and White (2006, 2010). There is therefore a high demand of long-term aggregate times series of bankruptcies to calibrate portfolio credit risk models. We contribute to this literature by forecasting the term structure of aggregate default rates in the long-run using a large panel of financial and macroeconomic predictors combined in different forecasts weighting schemes. These results have huge potential for policy implications as our analysis will provide a long-term view of corporate default risk in Switzerland and thus is of particular interest to Swiss institutions like the SNB or the SECO needing to understand better the economic factors which drive the survival or default probability of Swiss corporations. Moreover, our results offer to policymakers a genuine out-of-sample counterfactual to analyse and quantify the effects of policy choices.

The remainder of the paper is organized as follows. The next section illustrates our data collection process and discusses the resulting long-run time series of default rates. The third section provides details on the Markov regime-switching model approach. The fourth section describes the dynamic frailty factor model together with its empirical results. The fifth section investigates the out-of-sample forecasting results. The sixth section concludes.

3.2 Data

3.2.1 Default Rates Construction

The core series of our paper consists of our self-constructed limited liability companies time series of *realized* default rates in Switzerland. We focus mainly on *AG* (Aktiengesellschaft (AG), Societe anonyme (SA), Società anonima (SA)) limited liability companies for several reasons. First, AG companies are the most common legal form in Switzerland[3]. Moreover, among limited liability companies options in Switzerland, AGs are the ones with the longest time span as the other common limited liability company type, i.e. *GmbH* (Gesellschaft mit beschränkter

[3]https://www.kmu.admin.ch/kmu/en/home/concrete-know-how/setting-up-sme/les-differentes-formes-juridiques/limited-company.html

Haftung (GmbH), Société à responsabilité limitée (Sàrl), Società a garanzia limitata (Sagl)) has been introduced in Switzerland only in 1936. Finally, although sole proprietorships are the most common legal form in Switzerland, it is impossible to disentangle personal bankruptcy from the company's bankruptcy and the liability is unlimited. Nevertheless, we construct also GmbH default rate indices for completeness[4].

Information on corporate defaults in Switzerland had been made public starting as early as 1883 from the daily publications of the Swiss Official Gazette of Commerce. Publications from 2002 onwards can be retrieved electronically via subscription in a convenient database format. Each entry in the post-2002 database has a unique identifier for each corporate event which allows us to easily screen the bankruptcy openings of AG (and GmbH) companies. On the other hand, publications before 2002 are available only in printed paper and change considerably over time – e.g. in their structure, in the fonts and character sets used, and in the amount and precision of the information provided. Thanks to the efforts undertaken by the Swiss National Library, scanned pdf-files of all issues of the Swiss Official Gazette of Commerce before 2002 have been provided. We then performed a textual analysis on the "Bankruptcy" section of the Gazzette in order to collect all the single announcements of bankruptcy openings by AG or GmbH companies for the long period 1902-2001. Figure 3.1 shows one example of an AG bankruptcy notice extracted from the Swiss Official Gazzette of Commerce in year 1957. The data extraction was made even more challenging by the language of the announcements which varies between Cantons since Switzerland is a multilingual country with German, French and Italian as the main official languages of the Federal administration[5]. This

[4]The main differences between AG and GmbH legal forms in Switzerland are the following: *1)* AG have a minimum capitalization of CHF 100,000 (of which CHF 50,000 must be paid in) which is issued in shares with a face value of at least CHF 0.01, whereas for GmbH the minimum capital at inception is CHF 20,000 (it must be fully paid in), issued in equity shares with a face value not smaller than CHF 100. The higher miniumum capital required for AG firms offers them an easier access to credit. *2)* AG firms allow potential investors to take only a financial investment perspective in the company and they are only liable for the amount they invest. On the contrary, GmbH investors are entitled to manage the company and they can have non-competing clauses into the statutes which prevents them to assume competitive behaviours against the firm. *3)* GmbH are not allowed to enter the financial markets whereas AG firms can. *4)* Transfer of shares of AG companies can be in principle freely done while for GmbH the transfer must be approved by the general assembly of the company. *5)* Shareholders of AG companies are anonymous while GmbH shareholders names are published into the Commercial Registry with domicile and the amount of shares owned.

[5]Romansh, the fourth language spoken in Switzerland, has been recognized as national and official language in 1938 and 1996 respectively, however it is not used in the Swiss Official Gazzette of Commerce.

peculiarity increased the amount of regular expressions to consider in our codes dramatically. We therefore completed the extraction operation with a thourough manual check of the data by a team of research assistants. At the end of this process we were able to build a database with all the dates and locations of bankruptcy openings by limited liability companies in Switzerland over the last century[6].

For the default rate denominator up to 2001 we rely on the Statistical Yearbook of Switzerland, which publishes once a year the total of oustanding companies as of December 31st for every legal form[7]. Aggregate figures for the whole country are available as early as in year 1901. Disaggreagted AG statistics per Canton are available only from 1927 onwards, since before that date the cantonal AG statistics are aggregated with the Collective companies ones, which make the cantonal denominators unreliable. To this end, we restrict our regional default rate indices only from 1928 onwards. From 2002 to 2005 we manually calculate the number of outstanding companies in year t by adding to the total of outstanding companies in year $t-1$ the difference between the number of newly founded firms and the number of firms deletions that occur within the year t. For the last part of the sample up to 2015, we rely on the information provided directly by the Federal Office of Commercial Registry[8]. We finally compute the AG default rate in year t for the cross-section j (DR_{jt}) as the sum of AG bankruptcy openings in year t over the total of AG outstanding companies as of December 31st in year $t-1$ (Eq. 3.1):

$$DR_{j,t} = \frac{(Total\ AG\ Bankruptcy\ openings)_{j,t}}{(Total\ AG\ Outstanding)_{j,t-1}} \tag{3.1}$$

[6]Unfortunately, other important information regarding the companies, such as for example size and industry, are not available in the Bankruptcy section of the Gazzette. Part of this information could theoretically be extracted from the Commercial Registry section. However, the process is unfeasible as the data amount to be processed is enormous since the Commercial registry contains information regarding all the firms in Switzerland - also the ones that never fail, which are clearly the majority. To put some numbers, from 2002 to 2015, when we have digitalized .xml files, we have recorded 74'977 bankruptcy opening announcements across all legal forms while the Commercial registry contains 2'881'289 single entries. Moreover, Commercial Registry entries are highly heterogeneous in the formats, making a textual analysis difficult to perform. Finally, the .xml files in the Bankruptcy session miss the Business Identification Number (UID), unlike the Commercial Registry. Therefore, the only way to match the two section would be by a highly problematic fuzzy match of the company names. All these problems are amplified in the pre-2002 .pdf data, because they are not unfortunately in an easy to handle digitalized format, making a an additional manual check of the data mandatory.

[7]For the years 1991 and 1999-2001 we gather the number of companies from Müller and König (2011) due to some inconsistencies encountered in the reporting of the Statistical Yearbook in that period.

[8]https://ehra.fenceit.ch/fr/statistiques/

where the cross-section j is either the aggregate country or a Swiss macroegion as we'll discuss later.

Figure 3.2a plots the time series of the annual AG companies default rate in Switzerland over the full sample period 1901-2015. Figure 3.2b shows the distribution of default rates in the sample. Table 3.1 presents summary statistics of the aggregate AG default rates. The series exhibit substantial variation over time, especially in the first part of the sample. From the start of the sample until 1945 the average default rate is about 0.48% with a relatively high standard deviation of 0.234%. The first major peak coincides with the Post World War I depression. The Great Depression of the 30s correpsonds to the historical period where the AG default rate reached its maximum, slightly above 1%. After the World War II expansion, Switzerland experienced a booming period of economic growth that continued through the 60s and 70s, highlighted by the low default rate which averages 0.331%. Since the mid-80s, Switzerland started suffering from a Real Estate Bubble, which culminated in a severe Recession in the early 90s. In this period, the average default rates grow again to 0.42%, with a slightly skewed distribution (1.346). By contrast, the Great Financial Crisis of the late 00s seem to have had little impact on AG default rates. When looking at the full sample summary statistics, default rates are on average 0.42% and highly positively correlated, as indicated by the 0.675 AR(1) coefficient.

Figures 3.3a and 3.3b show respectively the annual GmbH default rate in Switzerland and its empirical distribution. The GmbH legal form time series starts in 1938 as it was introcuded in Switzerland only in the mid 30s. Table 3.2 presents its summary statistics. Overall, the series looks more noisy than the AG counterpart as confirmed by the serial correlation coefficient which is lower at 0.44. The average default rate is about 0.50% and the volatility is one and a half times larger compared to the AG series. The distribution is more symmetrical, has thinner tails and it reaches its maximum right after World War II at about 1.3%. The disaggregated statistics indicate that the first part of the sample is substantially more variable and fluctuating compared to the more recent sample. Part of the noise in the

early years could be explained by the relatively small number of defaults in the years right after the introduction of the GmbH legal form.

In addition to the nationwide aggregate indices, we also constructed *regional* default rate indices. We abstained ourselves from constructing cantonal default rates indices since for smaller cantons bankruptcy is a relatively infrequent event, especially in the first part of the sample, which would have made the series very noisy. In addition, certain cantons like Appenzell Innerrhoden have a total population comparable to the one of a neighborhood of a big city like Zurich, making difficult a meaningful comparison. We therefore decided to aggregate defaults at the Macroregion level as defined by the Swiss Federal Statistical Office[9] (Figure 3.4): Lake Geneva region (VD, VS, GE), Espace Mittelland (BE, FR, SO, NE, JU), Northwestern Switzerland (BS, BL, AG), Zurich (ZH), Eastern Switzerland (GL, SH, AR, AI, SG, GR, TG), Central Switzerland (LU, UR, SZ, OW, NW, ZG) and Ticino (TI). The resulting series for AG companies are summarized in Table 3.3 and Figure 3.5. The Zurich area is the region with both the highest average default rate (0.592%) and variability (0.406%) which are twice larger compared to the Eastern Switzerland region. This seems to indicate an extremely dynamic entrepreneurial environment in the Canton of Zurich, supported by the fact that it is the canton with the largest GDP within the country and has been historically the "economic engine" of Switzerland. Default rates are on average especially high also in the Northwestern Switzerland region, which is made of traditional highly industrial Cantons such as Aargau, Basel-Land and Basel-Stadt. Interestingly, it is also the region which shows the highest peak at 2.212%. The default rate distribution of Northwestern Switzerland, Ticino and Zurich are all highly skewed with particularly large fat tails. All the default rate series except for Central Switzerland are highly persistent, with a serial correlation coefficients in the range of 0.6 to 0.8. Finally, the correlations across regions are all positive and in general pretty high; most of them are larger than 0.5 with the ones related to Central Switzerland being notable exceptions (Table 3.4).

[9]This corresponds to the second level of the Nomenclature of Territorial Units for Statistics for Switzerland

3.2.2 Macroeconomic and Financial Predictors

Our risk factors are collected from a recent long-run macro-finance dataset for Switzerland made publicly available by Jordà et al. (2017) and Jordà et al. (2019) which include an extensive set of macroeconomic and financial predictors. Specifically, we collect the following macroeconomic variables from the database: real GDP per capita, nominal GDP, real consumption per capita, consumer prices index, imports, exports, narrow money, broad money, public debt-to-GDP ratio, government revenues, government expenditure and the housing prices index. Regarding the financial variables we gather the short-term interest rate, long-term interest rate, CHF to USD exchange rate, total loans to non-financial private sector, total loans to households, total loans to business, equity total return, government bond total return, housing total return, housing rental return, housing rental yield, real housing return, total return on wealth, total return on risky assets and the total return on safe assets. Most of the Jordà et al. (2017) series date back up to year 1870 with annual frequency and details regarding the acronyms used are summarized in the Appendix Table 3A.1. All variables are transformed into annual growth rates (if they are not already constructed as returns in the database), except for the short-term interest rate, long-term interest rate, Public-debt to GDP ratio, total loans to households over GDP ratio and the total loans to business over GDP ratio which are expressed in level. Tables 3.5 contains summary statistics of our risk factors. A few observations are worth mentioning. The real GDP per capita has on average increased over the sample period about 1.4% a year. Equity returns in Switzerland have an annual mean of 8.8% per year with a standard deviation of 18.7%, with the distribution relatively not too far from being normal. This goes in line with the idea that the Swiss stock market is rather defensive in nature compared to other developed markets. The level of aggregate indebtness is generally low, with an average of 37% of the GDP and never exceeds 90% over the last century. Regarding leverage, total loans to business are on average 43.4% of the GDP, which seems pretty managebale for the banking system. Overall, the macroeconomic and financial covariates reflect the general view that Switzerland is a prosperous and stable

country, which has well-managed the financial crises throughout the history.

3.3 Long-Run Analysis of Default Rates

In this section, we provide empirical results for our long-run analysis of default rates in Switzerland. Section 3.3.1 investigates the determinants of default rates with a regime-switching model. Section 3.3.2 analyses the excessive default clustering events by estimating a Swiss latent frailty factor model with an adapted version of the framework by Koopman et al. (2011). Finally, section 3.3.3 explores the out-of-sample forecasting performance of various combinations of the financial and macroeconomic predictors. All these sections focus mostly on AG companies since they are the available for a longer time span.

3.3.1 Regime-Switching Model

We first study the macroeconomic and financial determinants of default rates with a regime-switching model analogous to the one proposed by Giesecke et al. (2011). More specifically, we estimate with maximum likelihood a two-state Markov regime-switching model (Hamilton, 2010) with the following form:

$$DR_t = a_t + bDR_{t-1} + c'X_{t-1} + \epsilon_t \tag{3.2}$$

where a_t which follows a 2-state Markov chain, $X_{t-1} = (x_{1,t-1}, x_{2,t-1}, ..., x_{N,t-1})'$ is a vector of N macroeconomic and financial predictors and DR_{t-1} is the past default rate given the high persistence of the default rate series. Similarly to Giesecke et al. (2011), including the lagged default rate in the model allows us to interpret the vector of coefficients $c = (c_1, c_2, ..., c_N)'$ as the marginal effects of the macroeconomic and financial predictors on the expected default rate. We try to follow as close as possible the set up of Giesecke et al. (2011) and we include the following financial predictors: the annual stock market return (*eq_tr*), the risk-free short term yield (*stir*) and the total loans to business scaled by gdp (*tbus_gdp*) as a measure

of leverage[10]. We also include four macroeconomic variables to control for the change in economic conditions in Switzerland through the last century, namely the real gross domestic product annual growth rate (*rgdpr*), the annual inflation rate (*cpigr*), the annual growth rate in real consumption per capita (*rconpcgr*) and the annual growth rate in exports (*exportsgr*)[11].

Table 3.6 summarizes the empirical estimates of the model. According to Giesecke et al. (2011), the intercept a_t captures the "background" regime-dependent default rate. In our model we can distinguish two different regimes, with a “background” default rate of 0.213% in State 1 and 0.499% in State 2, all highly significant with t-stats of 4.79 and 8.1 respectively. These regimes indicate that Switzerland over the last century has experienced historical periods of high default rates especially in the first part of the sample, and more "quiet" periods as during the 60s and 70s. The regimes can also be partly recognized graphically from Figure 3.2a.

Starting with the macroeconomic predictors, we find the annual change in real GDP to be a strong predictor of default rates. Its coefficient is negative at -0.01329 with a highly significant t-stats of -4.12. This implies that for every 10% increase in real GDP we can expect a 0.13% decrease of default rates for AG companies the next year. Inflation rate is also significant with a coefficient of -0.00514 and a t-stats -2.03. The negative sign is in this case unexpected and might be related to a lead-lag effect of monetary policy easing, which lowers interest rates and increases inflation. Continuing with the financial predictors, we find the lagged stock market returns to be significant with a coefficient of -0.00098 and a t-stats of -1.96. This means that for a stress-test scenario of a -35% stock market crash, analogous to the largest annual stock market crash to date in Switzerland, all else equal AG default rates would increase by 0.034%. While the economic magnitude may appear limited, it is important to emphasize that our sample is mainly made of SMEs companies, which have different dynamics compared to public listed companies. Still, the negative sign is in line

[10] Giesecke et al. (2011) state that they would have included leverage in their model but they did not unfortunately have good measures available, especially to fit the first part of the sample. On the other hand, we do not have a measure of credit spread, which they include in their model.

[11] We include exports growth to proxy for the annual change in industrial production that is unavailable in the Jordà et al. (2017) macrohistory database

with the economic intuition of structural models as the Merton (1974) model, where option pricing theory is applied to the capital structure of companies, which is ultimately related to the default probability of firms. In contrast, all other predictors have no forecasting power. Turning to the lagged default rate we see that it is highly significant with a value of 0.35 and a t-stats of 4.79, corroborating the high persistence of default rates in Switzerland.

Panel A of Table 3.7 presents the transition probabilities of the two-state model. State 1 is highly persistent with a very high probability of 90.91% of remaining in the low-default rate regime. The high-default rate regime on the other hand is less persistent, with a probability of 55.59% of remaining in the "crisis-state" and a 44.41% probability of moving back to the low-default rate regime. This is confirmed by Panel B, which indicates the expected duration of the low- and high-default rate states which is on average five times larger for the former with respect to the latter (ca. 11 years vs. 2.25 years).

Overall, the significance and signs of the lagged GDP growth and stock market returns as well as the persistence of the low-default rate regime are consistent with what obtained by Giesecke et al. (2011). This is reassuring given that our sample differes in several ways from theirs - they focus on corporate debt of non-financial listed firms as well as it is in a different country than ours, i.e. the United States - and provides evidence that a large part of macroeconomic risk is systematic to the whole economy and cannot be diversified away, since our sample considers all firms that are active in Switzerland.

The lower panel of Figure 3.6 shows the probability of being in a high-default regime over time. This probability spikes several times in the first part of the sample, whereas it becomes very small, with the only exception being the recession of the early 90s. The upper panel of Figure 3.6 compares the fitted values from the regime-switching model with the actual realized default rate. It is immediately recognizable graphically that the regime-switching model seems to constantly understate the actual realized default rate during the highly turbulent periods, where we can observe excessive default clustering events. For example, in 1992 at the peak of the Swiss Real Estate Bubble, the model forecasts a default rate

of only 0.481%, compared to the actual realized of 0.752%, which corresponds to about a 36% difference. All these poor fits during high-default regimes indicate that there might be sources of default correlations in Switzerland beyond what is being captured by financial and macroeconomic predictors, something that we try to model and discuss in the next section.

3.3.2 Dynamic Frailty Factor Estimation

In the previous section we have seen that Swiss limited liability corporate defaults have experienced periods of excessive default clustering which are not captured by the regime-switching model. A recent literature, started with Das et al. (2007) and Duffie et al. (2009) and later extended by Lando and Nielsen (2010), Koopman et al. (2011) Koopman et al. (2012) among others states that macroeconomic variables and firm-specific accounting ratios fail to capture the joint defaults of firms that lead to defaults clustering events which are often observed in the data. The idea behind these papers is to model the excessive variation of defaults with an unobserved dynamic process. This factor is able to capture both the contagion effects (when the default of a firm affects important business relationships of other firms, worsening their financial prospects and triggering their defaults) as well as the so called "frailty" effects, which are latent systematic factors that capture default correlations on top of what is induced by the joint correlation to macroeconomic variables[12]. A thourough understanding of the default clustering effects is crucial for portfolio risk management approaches of banks and financial institutions that want to quantify credit risk losses through parametric models and simulations.

To this end, in this section we apply a simplified version of Koopman et al. (2011) default counts model to our new dataset to investigate the role of a latent frailty component in Switzerland in explaining the excess default clustering periods of limited liability companies.

[12] A recent paper by Azizpour et al. (2018) presents a discrete version model that is able to disentangle these two components. In this paper we proxy for the firm failure with the bankruptcy opening publication date, which although quite responsive it might be slightly deferred respect to the actual date where the firm went into financial troubles. Given that these actual dates are unknown, separating the Swiss contagion effects from the frailty effects would be behind the scope of this paper, as we cannot rely on precise default timing dates.

We provide a brief description of the model as follows. Our main modelling variable y_{jt} refers to the number of defaults counts in year t in the cross-section j. J is the total number of cross-section in which our dataset can be split. For our base case $J = 1$, i.e. we model just the national AG aggregate count of defaults over the full sample period 1902-2015. We also consider two extensions of the model. The first one has $J = 7$ as the number of Macroregions. Since we have only limited information regarding the total number of firms in each macroregion, this model will just start in 1928 and considers AG firms only. The second extension considers both AG and GmbH as well as the cross-section of regions, for a total of $J = 7 \times 2 = 14$ and will start in 1939, as the time series for the GmbH legal form are available only from that year onwards. The default count y_{jt}, conditional on the observed macroeconomic risk factors F_t and unobserved frailty factor f_t^{uc}, is assumed to follow a Binomial distribution:

$$y_{jt}|F_t, f_t^{uc} \sim Bin(k_{jt}, \pi_{jt}) \tag{3.3}$$

where the variable k_{jt} is equal to the total number of firms active as of December 31st of year $t-1$ in the cross-section j (i.e. our usual default rate denominator) and π_{jt} is a time-varying default probability. π_{jt} is the logistic transformation of an index function θ_{jt} which depends linearly on a fixed effect for the jth cross-section λ_j, on the frailty factor f_t^{uc} and on R observable business cycle indicators stacked into the $R \times 1$ vector F_t as defined in Equation (3.4) :

$$\theta_{jt} = \lambda_j + \beta_j f_t^{uc} + \gamma' F_t \tag{3.4}$$

where β_j is the sensitivity of the cross-section j to the unobservable frailty factor and γ is a $R \times 1$ vector of sensitivities to the macrofactors. The index function can be though also as the log-odds ratio of the time-varying defualt probability π_{jt}. Following Koopman et al. (2011), to model the impact of the cross-section of financial and macroeconomic predictors at

time t without selecting a subset of them, we extract the first 10 principal components from the Swiss macrohistory database ($R = 10$), which collectively capture 88.43% of the variation in the data, and collect them into the vector F_t.

The latent frailty factor f_t^{uc} is specified as an autoregressive model of order 1 (Eq. 3.5):

$$f_t^{uc} = \phi f_{t-1}^{uc} + \sqrt{1-\phi^2}\eta_t, \qquad \eta_t \sim NID(0,1), \qquad t = 1, ..., T \tag{3.5}$$

where we restrict ϕ to be strictly larger than 0 and strictly smaller than 1 to preserve the stationarity of the process. The model can be handily represented in state space form:

$$\begin{pmatrix} \alpha_{t+1} \\ \theta_{jt} \end{pmatrix} = \Phi_t \alpha_t + u_t \tag{3.6}$$

with:

$$\Phi_t = \begin{pmatrix} T \\ Z_{jt} \end{pmatrix}, \qquad u_t = \begin{pmatrix} H \\ G \end{pmatrix} \epsilon_t, \qquad \epsilon_t \sim NID(0,1) \tag{3.7}$$

The first equation is the *transition* equation which describes the evolution of the state vector $\alpha_t = (\lambda_1, ..., \lambda_J, \gamma_1, ..., \gamma_R, f_t^{uc})$, which contains the fixed effects, the sensitivities to the principal components of the macrofactors and the magnitude of the fraility factor. All parameters in the state vector are fixed over time except from the frailty factor intensity f_t^{uc}, therefore we set the transition matrix $T = diag(I, \phi)$ and $H = (0, ..., 0, \sqrt{1-\phi^2})'$ to be constant, where I is a $J + R$ identity matrix and ϕ is the autoregressive component of Eq. (3.5). For the initialization of the state vector, f_t^{uc} has zero mean and unit variance while all λ and γ parameters have diffuse initial conditions. The second equation of the state space model (3.6) is the *measurement* equation of the index function θ_{jt}. The matrix $Z_{jt} = (e_j', F_t' \otimes e_j', \beta_j)$ is varying both in the cross section j as well as over time while G is an identity matrix of dimension J. This non-Gaussian state space model be conveniently estimated with Monte Carlo maximum likelihood and importance sampling methods and a

detailed description of the estimation procedure is outlined in Koopman et al. (2011).

Table 3.8 highlights the empirical results of the model. Panel A presents the estimates for the longest time span we can use (AG companies, 1902-2015), with an without the frailty factor f_t^{uc}. This configuration corresponds to the case with $J = 1$, a model with a single fixed effect intercept λ and ten γ principal components sensitivities. Comapring the first two columns, adding f_t^{uc} to the model almost doubles the Log-likelihood of the model and the increase is statistically significant at 1% to the likelihood-ratio test. The sensitivity β_0 is positive and significant, meaning that firms have a joint exposure to the common latent factor even after controlling for a wide range of economic and financial obersvable risk factors.

Panel B considers the case $J = 1 \times 7$, where we allow the fixed effect λ to vary across macro regions. This sample just considers AG companies and goes back as early as 1928, due to the limited disaggregated information available regarding the regional exposure k_{jt}. Given perfect multicollinearity across macroregions, we normalize the results with respect to Espace Mittelland macroregion[13]. Again, in the first two columns we report the model with and without the frailty factor. We see that the model with the common latent component across macroregions increases the Log-likelihood function by more than 10% and the increase is highly statistically significant. The sensitivity is positive and similar in magnitude to the full sample case described above. The fixed effects across macroregions are significant, indicating heterogeneity in the default conditions across macroregions. In the third column of Panel B we go one step further and allow the β sensitivities to f_t^{uc} to vary across macroregions. We note that this specification further enhances the Log-likelihood of the model and most of the β are significant at the 1% level and all are greater than zero, indiciating a positive relation between the latent factor intensity and the log odds-ratio. Figure 3.7 plots the estimated fraility factor f_t^{uc} for this last specification of AG companies. The factor varies substantially over time and peaks during the the Great Depression of the 30s, the Real Estate Bubble of the early 90s and right after the two most recent financial crisis, i.e. the Tech Bubble and

[13]The normalization does not harm the empirical estimates and another macroregion might be in principle chosen for the baseline case.

the 2007-2008 Great Financial Crisis.

Figure 3.8 plots the aggregate default rate for the full sample of limited liability companies (lower graph), together with the total number of defaults and total number of outstanding LL companies in Switzerland. The sample starts only in 1939 and Panel C of Table 3.8 presents the set of results for the frailty factor model, with the base case related to the Espace Mittelland macroregion and the AG legal form. Again, including a common exposure to the frailty factor to the model increases the Log-likelihood by about 10%, an increase which is highly statistically significant to the Log-likelihood ratio test, and the β sensitivity is statistically significant in the model. In the last column we again allow the β to vary not only across macroregions but also across legal forms. The Log-likelihood further increases and most of the regional betas are positive and significant. Remarkably, the β related to the GmbH legal form is also greater than zero and significant.

Overall, we demonstrate that limited liability firms are exposed to a dynamic latent factor that drives defaults which is on top of the observed risk factors, in line with the results by Duffie et al. (2009), Koopman et al. (2011) and Azizpour et al. (2018). This latent factor helps explaining the excessive default clustering periods that have occured throughout the history. The impact of the factor varies over time and might proxy for several things, such as omitted industry effects, which we cannot control for, contagion effects, where the default of a large company triggers the defaults of related companies, or default correlations that is not captured by business cycle variables. The peaks of the frailty factor in 3.7 are aligned with the aftermath of Swiss economic crises, suggesting that it might proxy for enhanced credit risk during such periods. Finally, considering that GmbH firms are on average smaller than AG companies and have a simpler firm structure, the positive and significant β exposure to the frailty factor f_t^{uc} seems to indicate that smaller firms suffer on average more from frailty effects, which is possibly due to a more difficult access to credit. This means that for smaller firms actual default probabilites might potentially be understated when one omits the frailty factor effects.

3.3.3 Forecasting the Term Structure of Default Rates

In the last section of this paper we want to take an out-of-sample forecasting approach of the term-structure of default rates that is feasible in real-time to an econometrician and compare the default rates forecastability performance of various models using the simplest possible modelling assumptions. In fact, the unprecedented length of our time series enables us to calibrate the models with an extremely long time span for the burn-in sample, in contrast to most standard dataset that have much shorter sample periods and mainly focus on mature and public firms where such an approach is considerably more limited. The length of the time series allows us also to forecast default rates over longer horizons than one-year, without sacrificing too much data for the in sample parameters estimation, which is a usual limitation when using short datasets.

Given the high persistence of the default rates, the natural benchmark in this section is the simple autoregressive model, where default rates are regressed on the most recent default rate value DR_t, which we label with subscript 'N' in Eq. 3.8:

$$DR_k = c^N + \phi^N DR_t + \epsilon_k^N \tag{3.8}$$

where c^N is the benchmark's intercept, ϕ^N is the autoregressive coefficient and ϵ_k^N is the error term from the model. We focus on three forecasting horizons of the term-structure, namley (i) the one-year default rate ($k = t + 1$), (ii) the two-year average default rate ($k = (t + 1 : t + 2)$) and (iii) the three-year average default rate $k = (t + 1 : t + 3)$. For the alternative enhanced models, we focus on a linear conditional expectation specification, in order to evaluate the marginal forecasting gains from adding the macroeconomic and financial predictors to the autoregressive benchmark using as few assumptions as possible (Eq. 3.9):

$$DR_k = c^A + \delta_j^A x_t + \phi^A DR_t + \epsilon_k^A \tag{3.9}$$

where c^A is the alternative model's intercept, δ_j^A is the sensitivity of default's rates to

the macroeconomic or financial risk factor , ϕ^A is the alternative's autoregressive coefficient and ϵ_k^A is the error term from the alternative model. The 30 individual predictors x_t come from the Jordà et al. (2017) macrohistory database and we run Eq. (3.9) predictor by predictor. We estimate the model in a rolling fashion with OLS using at each point in time the last 40 years of data. We start our sample period in year t=1928 in order to facilitate the comparison between the aggregate nationwide default rate and the Macroregions ones which are only available from that year onwards. We evaluate the forecasts by means of two popular statistical criteria which are the mean squared forecast error (MSFE) and the mean absolute forecast error MAFE:

$$\text{MSFE}^s_{OOS} = \frac{1}{T_{OOS}} \sum_{\tau=1}^{T_{OOS}} ({\epsilon_\tau}^s)^2 \qquad \text{and} \qquad \text{MAFE}^s_{OOS} = \frac{1}{T_{OOS}} \sum_{\tau=1}^{T_{OOS}} |{\epsilon_\tau}^s| \tag{3.10}$$

with s which is either our fitted default rate forecast error (A) or the appropriate autoregressive benchmark error (N). Both criteria evaluate the deviation from the actual realized default rate and both are indifferent from the direction of the error term. While the MAFE is expressed in the same unit of the default rates variables, the MSFE gives a relatively high weight to large forecast errors since they get squared before taking the average.

Rapach et al. (2010) state that model uncertainty and instabilty of individual relationships can have a negative impact on the out-of-sample forecasting ability. To overcome this problem, they suggest to combine the individual forecasts with some simple weighting schemes to filter the substantial noise that prevents good forecasting performance. For this reason, we just consider various types of individual forecast combinations instead of relying on single predictors results, a common approach in the forecasting literature (see for example Granger and Ramanathan (1984); Aiolfi and Timmermann (2006); Rapach and Strauss (2008); Clark and McCracken (2010); Rapach et al. (2010); Pettenuzzo et al. (2014); Bakshi and Panayotov (2013); Gargano and Timmermann (2014); Guidolin and Timmermann (2009)). In addition to

the simple equally weighted forecast, where each conditional forecast gets a weight $w_{i,t} = 1/N$ with N being the total number of predictors used, we use the following two alternative weighting schemes. Both schemes are a function of the statistical criterions used. The first one consists in weighting each individual forecast at time t by the inverse of the MSFE/MAFE as in Elliott and Timmermann (2013):

$$w_{i,t} = \frac{\text{CRIT}_i^{-1}}{\sum_{i=1}^{I} \text{CRIT}_i^{-1}} \tag{3.11}$$

where CRIT is either the MSFE or MAFE criterion value as of time t.

The other alternative weighting scheme is based on the inverse rank of the statistical criterion average

$$w_{i,t} = \frac{\text{Rank}_i^{-1}}{\sum_{i=1}^{I} \text{Rank}_i^{-1}} \tag{3.12}$$

where Rank_i equals 1 for the model with lowest MSFE, it equals 2 for the model with the second lowest MSFE, and so forth and similar for the weighted average based on the MAFE criterion (Aiolfi and Timmermann, 2006). The weights are time-varying and are conditional to the information set I_t, as we compute the MSFE (and MAFE) of Eq.(3.10) at each time t until the end of the estimation sample. We report in our tables the out-of-sample R^2 with respect to the benchmark which is defined as follows:

$$R^2_{CRIT,OOS} = 1 - \left(\text{CRIT}^A_{OOS}/\text{CRIT}^N_{OOS}\right) \tag{3.13}$$

again with CRIT being either the MSFE or MAFE criterion value. Since the models are nested, we carry on statistical testing using the Clark and West (2007) *MSFE-adjusted* statistic, which has an asymptotic normal distribution and performs relatively well in finite samples (Rapach and Zhou, 2013).

Table 3.9 shows the OOS results, with each column that reports for a different forecasting horizon the percentage improvement in MSFE (left) and the percentage improvement in MAFE (right). Several results are worth mentioning. First, at the one year horizon an

equally-weighted forecast of the individual combinations delivers an out-of-sample MSFE improvement by 5.89%. Second, the inverse criteria schemes deliver up to an additional 1% improvement with respect to the EW average, with the inverse MSE peaking at 6.73% forecast gain. In addition, the inverse ranking schemes are the most robust weighting schemes and return the largest forecasting gains at 12.69%, more than two times larger than the simple EW forecast. Finally, we note that overall the MSFE based combinations perform consistently better than the MAFE-based counterparts. Turning to the 2-year and 3-year results, the forecasting gains deteriorate monotonically with the forecasting horizon, although less than linearly. Nevertheless, an inverse ranking MSE combination still reaches a substantial 8.11% improvement at the two-year horizon and a 5.74% gain at the three-year horizon. These gains are indeed remarkable, especially compared to the EW naive forecast which barely beats the benchmark at the three-year horizon in both MSFE and MAFE terms (0.66% and 0.48% respectively). Figure 3.9 plots for the one-year forecasting horizon the difference between the cumulative squared prediction errors of the benchmark and the cumulative squared prediction errors of the forecast combinations, analogously to the graphical tool by Welch and Goyal (2008)[14]. An increase upwards of the line corresponds to a larger error of the benchmark in that year compared to the enhanced model, and viceversa. We note that the inverse ranking MSFE model outperforms all other enhanced models at all times. The largest forecasting gains are obtained in the early 70s and late 80s - early 90s. This is extremely helpful since these periods correspond to the Oil Crisis of the 70s and the Real Estate Bubble of the early 90s, so high turbulent periods where appropirate portfolio risk management by banks is needed the most.

Until now, we have focused on forecasting the term structure of national aggregate default rates. However, it is well-known that Switzerland is a highly heterogeneous country in several aspects, such as demographics, cultures, geography and industrial specializations. Thus, in this section we want to quantify how much default predictability extends to the seven

[14]Figures 3A.1 and 3A.2 for the 2-year and respectively 3-year forecast are reported in the Appendix.

macroregions. Unfortunately we do not have long time series predictors of local variables[15], therefore we rely on the same set of 30 aggregate predictors. We repeat the same forecasting regressions of equations 3.8 and 3.9 for each macroregion and we report the MSFE and MAFE improvements results in Table 3.10 and Table 3.11 respectively. In general, we recognize the same patterns as for the aggregate index, i.e. that the equally weighted performance is outperformed by the inverse criteria forecasts, with the inverse ranking MSE which is still the most powerful combinations across all regions and forecasting horizons. Moreover, the MSFE based combinations are generally more robust than the MAFE based ones. Nevertheless, there is a great degree of heterogeneity in the default rates forecastability in the cross-section of regions. At the 1-year horizon, the EW forecast is about 5% in all regions except Ticino, Central Switzerland, and Zurich, with the last one which is even negative. The inverse ranking MSFE combination ranges from the 3.41% MSFE improvement in Zurich to the 11.24% forecasting gain in MSFE in Ticino over the out of sample period. Unlike the aggregate default rate index, moving to the longer forecasting horizons, the inverse ranking combinations do not decrease in forecasting performance in all the macroregions, consistently beating the benchmark. Finally, regarding the MAFE percentage improvements reported in Table 3.11, the results and conclusions are consistent with Table 3.10, although in general slightly smaller in magnitude.

3.4 Concluding Remarks

Default risk estimation is an essential activity performed by loans granting banks and financial institutions and recognizing the determinants of default rates over time and in the cross-section of firms is of crucial importance for effective risk management practices. Unfortunately, limited data availability forces many financial institutions to rely on relatively short and partial time series of bankruptcies events, impeding an efficient calibration of credit

[15] For example, the Gross Domestic Product statistics disaggregated by Canton/Macroregion has been disappointingly published by the Federal Statistical Office only since 2008, see https://www.bfs.admin.ch/bfs/en/home/statistics/national-economy/national-accounts/gross-domestic-product-canton.html

risk models. To this end, in this paper we build and analyse time series of limited liability companies (AG and GmbH) default rates in Switzerland over the exceptionally long time period 1902-2015. Our data considers the full universe of firms registered in the Swiss Official Gazzette of Commerce. In itself, the availability of such long time series of default rates is unprecedented for developed countries and to our knowledge the first that encompasses all economic activities that are present in a country, including small businesses.

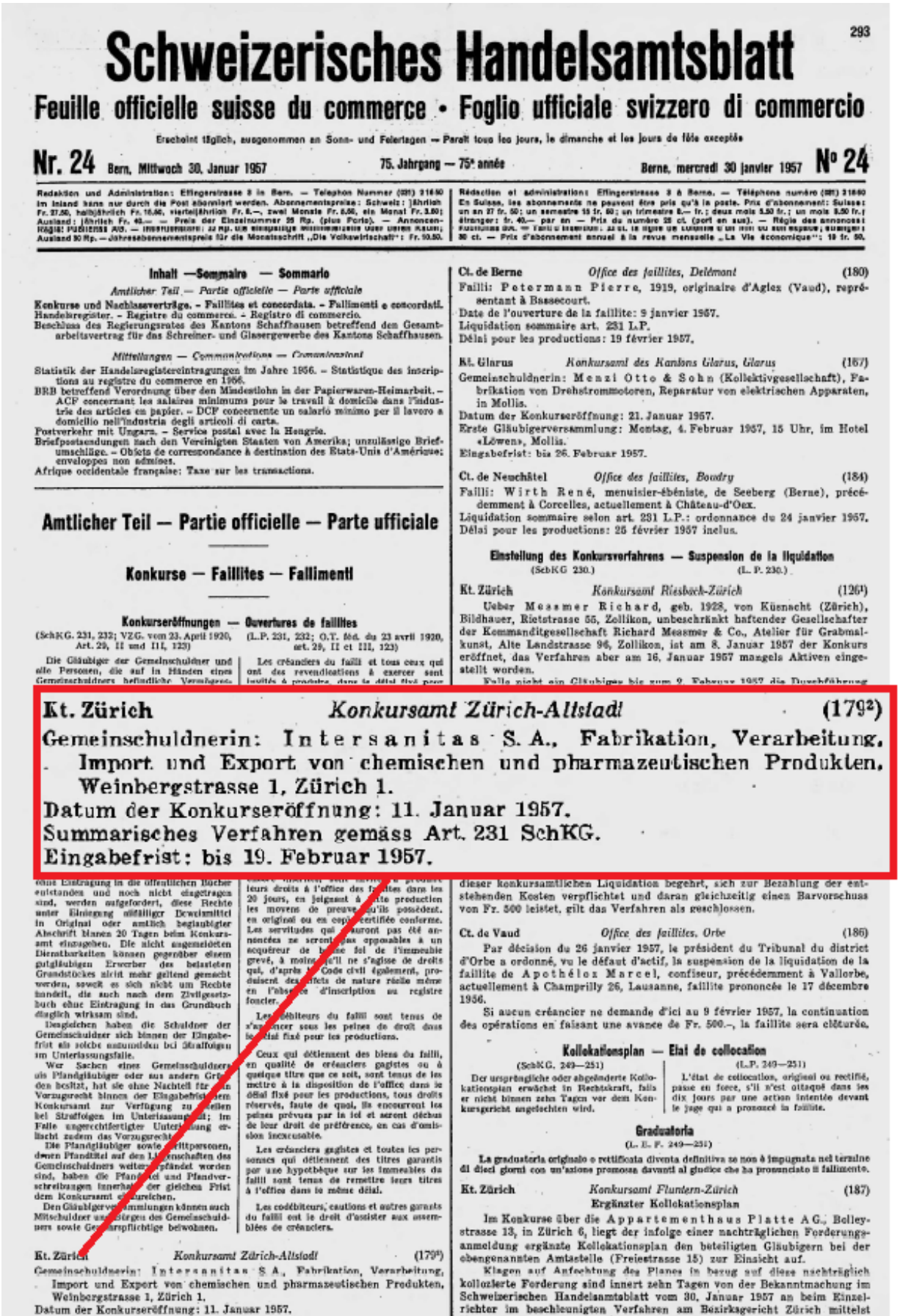
Armed with this unique database, we find that default rates in Switzerland are highly persistent and have been subject to substantial variation over time, with repeated periods of high default rates in the aftermath of known economic crises, as well as in the cross-section of legal forms and macroregions. We then adopt a non-linear regime-shifting model and analyze the economic drivers of default rates, finding both lagged real GDP growth and lagged Swiss equity returns to be negatively related to the subsequent year's default rates. The model alternates between prolonged periods of low and stable default rates and shorter periods of high severity and stress, with the former being on average five times longer than the latter. Interestingly, all these results are consistent with what obtained by Giesecke et al. (2011) in a U.S. dataset of corporate bonds defaults. Yet, default rate predictions by the regime-switching model seem to have poor fit in explaining the excess default clustering of high-default rate periods. To this end, we explore whether a dynamic frailty factor is significant after controlling for a large cross-section of financial and macroeconomic variables and study its behaviour. With a parsimonious economic framework adapted from Koopman et al. (2011), we find that the dynamic latent component is significantly and positively related to excessive default clustering events in Switzerland. The impact of f_t^{uc} varies over time and its peaks coincides with well-known Swiss economic crises. We find a larger impact of the frailty factor on smaller and less structured firms, suggesting that the frailty factor might proxy for tighter credit conditions.

Finally, given the high persistence of default rates, we examine in a simple framewe-ork whether various combinations schemes of individual forecasts based on financial and

macroeconomic predictors can forecast the term structure of defaults rates out-of-sample better than a parsimonious autoregressive benchmark. We show that our enhanced models consistently beat the benchmark both nationwide as well as in all seven macroregions. The forecasting improvements deteriorate monotonically with the horizon and the inverse ranking MSE weighted combinations remarkably outperform all other weighting schemes at each forecasting horizon.

Figure 3.1: Bankruptcy Opening Example

This figure shows an example of bankruptcy opening announcement by an AG company (*"Intersanitas S.A."*) from the Canton of Zurich extracted from the Swiss Official Gazzette of Commerce published on January 30th, 1957.



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Schweizerisches Handelsamtsblatt

Feuille officielle suisse du commerce • Foglio ufficiale svizzero di commercio

Erscheint täglich, ausgenommen an Sonn- und Feiertagen — Paraît tous les jours, le dimanche et les jours de fête exceptés

Nr. 24 Bern, Mittwoch 30. Januar 1957 — 75. Jahrgang — 75e année — Berne, mercredi 30 janvier 1957 **No 24**

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Inhalt — Sommaire — Sommario

Amtlicher Teil — Partie officielle — Parte ufficiale

Konkurse und Nachlassverträge. – Faillites et concordats. – Fallimenti e concordati.
Handelsregister. – Registre du commerce. – Registro di commercio.
Beschluss des Regierungsrates des Kantons Schaffhausen betreffend den Gesamtarbeitsvertrag für das Schreiner- und Glasergewerbe des Kantons Schaffhausen.

Mitteilungen — Communications — Comunicazioni

Statistik der Handelsregistereintragungen im Jahre 1956. – Statistique des inscriptions au registre du commerce en 1956.
BRB betreffend Verordnung über den Mindestlohn in der Papierwaren-Heimarbeit. – ACF concernant les salaires minimums pour le travail à domicile dans l'industrie des articles en papier. – DCF concernente un salario minimo per il lavoro a domicilio nell'industria degli articoli di carta.
Postverkehr mit Ungarn. – Service postal avec la Hongrie.
Briefpostsendungen nach den Vereinigten Staaten von Amerika; unzulässige Briefumschläge. – Objets de correspondance à destination des Etats-Unis d'Amérique; enveloppes non admises.
Afrique occidentale française: Taxe sur les transactions.

Amtlicher Teil — Partie officielle — Parte ufficiale

Konkurse — Faillites — Fallimenti

Konkurseröffnungen — Ouvertures de faillites

(SchKG. 231, 232; VZG. vom 23. April 1920, Art. 29, II und III, 123) — (L.P. 231, 232; O.T. fédé. du 23 avril 1920, art. 29, II et III, 123)

Die Gläubiger der Gemeinschuldner und alle Personen, die auf in Händen eines Gemeinschuldners befindliche Vermögens-

Les créanciers du failli et tous ceux qui ont des revendications à exercer sont invités à produire, dans le délai fixé pour

Kt. Zürich — *Konkursamt Zürich-Altstadt* — (179²)

Gemeinschuldnerin: Intersanitas S. A., Fabrikation, Verarbeitung, Import und Export von chemischen und pharmazeutischen Produkten, Weinbergstrasse 1, Zürich 1.
Datum der Konkurseröffnung: 11. Januar 1957.
Summarisches Verfahren gemäss Art. 231 SchKG.
Eingabefrist: bis 19. Februar 1957.

ohne Eintragung in die öffentlichen Bücher entstanden und noch nicht eingetragen sind, werden aufgefordert, diese Rechte unter Einsendung allfälliger Beweismittel in Original oder amtlich beglaubigter Abschrift binnen 20 Tagen beim Konkursamt einzugeben. Die nicht angemeldeten Dienstbarkeiten können gegenüber einem gutgläubigen Erwerber des belasteten Grundstückes nicht mehr geltend gemacht werden, sowei es sich nicht um Rechte handelt, die auch nach dem Zivilgesetzbuch ohne Eintragung in das Grundbuch dinglich wirksam sind.

Desgleichen haben die Schuldner der Gemeinschuldner sich binnen der Eingabefrist als solche anzumelden bei Straffolgen im Unterlassungsfalle.

Wer Sachen eines Gemeinschuldners als Pfandgläubiger oder aus andern Gründen besitzt, hat sie ohne Nachteil für ihr Vorzugsrecht binnen der Eingabefrist dem Konkursamt zur Verfügung zu stellen bei Straffolgen im Unterlassungsfall; im Falle ungerechtfertigter Unterlassung erlischt zudem das Vorzugsrecht.

Die Pfandgläubiger sowie Drittpersonen, deren Pfandtitel auf den Liegenschaften des Gemeinschuldners weiterverpfändet worden sind, haben die Pfandtitel und Pfandverschreibungen innerhalb der gleichen Frist dem Konkursamt einzureichen.

Den Gläubigerversammlungen können auch Mitschuldner und Bürgen des Gemeinschuldners sowie Gewährspflichtige beiwohnen.

leurs droits à l'office des faillites dans les 20 jours, en joignant à cette production les moyens de preuve qu'ils possèdent, en original ou en copie certifiée conforme. Les servitudes qui n'auront pas été annoncées ne seront plus opposables à un acquéreur de bonne foi de l'immeuble grevé, à moins qu'il ne s'agisse de droits qui, d'après le Code civil également, produisent des effets de nature réelle même en l'absence d'inscription au registre foncier.

Les débiteurs du failli sont tenus de s'annoncer sous les peines de droit dans le délai fixé pour les productions.

Ceux qui détiennent des biens du failli, en qualité de créanciers gagistes ou à quelque titre que ce soit, sont tenus de les mettre à la disposition de l'office dans le délai fixé pour les productions, tous droits réservés, faute de quoi, ils encourront les peines prévues par la loi et seront déchus de leur droit de préférence, en cas d'omission inexcusable.

Les créanciers gagistes et toutes les personnes qui détiennent des titres garantis par une hypothèque sur les immeubles du failli sont tenus de remettre leurs titres à l'office dans le même délai.

Les codébiteurs, cautions et autres garants du failli ont le droit d'assister aux assemblées de créanciers.

Kt. Zürich — *Konkursamt Zürich-Altstadt* — (179²)

Gemeinschuldnerin: Intersanitas S. A., Fabrikation, Verarbeitung, Import und Export von chemischen und pharmazeutischen Produkten, Weinbergstrasse 1, Zürich 1.
Datum der Konkurseröffnung: 11. Januar 1957.

Ct. de Berne — *Office des faillites, Delémont* — (180)

Failli: Petermann Pierre, 1919, originaire d'Aglex (Vaud), représentant à Bassecourt.
Date de l'ouverture de la faillite: 9 janvier 1957.
Liquidation sommaire art. 231 L.P.
Délai pour les productions: 19 février 1957.

Kt. Glarus — *Konkursamt des Kantons Glarus, Glarus* — (187)

Gemeinschuldnerin: Menzi Otto & Sohn (Kollektivgesellschaft), Fabrikation von Drehstrommotoren, Reparatur von elektrischen Apparaten, in Mollis.
Datum der Konkurseröffnung: 21. Januar 1957.
Erste Gläubigerversammlung: Montag, 4. Februar 1957, 15 Uhr, im Hotel «Löwen», Mollis.
Eingabefrist: bis 26. Februar 1957.

Ct. de Neuchâtel — *Office des faillites, Boudry* — (184)

Failli: Wirth René, menuisier-ébéniste, de Seeberg (Berne), précédemment à Corcelles, actuellement à Château-d'Oex.
Liquidation sommaire selon art. 231 L.P.: ordonnance du 24 janvier 1957.
Délai pour les productions: 25 février 1957 inclus.

Einstellung des Konkursverfahrens — Suspension de la liquidation

(SchKG 230.) — (L. P. 230.)

Kt. Zürich — *Konkursamt Riesbach-Zürich* — (126¹)

Ueber Messmer Richard, geb. 1928, von Küsnacht (Zürich), Bildhauer, Rietstrasse 55, Zollikon, unbeschränkt haftender Gesellschafter der Kommanditgesellschaft Richard Messmer & Co., Atelier für Grabmalkunst, Alte Landstrasse 96, Zollikon, ist am 8. Januar 1957 der Konkurs eröffnet, das Verfahren aber am 16. Januar 1957 mangels Aktiven eingestellt worden.

Falls nicht ein Gläubiger bis zum 2. Februar 1957 die Durchführung

dieser konkursamtlichen Liquidation begehrt, sich zur Bezahlung der entstehenden Kosten verpflichtet und daran gleichzeitig einen Barvorschuss von Fr. 500 leistet, gilt das Verfahren als geschlossen.

Ct. de Vaud — *Office des faillites, Orbe* — (186)

Par décision du 26 janvier 1957, le président du Tribunal du district d'Orbe a ordonné, vu le défaut d'actif, la suspension de la liquidation de la faillite de Apothéloz Marcel, confiseur, précédemment à Vallorbe, actuellement à Champrilly 26, Lausanne, faillite prononcée le 17 décembre 1956.

Si aucun créancier ne demande d'ici au 9 février 1957, la continuation des opérations en faisant une avance de Fr. 500.—, la faillite sera clôturée.

Kollokationsplan — Etat de collocation

(SchKG. 249—251) — (L.P. 249—251)

Der ursprüngliche oder abgeänderte Kollokationsplan erwächst in Rechtskraft, falls er nicht binnen zehn Tagen vor dem Konkursgericht angefochten wird.

L'état de collocation, original ou rectifié, passe en force, s'il n'est attaqué dans les dix jours par une action intentée devant le juge qui a prononcé la faillite.

Graduatoria

(L. E. F. 249—251)

La graduatoria originale o rettificata diventa definitiva se non è impugnata nel termine di dieci giorni con un'azione promossa davanti al giudice che ha pronunciato il fallimento.

Kt. Zürich — *Konkursamt Fluntern-Zürich* — (187)

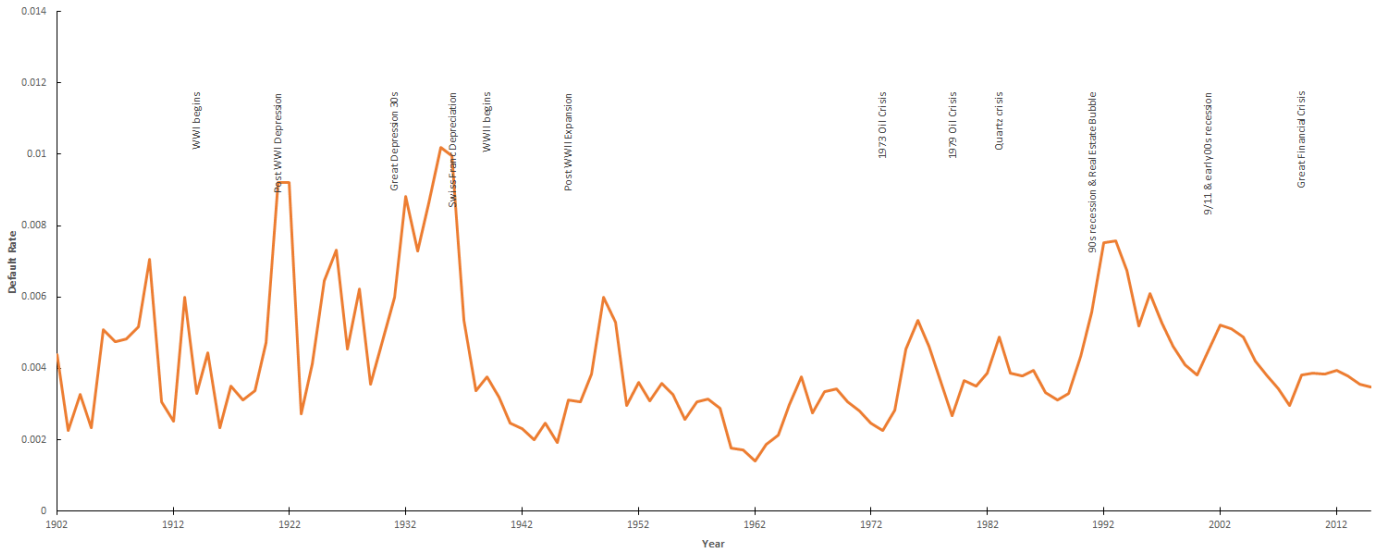
Ergänzter Kollokationsplan

Im Konkurse über die Appartementhaus Platte AG., Belleystrasse 13, in Zürich 6, liegt der infolge einer nachträglichen Forderungsanmeldung ergänzte Kollokationsplan den beteiligten Gläubigern bei der obengenannten Amtsstelle (Freiestrasse 15) zur Einsicht auf.

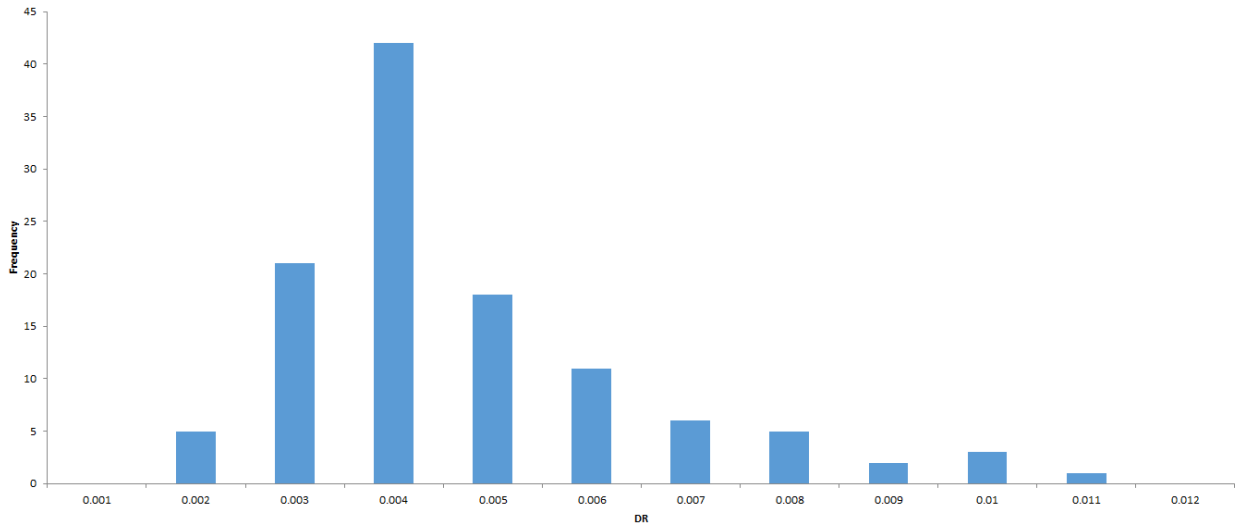
Klagen auf Anfechtung des Planes in bezug auf diese nachträglich kollozierte Forderung sind innert zehn Tagen von der Bekanntmachung im Schweizerischen Handelsamtsblatt vom 30. Januar 1957 an beim Einzelrichter im beschleunigten Verfahren am Bezirksgericht Zürich mittelst

Figure 3.2: Historical Annual Realized AG Default Rate

This figure plots the historical annual realized default rate of AG limited liability companies in Switzerland (3.2a) and its distribution (3.2b) over the full sample period 1902-2015. Annual default rates are computed as the ratio between the number of AG bankruptcy openings that are recorded in the "Bankruptcy" section of the Swiss Official Gazzette of Commerce in year t over the number of AG outstanding companies in year $t-1$ in Switzerland



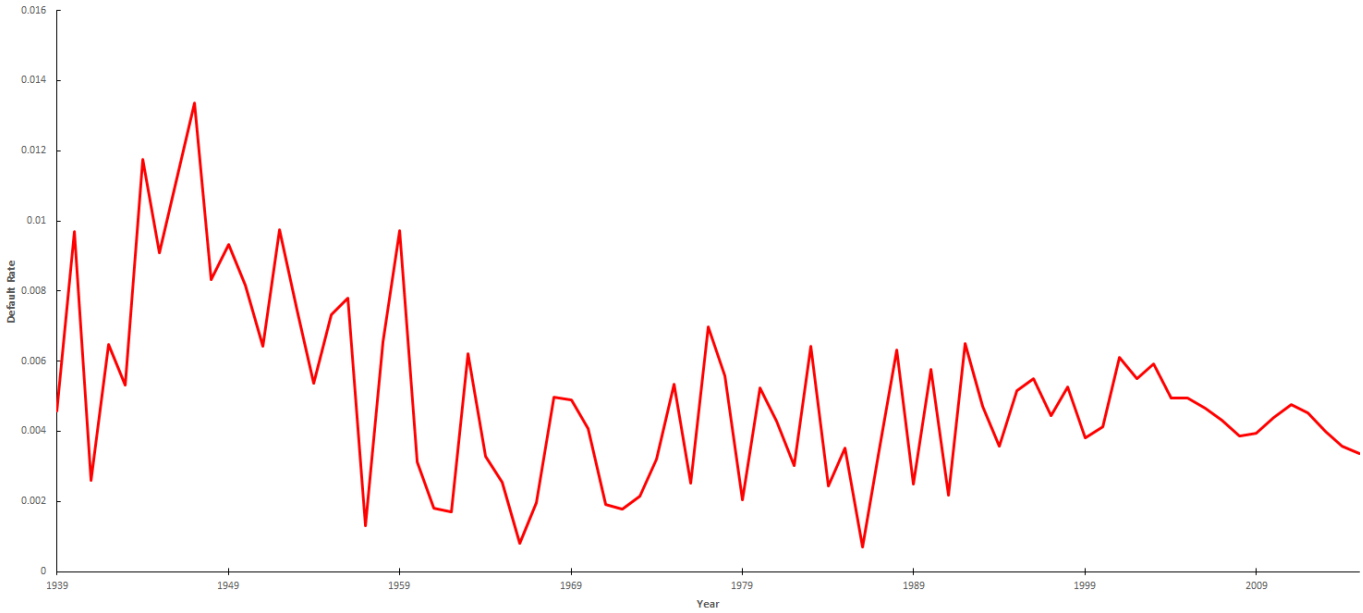
(a) Time Series



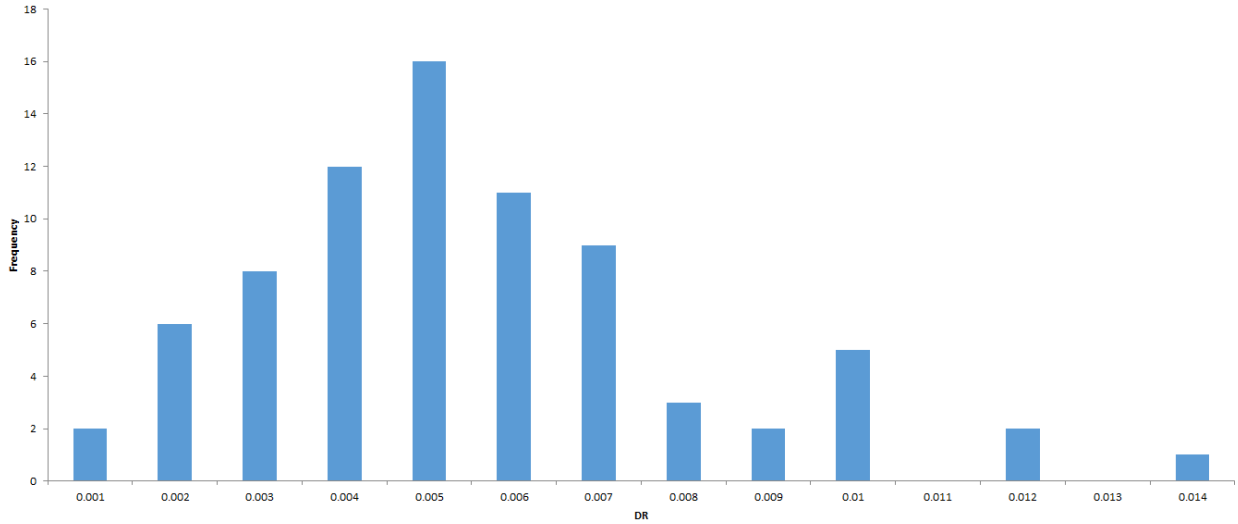
(b) Distribution

Figure 3.3: Historical Annual Realized GmbH Default Rate

This figure plots the historical annual realized default rate of GmbH limited liability companies in Switzerland (3.3a) and its distribution (3.3b) over the full sample period 1938-2015. Annual default rates are computed as the ratio between the number of GmbH bankruptcy openings that are recorded in the "Bankruptcy" section of the Swiss Official Gazzette of Commerce in year t over the number of GmbH outstanding companies in year $t-1$ in Switzerland



(a) Time Series



(b) Distribution

Figure 3.4: Swiss Macroregions Partitioning

This figure displays the partitioning of the 26 Swiss Cantons into seven Macroregions defined by the Swiss Federal Statistical Office: (1) *Lake Geneva region* (VD, VS, GE), (2) *Espace Mittelland* (BE, FR, SO, NE, JU), (3) *Northwestern Switzerland* (BS, BL, AG), (4) *Zurich* (ZH), (5) *Eastern Switzerland* (GL, SH, AR, AI, SG, GR, TG), (6) *Central Switzerland* (LU, UR, SZ, OW, NW, ZG) and (7) *Ticino* (TI) (source: Federal Statistical Office).

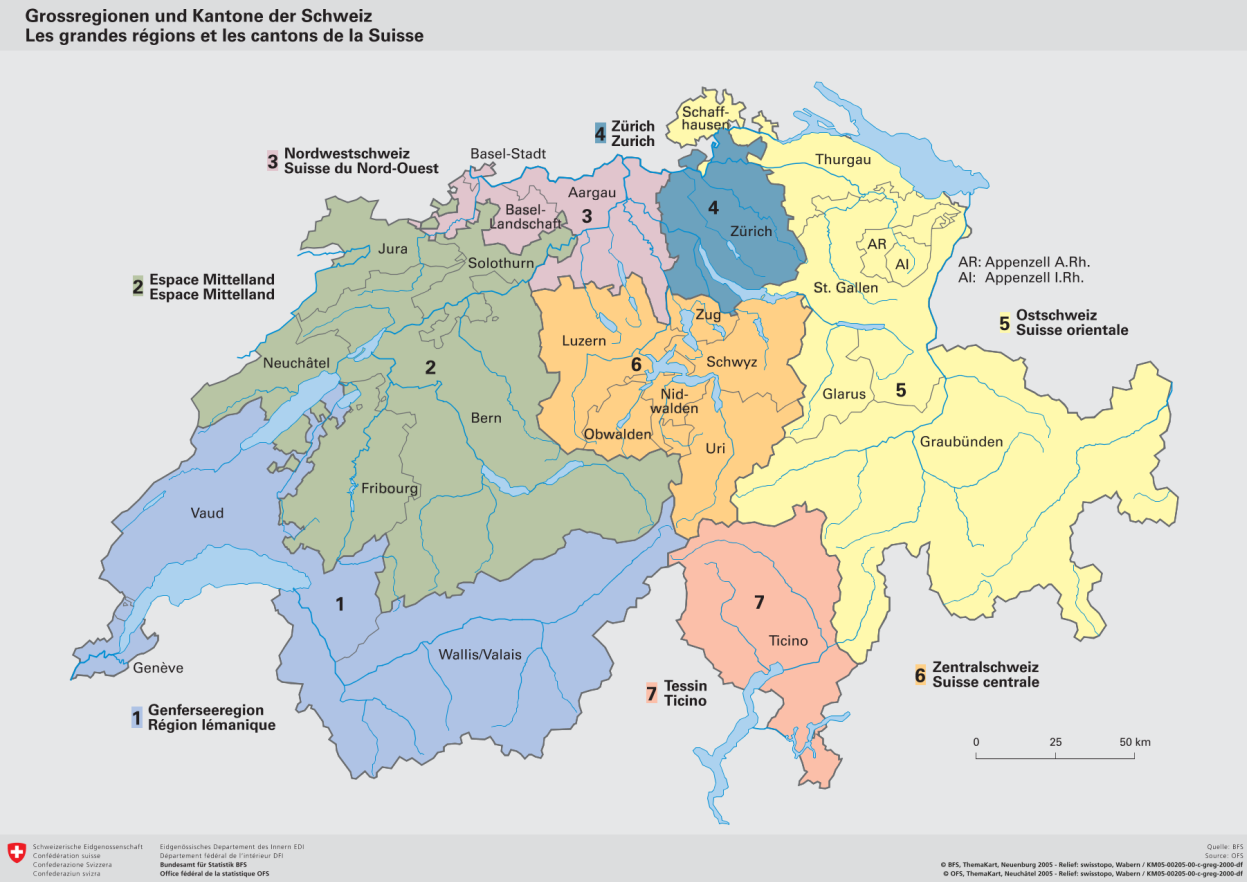


Figure 3.5: Macroregional Historical Annual Realized AG Default Rates - Time Series

This figure plots the historical annual realized default rate of AG limited liability companies in each of the seven Macroregions over the sample period 1928-2015. Annual default rates are computed as the ratio between the number of AG bankruptcy openings that are recorded in the "Bankruptcy" section of the Swiss Official Gazzette of Commerce in year t in a macroregion over the number of AG outstanding companies in year $t-1$ in that macroregion.

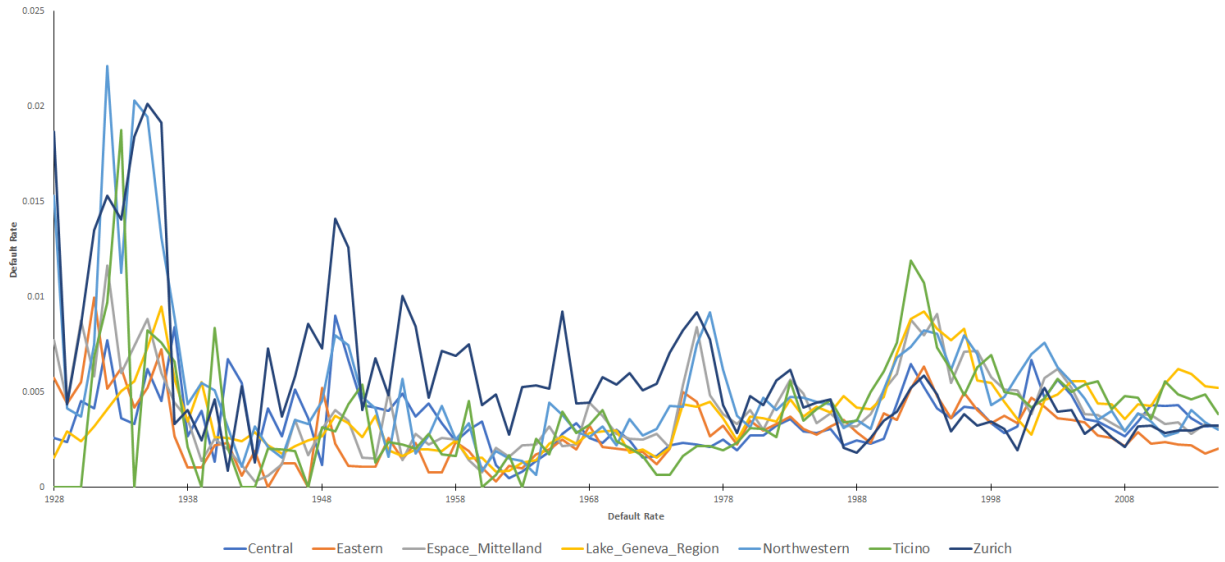


Figure 3.6: Regime Switching Model

The upper panel of this figure plots the historical annual realized default rate of AG limited liability companies in Switzerland (blue line) versus the fitted value of the two-state Regime-switching model presented in Eq. (3.2) (red line). The lower panel plots the estimated probability of being in a high-default state in every year as predicted by the model. The time span is 1902-2015.

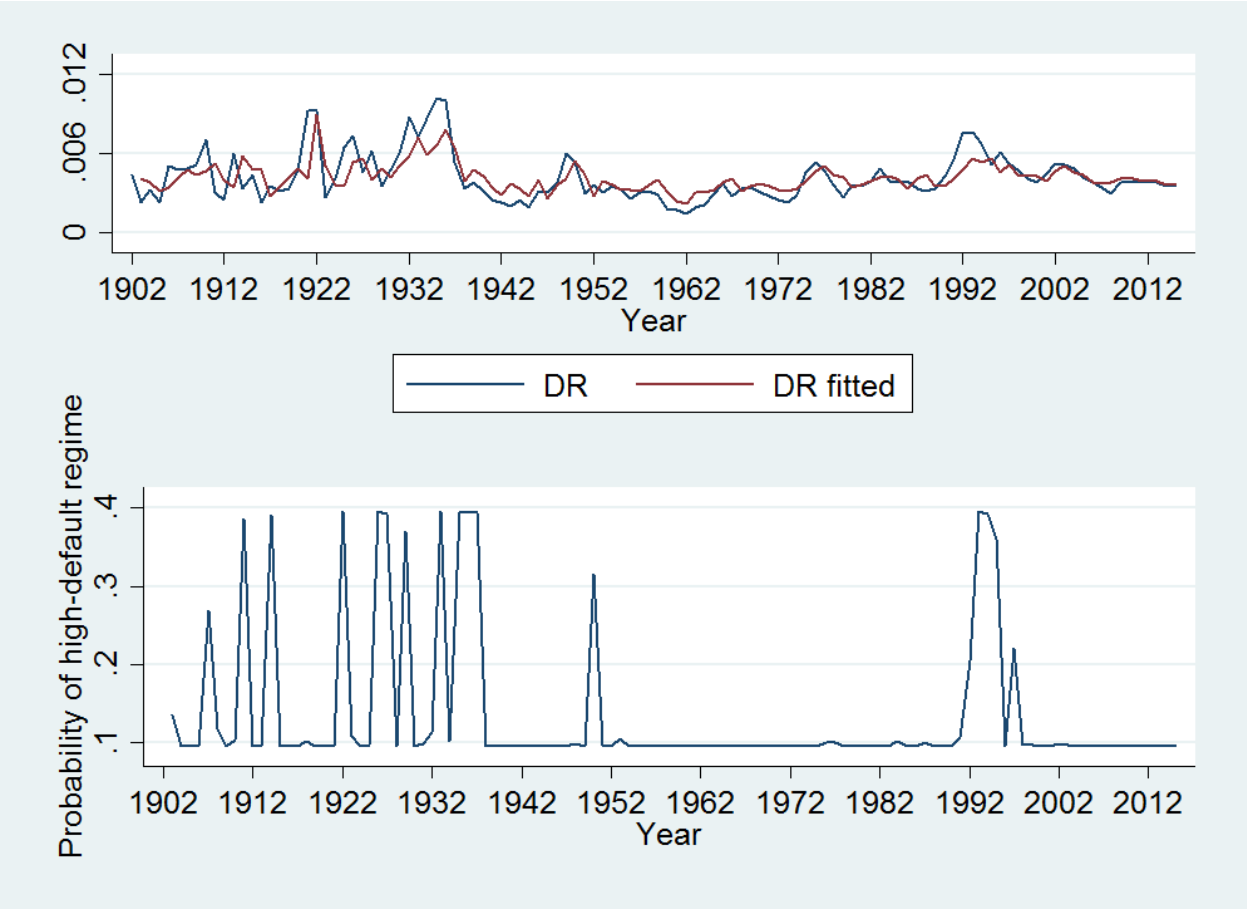


Figure 3.7: Frailty Factor Dynamics

This figure plots the evolution of the fraility factor f_t^{uc} (red line) over time estimated with the frailty-correlated defaults model by Koopman et al. (2011) together with the standard errors bands (green and blue lines). In the model we allow the β sensitivities to the frailty factor to vary across macroregions. The sample period is 1928-2015 and includes only the AG legal form ($J = 1 \times 7$).

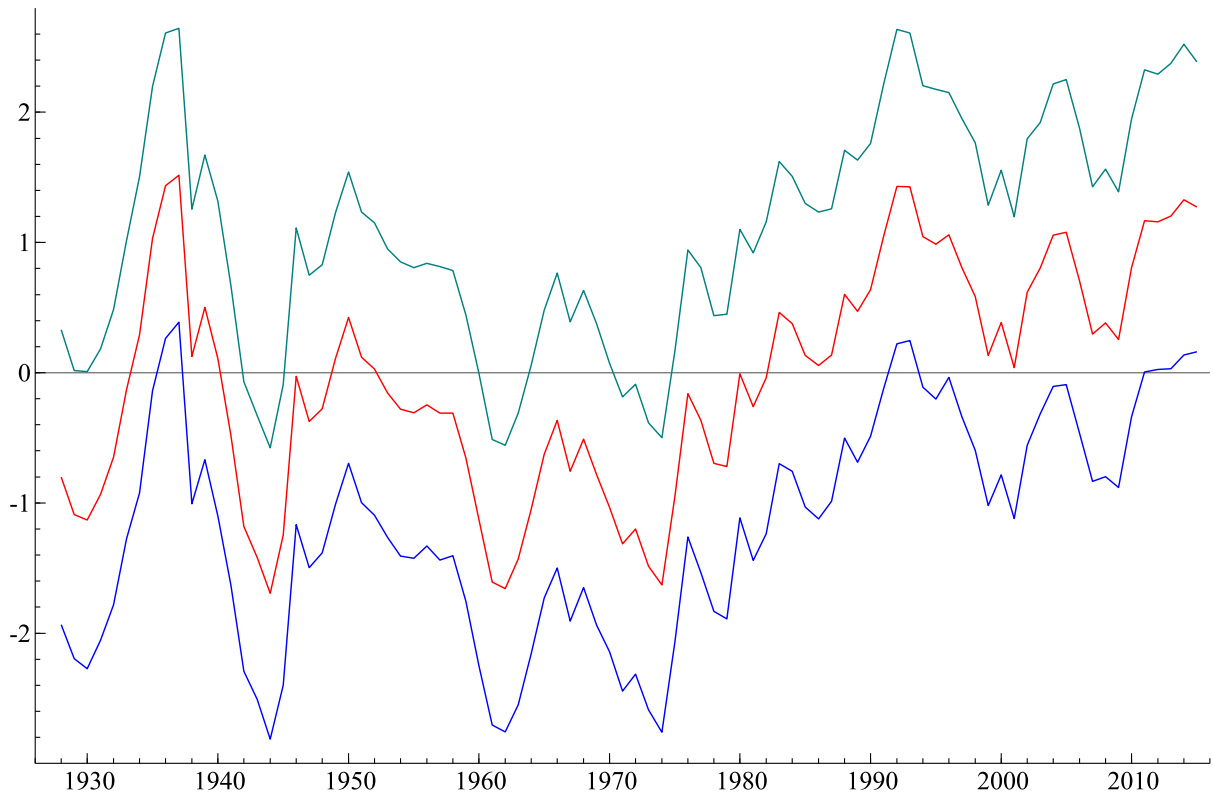


Figure 3.8: Total Number of Defaults Limited Liability Companies in Switzerland

The upper panel of this figure plots the total number of defaults in a year for all limited liability companies in Switzerland (both AG and GmbH). The middle panel shows the total number of limited liability companies in Switzerland over time. The lower panel plots the aggregate national limited liability companies default rate, which considers both AG and GmbH companies. The sample period is 1939-2015.

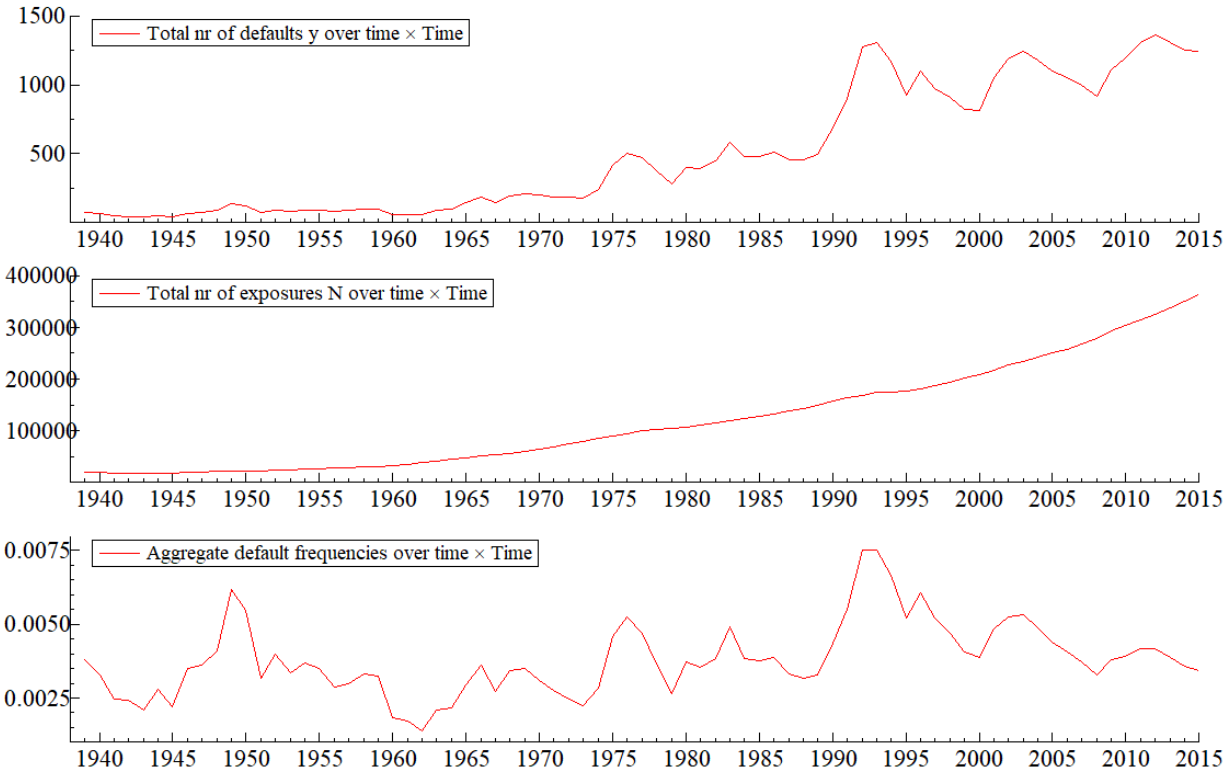


Figure 3.9: Cumulative SSE OOS - 1-year horizon

This figure plots for the 1-year out-of-sample forecasting horizon the cumulative sum of the difference between the forecasts errors from the benchmark model and the ones coming from each of the five forecasts combinations considered. As suggested by Welch and Goyal (2008), when the lines goes up the benchmark underperforms the forecast combinations, and viceversa. The time span for the out-of-sample period forecasts is 1969-2015.

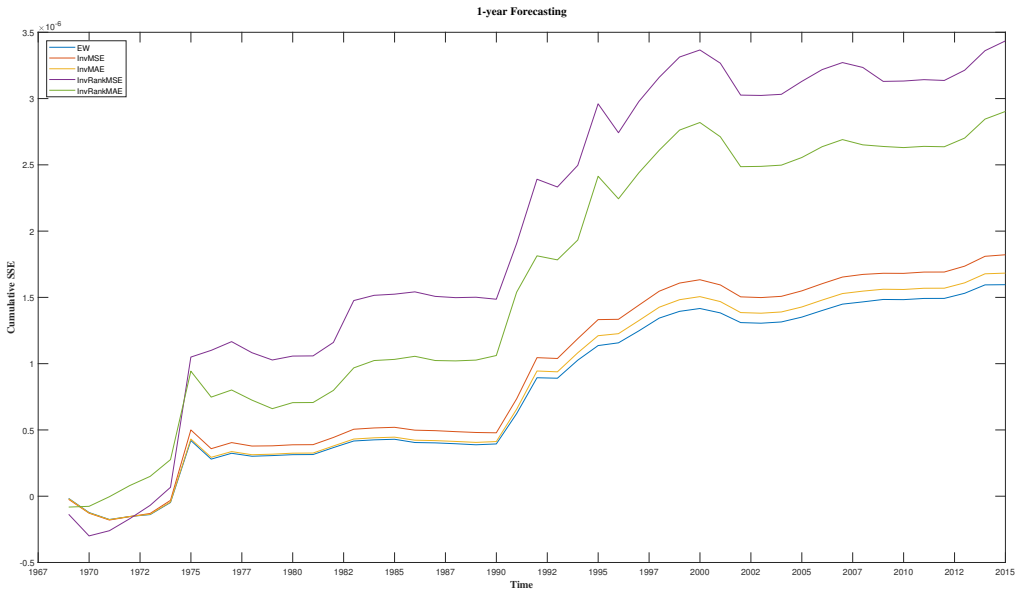


Table 3.1: Summary Statistics AG Default Rate

This table reports the summary statistics for default rates of AG limited liability companies in Switzerland disaggregated over three subperiods (1902-1945, 1946-1985, 1986-2015) and over the full sample 1902-2015. Annual default rates are computed as the ratio between the number of AG bankruptcy openings that are recorded in the Swiss Official Gazzette of Commerce in year t over the number of AG outstanding companies in year $t-1$. Reported are the average value, standard deviation, 50th percentile of the distribution, skewness, kurtosis, minimum value, maximum and the serial correlation coefficient.

	1902-1945	1946-1985	1986-2015	1902-2015
Mean	0.480%	0.331%	0.453%	0.420%
Std. Dev.	0.234%	0.100%	0.123%	0.180%
Median	0.440%	0.314%	0.411%	0.378%
Skewness	0.863	0.584	1.171	1.346
Kurtosis	-0.225	0.630	0.866	1.803
Min	0.192%	0.139%	0.295%	0.139%
Max	1.019%	0.599%	0.758%	1.019%
AR(1)	0.578	0.651	0.820	0.675

Table 3.2: Summary Statistics GmbH Default Rate

This table reports the summary statistics for default rates of GmbH limited liability companies in Switzerland disaggregated over two subperiods (1939-1970, 1971-2015) and over the full sample 1939-2015. Annual default rates are computed as the ratio between the number of GmbH bankruptcy openings that are recorded in the Swiss Official Gazzette of Commerce in year t over the number of GmbH outstanding companies in year $t-1$. Reported are the average value, standard deviation, 50th percentile of the distribution, skewness, kurtosis, minimum value, maximum value and the serial correlation coefficient.

	1939-1970	1971-2015	1939-2015
Mean	0.616%	0.421%	0.502%
Std. Dev.	0.333%	0.146%	0.259%
Median	0.633%	0.431%	0.472%
Skewness	0.213	-0.264	0.909
Kurtosis	-0.757	-0.491	0.939
Min	0.080%	0.070%	0.070%
Max	1.337%	0.698%	1.337%
AR(1)	0.449	-0.032	0.440

Table 3.3: Summary Statistics Macroregional AG Default Rates

This table reports the summary statistics for default rates of AG limited liability companies in seven Macroregions defined by the Swiss Federal Statistical Office: Lake Geneva region (LakGen: VD, VS, GE), Espace Mittelland (EspMit: BE, FR, SO, NE, JU), Northwestern Switzerland (NorSwi: BS, BL, AG), Zurich (Zurich: ZH), Eastern Switzerland (EasSwi: GL, SH, AR, AI, SG, GR, TG), Central Switzerland (CenSwi: LU, UR, SZ, OW, NW, ZG) and Ticino (Ticino: TI). The sample period for the series is 1928-2015. Annual default rates are computed as the ratio between the number of AG bankruptcy openings that are recorded in the Swiss Official Gazzette of Commerce in year t in the macroregion over the number of AG outstanding companies in year $t-1$ in the macroregion. Reported are the average value, standard deviation ,50th percentile of the distribution, skewness, kurtosis, minimum value, maximum value and the serial correlation coefficient.

	EspMit	LakGen	NorSwi	EasSwi	Ticino	CenSwi	Zurich
Mean	0.405%	0.381%	0.520%	0.299%	0.435%	0.360%	0.592%
Std. Dev.	0.220%	0.192%	0.386%	0.165%	0.284%	0.162%	0.406%
Median	0.358%	0.362%	0.421%	0.266%	0.405%	0.340%	0.468%
Skewness	0.962	1.032	2.532	1.243	2.128	0.950	1.942
Kurtosis	0.975	0.989	7.659	2.796	7.901	1.396	3.628
Min	0.030%	0.082%	0.065%	0.032%	0.064%	0.051%	0.088%
Max	1.167%	0.948%	2.212%	0.996%	1.875%	0.902%	2.016%
AR(1)	0.678	0.844	0.672	0.669	0.726	0.346	0.650

Table 3.4: Correlations Macroregional Default Rates

This table reports the correlation matrix for the macroregional default rate series. The regions are defined according to the Swiss Federal Statistical Office Classification: Lake Geneva region (LakGen: VD, VS, GE), Espace Mittelland (EspMit: BE, FR, SO, NE, JU), Northwestern Switzerland (NorSwi: BS, BL, AG), Zurich (Zurich: ZH), Eastern Switzerland (EasSwi: GL, SH, AR, AI, SG, GR, TG), Central Switzerland (CenSwi: LU, UR, SZ, OW, NW, ZG) and Ticino (Ticino: TI). The time span for the sample is 1928-2015.

	EspMit	LakGen	NorSwi	EasSwi	Ticino	CenSwi	Zurich
EspMit	1.00						
LakGen	0.60	1.00					
NorSwi	0.72	0.46	1.00				
EasSwi	0.76	0.53	0.57	1.00			
Ticino	0.51	0.62	0.40	0.53	1.00		
CenSwi	0.35	0.38	0.42	0.19	0.35	1.00	
Zurich	0.41	0.06	0.73	0.42	0.13	0.27	1.00

Table 3.5: Summary Statistics Swiss Financial and Economic Predictors

This table reports the summary statistics for the financial and economic predictors, collected from Jordà et al. (2017) and Jordà et al. (2019) over the full sample period 1902-2015. Short-term interest rate (*stir*), long-term interest rate (*ltrate*), Public-debt to GDP ratio (*debtgdp*), total loans to households over GDP ratio (*thh_gdp*) and the total loans to business over GDP ratio (*tbus_gdp*) are expressed in level form. All other variables are expressed in annual growth rates.

	Mean	Std. Dev.	Median	Skewness	Kurtosis	Min	Max
bond_tr	0.044	0.048	0.037	1.066	5.495	-0.081	0.217
capital_tr	0.078	0.058	0.077	0.337	3.460	-0.069	0.254
cpigr	0.023	0.049	0.017	0.435	10.062	-0.198	0.244
debtgdp	0.372	0.191	0.356	0.023	2.582	0.029	0.869
eq_tr	0.088	0.187	0.078	0.328	3.503	-0.340	0.614
expenditureg r	0.062	0.126	0.046	1.597	9.295	-0.236	0.628
exportsgr	0.048	0.141	0.053	-0.193	8.596	-0.521	0.596
gdpgr	0.047	0.061	0.049	-1.200	11.298	-0.295	0.225
housing_rent_rtn	0.046	0.008	0.047	0.141	2.200	0.031	0.064
housing_rent_yd	0.045	0.009	0.044	0.321	2.275	0.030	0.065
housing_tr	0.080	0.057	0.078	0.438	4.188	-0.067	0.280
hpnomgr	0.031	0.055	0.031	0.233	3.636	-0.105	0.214
importsgr	0.044	0.168	0.055	1.090	13.976	-0.614	1.028
ltrate	0.039	0.013	0.037	-0.208	3.862	0.000	0.072
moneygr	0.056	0.037	0.059	-0.451	3.510	-0.062	0.147
narrowmgr	0.062	0.109	0.053	2.122	12.800	-0.198	0.682
r_housing_tr_histbm	0.049	0.067	0.061	-0.342	3.508	-0.128	0.246
rconpcgr	0.012	0.038	0.013	1.726	14.206	-0.079	0.244
revenuegr	0.062	0.139	0.050	1.469	12.616	-0.341	0.858
rgdpmadgr	0.014	0.042	0.019	-0.092	8.609	-0.170	0.185
rgdppcgr	0.014	0.035	0.019	-0.422	4.338	-0.112	0.119
risky_tr	0.087	0.068	0.083	0.235	3.174	-0.085	0.284
safe_tr	0.036	0.024	0.033	1.299	6.711	-0.020	0.130
stir	0.027	0.019	0.021	0.864	4.453	-0.020	0.097
tbus_gdp	0.434	0.125	0.409	0.707	2.792	0.247	0.751
tbusgr	0.044	0.078	0.058	-0.502	4.501	-0.270	0.264
thh_gdp	0.739	0.222	0.661	0.456	1.777	0.390	1.210
thhgr	0.053	0.033	0.054	0.073	2.629	-0.021	0.132
tloansgr	0.050	0.040	0.050	-0.062	2.202	-0.043	0.138
xrusdgr	-0.014	0.095	0.000	-0.384	4.222	-0.265	0.275

Table 3.6: Regime-switching Model Results

This table reports the results from the two-state Regime-switching model fitted on the annual AG limited liability companies default rate defined in Eq. (3.2). The intercept of the model a_t follows a two-state Markov chain. The model includes as explanatory variables the lagged AG default rate (*DR*), equity returns (*eq_tr*), the short-term interest rate (*stir*), the growth rate in consumption per capita (*rconpcgr*), the inflation rate (*cpigr*), the real gross domestic product growth rate (*rgdpgr*), the ratio of total loans to business to GDP (*tbus_gdp*) and the growth rate of exports (*exportsgr*). The first column reports the maximum likelihood estimates of the coefficients. The second column reports the t-statistics of the parameter. The time span for the model is 1902-2015.

Parameter	Coefficient	t-statistics
a1	0.00213	4.79
a2	0.00499	8.1
DR	0.35133	4.79
eq_tr	-0.00098	-1.96
stir	-0.00028	-0.03
rconpcgr	0.00141	0.38
cpigr	-0.00514	-2.03
rgdpgr	-0.01329	-4.12
tbus_gdp	0.00108	0.88
exportsgr	0.00143	1.65
σ	0.00082	12.09

Table 3.7: Transition Probabilities and Expected Regime Duration

This table reports the transition probabilities and expected regime durations for the Regime-switching model fitted on the annual AG limited liability companies default rate defined in Eq. (3.2). Panel A reports the estimates (first column), standard errors (second column) and 95% confidence interval (third and fourth column) of the 2×2 transition probability matrix of the two-state regime-switching model. Panel B shows the expected duration in years of the low-default regime (*State 1*) and high-default regime (*State 2*). The time span for the model is 1902-2015.

Panel A: Transition Probabilities				
	Estimate	Std. Err.	[95% Conf. Interval]	
π_{11}	0.909	0.035	0.814	0.958
π_{12}	0.091	0.035	0.042	0.186
π_{21}	0.444	0.129	0.223	0.690
π_{22}	0.556	0.129	0.310	0.777
Panel B: Regime Expected Duration				
	Estimate	Std. Err.	[95% Conf. Interval]	
State 1	10.997	4.229	5.363	23.907
State 2	2.252	0.655	1.448	4.493

Table 3.8: Dynamic Frailty Factor Estimates

This table reports the maximum likelihood estimates from our adapted version of the Koopman et al. (2011) dynamic frailty factor model. Reported are the results for the (i) AG only national sample from 1902-2015 (Panel A), (ii) AG only sample across macroregions from 1928 to 2015 (Panel B) and (iii) AG and GmbH sample across macroregions from 1939 to 2015 (Panel C). For each model we use 500 importance samples for the maximum likelihood estimation and 1000 importance samples for the signal extraction. λ coefficients are the fixed effects of the log-odds ratio signal θ. β coefficients are the frailty factor sensitivities. γ coefficients are the sensitivities to the 10 principal components extracted from the Jordà et al. (2017) macrohistory database for Switzerland. In (ii) and (iii) the baseline scenario for the normalization is with respect to AG - Espace Mittelland.

	Panel A: AG 1902-2015				Panel B: AG 1928-2015						Panel C: AG & GmbH 1939-2015					
Parameter	No frailty		Single Beta		No frailty		Single Beta		Multiple Beta		No frailty		Single Beta		Multiple Beta	
	Coeff.	t-stats	Coeff.	t-stats	Coeff.	t-stats	Coeff.	t-stats	Coeff.	t-stats	Coeff.	t-stats	Coeff.	t-stats	Coeff.	t-stats
λ_0	-5.491	703.459	-5.548	87.195	-5.543	383.360	-5.567	67.255	-5.412	362.563	-5.631	419.724	-5.687	54.127	-5.636	16.301
λ_{GE}					0.048	2.455	0.049	2.508	-0.136	0.754	0.222	9.510	0.252	10.663	0.294	11.575
λ_{NW}					0.034	1.963	0.039	2.208	-0.231	0.898	0.210	8.074	0.239	9.014	0.269	8.505
λ_{ES}					0.140	6.602	0.141	6.572	-0.003	0.023	0.173	6.096	0.206	7.062	0.234	6.952
λ_{TI}					-0.296	12.738	-0.296	12.693	-0.436	3.063	0.079	4.629	0.087	5.103	-0.073	0.628
λ_{CS}					0.082	3.566	0.081	3.482	-0.274	0.925	0.166	11.346	0.169	11.680	0.002	0.017
λ_{ZH}					-0.149	6.797	-0.148	6.759	-0.382	1.887	-0.044	2.565	-0.045	2.593	-0.231	1.756
λ_{GmbH}											-0.073	6.686	-0.069	6.276	-0.112	3.206
β_0			0.268	4.877			0.287	3.389	0.000	0.346			0.296	2.239	1.000	0.521
β_{GE}									0.610	3.393					0.498	0.214
β_{NW}									0.655	3.431					0.490	0.763
β_{ES}									0.590	3.333					0.489	0.856
β_{TI}									0.587	3.320					0.418	12.146
β_{CS}									0.677	3.408					0.410	13.061
β_{ZH}									0.624	3.356					0.407	12.036
β_{GmbH}															0.476	5.331
γ_1	0.287	34.856	0.181	4.752	0.277	29.617	0.199	4.157	0.170	9.679	0.169	18.889	0.085	1.967	0.465	15.793
γ_2	-0.013	1.416	-0.028	0.721	-0.001	0.107	0.005	0.130	-0.082	5.658	-0.004	0.545	0.056	1.213	-0.022	0.794
γ_3	0.031	3.764	0.034	1.206	-0.034	4.840	-0.008	0.199	-0.164	11.774	-0.018	2.378	0.054	1.449	0.075	2.962
γ_4	0.143	15.266	0.116	3.289	0.040	4.868	0.096	2.796	0.026	1.756	-0.045	7.982	-0.047	1.342	-0.095	4.540
γ_5	-0.033	4.602	0.023	0.673	0.100	12.346	0.082	2.290	0.065	4.103	0.083	12.525	0.068	2.079	0.456	17.389
γ_6	0.071	11.033	0.079	2.547	-0.049	7.161	-0.046	1.397	-0.087	6.365	0.111	16.201	0.018	0.360	0.483	18.946
γ_7	-0.046	7.257	0.002	0.105	-0.066	9.978	-0.013	0.539	0.054	4.335	-0.021	2.913	-0.049	1.464	-0.341	12.830
γ_8	0.001	0.091	-0.019	0.758	-0.088	12.386	0.006	0.275	-0.008	0.581	-0.101	14.090	0.005	0.206	0.138	5.629
γ_9	-0.028	4.006	0.022	0.792	0.044	7.740	-0.021	0.810	0.092	8.039	0.031	6.148	-0.006	0.329	0.055	2.938
γ_{10}	-0.039	5.893	-0.025	0.913	-0.056	7.594	-0.009	0.269	0.143	10.705	-0.023	4.170	-0.026	1.053	-0.048	2.405
Log-likelihood	-1045.064		-573.795		-3434.888		-3073.835		-2719.847		-4397.686		-3984.999		-3701.824	

Table 3.9: Forecasting the Term Structure of AG Default Rates

This table reports the out-of-sample results from predicting the term structure of AG limited liability companies default rates using forecast combinations. Reported are results for the 1-year default rate (first column) the two-year average default rate (second column) and three-year average default rate (third column). The first row of each forecast horizon reports the MSFE results (left) and MAFE results (right) of the autoregressive benchmark model, as defined in Eq. (3.8). Regressions coefficients are calculated using rolling regressions with the first burn-in sample that ends in 1968, and the OOS period is 1969-2015. The other rows report percentage improvement in MSFE and MAFE respectively as defined in Eq. (3.13) from a forecast combinations of the models described in Eq. (3.9). The combinations are based on equal weights (*EW*), on weights relative to the inverse of the MSFE (*InvMSE*) or MAFE (*InvMAE*), or on weights relative to the inverse of rank MSFE (*InvRankMSE*) or MAFE (*InvRankMAE*). Boldface denotes entries that are significant at the 5% level based on the Clark and West (2007) test statistics. The time span of the sample is 1928-2015.

	1-year DR		2-years DR		3-years DR	
Model	MSE	MAE	MSE	MAE	MSE	MAE
Benchmark	5.76E-07	5.74E-04	8.90E-07	7.00E-04	1.09E-06	7.43E-04
EW	**5.89%**	**3.76%**	**4.17%**	**3.16%**	0.66%	0.48%
InvMSE	**6.73%**	**4.38%**	**5.02%**	**4.01%**	0.94%	0.78%
InvMAE	**6.22%**	**4.00%**	**4.51%**	**3.49%**	0.81%	0.66%
InvRankMSE	**12.69%**	**10.54%**	**8.11%**	**7.79%**	**5.74%**	**3.36%**
InvRankMAE	**10.72%**	**9.45%**	**7.81%**	**6.14%**	2.42%	1.92%

Table 3.10: Forecasting the Term Structure of Macroregional AG Default Rates - MSFE Results

This table reports the MSFE out-of-sample results from predicting the term structure of the seven macroregional AG limited liability companies default rates using forecast combinations. Reported are results for the 1-year default rate (Panel A) the two-year average default rate (Panel B) and three-year average default rate (Panel C). The first row of each panel reports the MSFE results of the autoregressive benchmark model, as defined in Eq. (3.8). Regressions coefficients are calculated using rolling regressions with the first burn-in sample that ends in 1968, and the OOS period is 1969-2015. The other rows report percentage improvement in MSFE as defined in Eq. (3.13) from a forecast combinations of the models described in Eq. (3.9). The combinations are based on equal weights (EW), on weights relative to the inverse of the MSFE ($InvMSE$) or MAFE ($InvMAE$), or on weights relative to the inverse of rank MSFE ($InvRankMSE$) or MAFE ($InvRankMAE$). Boldface denotes entries that are significant at the 5% level based on the Clark and West (2007) test statistics. The time span of the sample is 1928-2015.

	EspMit	LakGen	NorSwi	EasSwi	Ticino	CenSwi	Zurich
				Panel A: 1-year DR			
Benchmark	2.06E-06	1.02E-06	1.83E-06	9.29E-07	2.59E-06	9.74E-07	1.70E-06
EW Average	**4.74%**	**4.49%**	**4.52%**	**5.11%**	2.46%	2.11%	-0.07%
Inverse MSE Average	**5.19%**	**4.97%**	**4.66%**	**5.44%**	3.10%	2.56%	0.32%
Inverse MAE Average	**5.03%**	**4.65%**	**4.68%**	**5.31%**	2.71%	2.34%	0.12%
Inverse Rank MSE Average	**7.46%**	**9.71%**	**5.98%**	**5.90%**	**11.24%**	6.60%	**3.41%**
Inverse Rank MAE Average	**6.50%**	**9.68%**	**7.45%**	**8.36%**	**10.07%**	**10.49%**	**3.69%**
				Panel B: 2-years DR			
Benchmark	2.31E-06	1.46E-06	2.28E-06	1.05E-06	3.41E-06	9.94E-07	2.07E-06
EW Average	**2.62%**	3.75%	2.22%	**4.15%**	1.86%	**6.03%**	**4.11%**
Inverse MSE Average	**3.17%**	4.14%	2.15%	**4.48%**	**3.31%**	**6.91%**	**5.47%**
Inverse MAE Average	**2.90%**	3.92%	2.39%	**4.57%**	2.58%	**6.31%**	**4.73%**
Inverse Rank MSE Average	5.29%	**9.90%**	3.72%	**4.26%**	**13.69%**	**18.20%**	**14.94%**
Inverse Rank MAE Average	5.26%	**9.28%**	2.35%	**11.07%**	**15.51%**	**11.81%**	**10.23%**
				Panel C: 3-years DR			
Benchmark	2.58E-06	2.00E-06	2.55E-06	1.09E-06	3.75E-06	1.04E-06	2.27E-06
EW Average	0.97%	3.21%	-0.80%	1.74%	3.10%	**5.13%**	**8.25%**
Inverse MSE Average	1.22%	3.22%	-1.38%	1.13%	4.63%	**6.75%**	**10.40%**
Inverse MAE Average	1.05%	3.37%	-0.95%	1.75%	3.87%	**5.57%**	**9.29%**
Inverse Rank MSE Average	0.92%	2.72%	-4.00%	-4.18%	**16.10%**	**19.96%**	**21.89%**
Inverse Rank MAE Average	3.47%	**8.75%**	-7.51%	2.37%	**15.96%**	**16.84%**	**20.11%**

Table 3.11: Forecasting the Term Structure of Macroregional AG Default Rates - MAFE Results

This table reports the MAFE out-of-sample results from predicting the term structure of the seven macroregional AG limited liability companies default rates using forecast combinations. Reported are results for the 1-year default rate (Panel A) the two-year average default rate (Panel B) and three-year average default rate (Panel C). The first row of each panel reports the MSFE results of the autoregressive benchmark model, as defined in Eq. (3.8). Regressions coefficients are calculated using rolling regressions with the first burn-in sample that ends in 1968, and the OOS period is 1969-2015. The other rows report percentage improvement in MAFE as defined in Eq. (3.13) from a forecast combinations of the models described in Eq. (3.9). The combinations are based on equal weights (*EW*), on weights relative to the inverse of the MSFE (*InvMSE*) or MAFE (*InvMAE*), or on weights relative to the inverse of rank MSFE (*InvRankMSE*) or MAFE (*InvRankMAE*). The time span of the sample is 1928-2015.

	EspMit	LakGen	NorSwi	EasSwi	Ticino	CenSwi	Zurich
				Panel A: 1-year DR			
Benchmark	1.03E-03	7.48E-04	1.04E-03	7.28E-04	1.13E-03	7.16E-04	1.02E-03
EW Average	1.22%	2.06%	3.67%	1.33%	-0.15%	1.47%	1.63%
Inverse MSE Average	1.28%	2.17%	3.84%	1.29%	0.23%	1.73%	2.28%
Inverse MAE Average	1.35%	2.09%	3.74%	1.30%	0.01%	1.59%	1.95%
Inverse Rank MSE Average	-0.59%	2.48%	2.43%	-0.21%	5.55%	2.65%	5.05%
Inverse Rank MAE Average	-0.03%	3.95%	2.39%	0.86%	4.85%	3.57%	4.81%
				Panel B: 2-years DR			
Benchmark	1.09E-03	9.34E-04	1.19E-03	8.20E-04	1.24E-03	7.38E-04	1.17E-03
EW Average	1.11%	1.40%	1.13%	0.47%	-0.43%	3.31%	4.16%
Inverse MSE Average	1.33%	1.57%	1.07%	0.32%	-0.04%	3.70%	5.56%
Inverse MAE Average	1.30%	1.49%	1.36%	0.57%	-0.20%	3.41%	4.85%
Inverse Rank MSE Average	2.02%	4.76%	1.74%	-0.91%	3.24%	8.60%	12.61%
Inverse Rank MAE Average	2.28%	4.76%	2.41%	2.97%	4.65%	6.09%	12.05%
				Panel C: 3-years DR			
Benchmark	1.20E-03	1.12E-03	1.30E-03	8.73E-04	1.29E-03	7.69E-04	1.27E-03
EW Average	0.44%	1.07%	-0.77%	-0.90%	0.34%	3.04%	5.35%
Inverse MSE Average	0.69%	0.89%	-1.11%	-1.75%	1.18%	3.77%	7.43%
Inverse MAE Average	0.65%	1.08%	-0.69%	-1.08%	0.78%	3.12%	6.34%
Inverse Rank MSE Average	0.46%	0.21%	-1.21%	-6.78%	5.22%	10.13%	16.17%
Inverse Rank MAE Average	2.58%	3.34%	-0.30%	-3.57%	4.15%	7.46%	14.95%

Appendix 3.A Additional Tables and Figures

Table 3A.1: Variables Mnemonics

This table reports the description of the 30 macroeconomic and financial predictors available at the annual frequency used in our study. Reported are the acronym of the variable (first column), a brief description of the predictor (second column), the source of the data (third column), the start date of the available series (fourth column) and the frequency (fifth column).

Code	Description	Source	Start Series	Frequency
		Panel A: Yearly Predictors		
rgdpmad	Real GDP per capita (PPP)	Jordà-Schularick-Taylor Macrohistory Database	1870	Y
rgdppc	Real GDP per capita (index)	Jordà-Schularick-Taylor Macrohistory Database	1870	Y
rconpc	Real Consumption per capita (index)	Jordà-Schularick-Taylor Macrohistory Database	1870	Y
gdp	GDP (nominal, local currency)	Jordà-Schularick-Taylor Macrohistory Database	1870	Y
cpi	Consumer prices (index)	Jordà-Schularick-Taylor Macrohistory Database	1870	Y
imports	Imports (nominal, local currency)	Jordà-Schularick-Taylor Macrohistory Database	1885	Y
exports	Exports (nominal, local currency)	Jordà-Schularick-Taylor Macrohistory Database	1885	Y
narrowm	Narrow money (nominal, local currency)	Jordà-Schularick-Taylor Macrohistory Database	1870	Y
money	Broad money (nominal, local currency)	Jordà-Schularick-Taylor Macrohistory Database	1880	Y
stir	Short-term interest rate (nominal, percent per year)	Jordà-Schularick-Taylor Macrohistory Database	1870	Y
ltrate	Long-term interest rate (nominal, percent per year)	Jordà-Schularick-Taylor Macrohistory Database	1880	Y
debtgdp	Public debt-to-GDP ratio	Jordà-Schularick-Taylor Macrohistory Database	1880	Y
revenue	Government revenues (nominal, local currency)	Jordà-Schularick-Taylor Macrohistory Database	1870	Y
expenditure	Government expenditure (nominal, local currency)	Jordà-Schularick-Taylor Macrohistory Database	1871	Y
xrusd	USD Exchange rate (CHF/USD)	Jordà-Schularick-Taylor Macrohistory Database	1870	Y
tloans	Total loans to non-financial private sector (nominal, local currency)	Jordà-Schularick-Taylor Macrohistory Database	1870	Y
thh	Total loans to households (nominal, local currency)	Jordà-Schularick-Taylor Macrohistory Database	1870	Y
tbus	Total loans to business (nominal, local currency)	Jordà-Schularick-Taylor Macrohistory Database	1870	Y
thh_gdp	Total loans to households (nominal, local currency) over nominal GDP	Jordà-Schularick-Taylor Macrohistory Database	1870	Y
tbus_gdp	Total loans to business (nominal, local currency) over nominal GDP	Jordà-Schularick-Taylor Macrohistory Database	1870	Y
hpnom	House prices (nominal index)	Jordà-Schularick-Taylor Macrohistory Database	1901	Y
eq_tr	Equity total return, nominal	Jordà-Schularick-Taylor Macrohistory Database	1900	Y
housing_tr	Housing total return, nominal	Jordà-Schularick-Taylor Macrohistory Database	1902	Y
bond_tr	Government bond total return, nominal	Jordà-Schularick-Taylor Macrohistory Database	1900	Y
housing_rent_rtn	Housing rental return	Jordà-Schularick-Taylor Macrohistory Database	1902	Y
housing_rent_yd	Housing rental yield	Jordà-Schularick-Taylor Macrohistory Database	1901	Y
capital_tr	Total return on wealth, nominal	Jordà-Schularick-Taylor Macrohistory Database	1902	Y
risky_tr	Total return on risky assets, nominal	Jordà-Schularick-Taylor Macrohistory Database	1902	Y
safe_tr	Total return on safe assets, nominal	Jordà-Schularick-Taylor Macrohistory Database	1900	Y
r_housing_tr_histbm	Real housing return, yields match all available bencharks pre 1980	Jordà et al. (2015)	1902	Y

Table 3A.2: Forecasting AG Default Rates - OOS Performance Individual Models

This table reports the out-of-sample results for the individual forecasts of the AG limited liability companies default rates as defined in Eq. (3.9). Reported are results for the 1-year default rate (first column) the two-year average default rate (second column) and three-year average default rate (third column). The first row of each panel reports the MSFE (left) and MAFE (right) results of the autoregressive benchmark model, as defined in Eq. (3.8). Regressions coefficients are calculated using rolling regressions with the first burn-in sample that ends in 1968, and the OOS period is 1969-2015. The other rows report percentage improvement in MSFE (left) and MAFE (right) as defined in Eq. (3.13). Boldface denotes entries that are significant at the 5% level based on the Clark and West (2007) test statistics. The time span of the sample is 1928-2015.

	1-year DR		2-years DR		3-years DR	
Model	MSE	MAE	MSE	MAE	MSE	MAE
Benchmark	5.76E-07	5.74E-04	8.90E-07	7.00E-04	1.09E-06	7.43E-04
stir	5.92E-07	5.59E-04	1.03E-06	7.24E-04	1.44E-06	8.36E-04
ltrate	5.83E-07	5.97E-04	9.66E-07	7.73E-04	1.27E-06	8.70E-04
debtgdp	5.94E-07	5.69E-04	9.63E-07	7.21E-04	1.33E-06	8.84E-04
eq_tr	6.23E-07	5.94E-04	8.56E-07	6.94E-04	1.05E-06	7.63E-04
housing_tr	6.20E-07	6.06E-04	9.52E-07	7.23E-04	1.15E-06	7.49E-04
bond_tr	6.94E-07	5.88E-04	1.10E-06	7.73E-04	1.27E-06	8.61E-04
housing_rent_rtn	6.61E-07	6.26E-04	1.10E-06	7.94E-04	1.42E-06	8.42E-04
housing_rent_yd	6.50E-07	6.12E-04	1.09E-06	7.85E-04	1.42E-06	8.47E-04
capital_tr	5.94E-07	5.86E-04	8.83E-07	7.09E-04	1.11E-06	7.63E-04
risky_tr	5.72E-07	5.73E-04	8.56E-07	6.95E-04	1.09E-06	7.56E-04
safe_tr	6.20E-07	5.57E-04	1.07E-06	7.31E-04	1.32E-06	8.40E-04
r_housing_tr_histbm	6.16E-07	6.18E-04	9.65E-07	7.26E-04	1.16E-06	7.45E-04
rgdpmadgr	5.34E-07	5.53E-04	8.85E-07	6.85E-04	1.13E-06	7.47E-04
rgdppcgr	5.62E-07	5.78E-04	9.31E-07	7.11E-04	1.18E-06	7.71E-04
rconpcgr	5.82E-07	6.00E-04	9.11E-07	7.34E-04	1.13E-06	7.79E-04
gdpgr	5.73E-07	5.87E-04	9.44E-07	6.94E-04	1.19E-06	7.33E-04
cpigr	5.06E-07	5.20E-04	8.03E-07	6.43E-04	1.02E-06	7.00E-04
importsgr	5.69E-07	5.78E-04	8.97E-07	7.01E-04	1.10E-06	7.52E-04
exportsgr	5.90E-07	5.88E-04	9.11E-07	7.00E-04	1.11E-06	7.57E-04
narrowmgr	5.79E-07	5.77E-04	8.58E-07	6.93E-04	1.09E-06	7.80E-04
moneygr	6.06E-07	5.77E-04	9.01E-07	6.84E-04	1.14E-06	7.91E-04
revenuegr	5.91E-07	5.90E-04	8.92E-07	6.97E-04	1.10E-06	7.45E-04
expenditurregr	5.90E-07	5.73E-04	8.82E-07	6.83E-04	1.06E-06	7.21E-04
xrusdgr	5.83E-07	5.86E-04	8.71E-07	7.03E-04	1.07E-06	7.72E-04
tloansgr	5.96E-07	5.93E-04	9.41E-07	7.21E-04	1.19E-06	7.85E-04
thhgr	5.72E-07	5.69E-04	9.50E-07	6.92E-04	1.27E-06	7.58E-04
tbusgr	5.87E-07	5.80E-04	9.79E-07	7.28E-04	1.32E-06	8.11E-04
hpnomgr	6.11E-07	5.97E-04	9.42E-07	7.19E-04	1.15E-06	7.58E-04
thh_gdp	5.77E-07	6.23E-04	9.60E-07	8.00E-04	1.26E-06	9.11E-04
tbus_gdp	6.44E-07	6.27E-04	1.06E-06	7.81E-04	1.32E-06	8.16E-04

Figure 3A.1: Cumulative SSE OOS - 2-year horizon

This figure plots for the average 2-year out-of-sample forecasting horizon the cumulative sum of the difference between the forecasts errors from the benchmark model and the ones coming from each of the five forecasts combinations considered. As suggested by Welch and Goyal (2008), when the lines goes up the benchmark underperforms the forecast combinations, and viceversa. The time span for the out-of-sample period forecasts is 1969-2015.

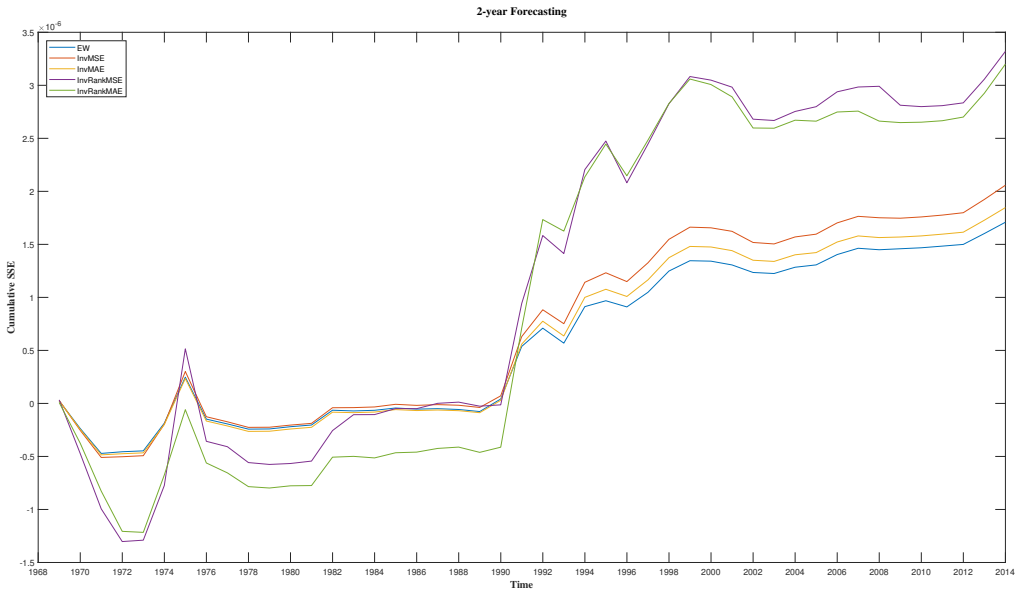
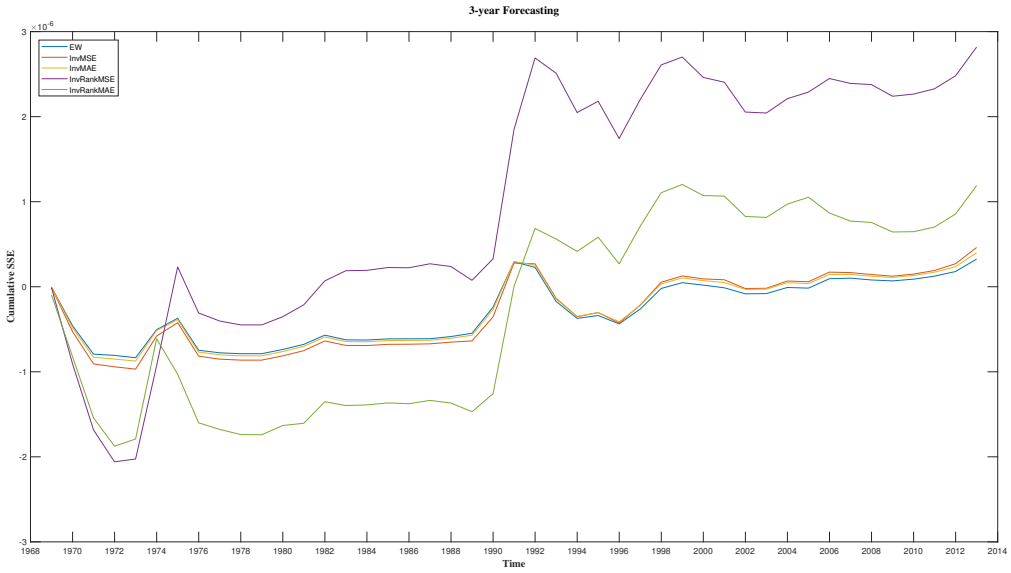


Figure 3A.2: Cumulative SSE OOS - 3-year horizon

This figure plots for the average 3-year out-of-sample forecasting horizon the cumulative sum of the difference between the forecasts errors from the benchmark model and the ones coming from each of the five forecasts combinations considered. As suggested by Welch and Goyal (2008), when the lines goes up the benchmark underperforms the forecast combinations, and viceversa. The time span for the out-of-sample period forecasts is 1969-2015.



Chapter 4

Downside Risk and International Diversification: The Role of Country and Industry Effects

4.1 Introduction

A long-standing debate in international finance revolves around the relative importance of country versus industry diversification in reducing the risk of globally-invested portfolios (Lessard, 1974). Understanding which of the two dimensions plays a greater role requires disentangling geographic and industry factors and studying their covariation properties with international stock returns. A clean separation of these components is, however, not a straightforward task, as countries tend to concentrate in industries where they possess a comparative advantage. As a result, the national stock market mirrors a country's industrial specialization (Roll, 1992). The Heston and Rouwenhorst (1994)'s approach to overcome this issue consists of estimating cross-sectional dummy regressions on stock-level data to separately identify pure country and industry effects. Working on European data over 1978–1992, they conclude that cross-country diversification (within the same industry) provides a larger

reduction in variance compared to cross-industry diversification (within the same country), due to the low correlation in countries pure effects.

In this paper, we re-examine the role of country and industry factors in driving international diversification. Our contribution is threefold. First, we expand the discussion in Heston and Rouwenhorst (1994) and subsequent works, which has mainly focused on variance reduction, by looking at the impact of portfolio formation on higher moments. Our analysis is inspired by recent research showing that pooling individual stocks amplifies downside risk, as measured by (more negative) return skewness (Albuquerque, 2012; Bessembinder, 2018). This finding implies that, when allocating assets into portfolios, investors might give up some variance reduction benefits in exchange of exposure to positive skewness, which would explain their tendency to hold undiversified positions (Mitton and Vorkink, 2007; Goetzmann and Kumar, 2008). Whether this argument works against country or industry diversification depends on their impact on aggregate skewness and is ultimately an empirical question.

Second, we revisit the conclusions of Heston and Rouwenhorst (1994) using equity data spanning the last three decades. Several authors have documented an increase in global market integration over the years (Bekaert et al., 2009; Pukthuanthong and Roll, 2009; Eiling et al., 2012). Moreover, the Global Financial Crisis stands out as a major realization of downside risk, which potentially triggered a repricing of tail risk causing long-lasting consequences on international diversification. Therefore, a natural question that arises is whether differences in variance reduction between within-country and within-industry diversification have changed throughout the sample and, if so, in what direction.

Third, we move away from a "static" perspective by considering a "dynamic" extension that considers the role of *conditional* skewness in driving the portfolio composition of international investors. Using the time-varying asymmetry measure proposed by Ghysels et al. (2016b), we ask whether predictable time variation in the upside and downside risk of country versus industry indices alters an investor's optimal allocation and delivers economic gains.

To study international portfolio diversification benefits, we work on a comprehensive

sample of equities spanning 1990–2020 across 19 developed countries and 18 global industries. The final dataset consists of more than 33'000 stocks and their country and industry indices from Thomson Reuters Datastream. As a first step in our analysis, we apply the Heston and Rouwenhorst (1994) framework to our data. We confirm the evidence in their work that pure country and industry effects are the driving force of variability in each group of indices. However, a few important differences emerge. Notably, the variances of pure (country and industry) effects has significantly declined, compared to their sample, possibly due to the surge in global financial and economic integration. Moreover, the importance of pure country effects in driving the variance of country indices is now at par with that of pure industry effects in explaining the variance of industry indices. This result contrasts with the finding in Heston and Rouwenhorst (1994) that pure country effects play the dominant role. When splitting the sample in the pre- and post-crisis periods, we find that in the latter the relative importance of the industry structure in explaining country indices variance has increased by large, while at the same time the importance of country effects in driving the variance of industry indices has decreased.

We extend the evidence on second moments by looking at the decomposition for skewness. To that end, we adopt the robust co-skewness matrix estimation approach of Boudt et al. (2020) to model all skewness and co-skewness elements associated with the country and industry factors. In line with the variance results, we find that pure country and industry effects play the lion's share in explaining total skewness. Moreover, their relative importance is of comparable magnitude.

The change over time in the relative contribution of pure country and industry effects spurs us to examine their effect on portfolio risk. For variance, can directly compare the variance of a large diversified portfolio with that of the average individual stock. We find that the difference in variance reduction between diversifying across countries and across industries is negligible. In other words, pooling stocks in either dimension leads to a decrease in second moment that is of the same magnitude. This fact is consistent with increasing

global market integration over the last decades, which eroded most of the international diversification benefits in terms of variance risk (Eiling et al., 2012).

The effects on skewness of portfolio aggregation are, by contrast, more difficult to quantify, as they involve cross and quadratic terms. In other words, it is not obvious how portfolio skewness changes as we increase the number of stocks in the portfolio N. To overcome this issue, we rely on a stratified bootstrap procedure. In particular, for each year from 1990 to 2020, we randomly construct country (industry) portfolios that are "forced" to achieve the maximum diversification across all industries (countries) that are available to an investor to pick from at the begin of each year. We construct these portfolios for an increasing number of stocks N. Each resulting portfolio corresponds to the possible outcome of a strategy that holds N stocks that are as diversified as possible across countries (industries), subject to annual rebalancing. We run the re-sampling scheme for each country and industry, and compute the average (across simulations) of the first three moments, the certainty equivalent for a CRRA power utility investor, and a modified-VaR measure taking into account the impact of higher moments.

The bootstrap highlights that, over the full sample, the unconditional variance of large ($N = 40$) international portfolios that diversify across countries (in the same industry) is at par with that of portfolios that invest across industries (in the same country), consistently with the evidence above. On the other hand, the skewness of portfolios that load on industry is more positive than that of portfolios invested across countries. Overall, investors who cannot achieve full global diversification would favour the former, in contrast with the conclusions by Heston and Rouwenhorst (1994).

To delve into this result, we carry the bootstrap on rolling samples of 10 years each. This exercise reveals that the Global Financial Crisis is associated with a major re-shaping of the sources of international asset allocation benefits. Around that period, the return variance turned larger for portfolios diversified within-industry than within-country. The opposite holds for skewness, with the latter portfolios delivering more positive skewed returns. As

a result, starting in 2009 portfolios that pool stocks across industries of the same country consistently delivered, on average, a higher certainty equivalent and a lower modified-VaR compared to cross-country allocation.

In the last part of the paper, we adopt a dynamic-allocation perspective and investigate whether our conclusions continue to hold when taking conditional (i.e., time-varying) return asymmetries into account. To this end, we rely on the robust conditional skewness estimator developed by Ghysels et al. (2016b), which efficiently takes advantage of high-frequency (daily) information data to compute return asymmetry from conditional quantiles estimates. We extend the cross-country evidence in their work by computing the conditional skewness of our country and industry indices, and ask whether investors tend to tilt their allocation toward either group of indices when incorporating time-variation in skewness in their investment decisions. We accomplish this goal by casting the resulting estimates in the Brandt et al. (2009) dynamic portfolio approach modelling portfolio weights as a parametric function of indices characteristics, such as Momentum and Dividend Yield, and look at the effect of adding skewness to the set of predictors.

We find that incorporating time-varying skewness in international asset allocation decisions leads to an over-weighting of country indices in the optimal portfolio at the expenses of industry indices. The tilt is economically large, as it increases the average fraction of wealth invested in country indices from 51% to 66%, and is associated with certainty equivalent gains of about 1.5% per year compared to the benchmark model that excludes skewness. This result is due to the fact that, throughout the sample, country indices are generally more positively skewed than country indices. The optimal weight assigned to countries for their skewness contribution varies over time, but is consistently positive. This finding is robust to various relative risk aversion coefficient, and to reasonable transaction costs estimates. We thus confirm that the argument from the unconditional framework extend to, and is even more pronounced in economic terms, a conditional setting.

Our paper contributes to several strands of literature. Griffin and Karolyi (1998) expand

the set of countries and industries in Heston and Rouwenhorst (1994) reaching similar conclusions. Other works in this area include Brooks and Del Negro (2004), Ehling and Ramos (2006), Campa and Fernandes (2006), and Bekaert et al. (2009). The view that cross-country (as opposed to cross-industry) diversification is mostly beneficial for risk reduction has been, however, challenged by other authors; see, among others, Cavaglia et al. (2000), Ferreira and Ferreira (2006), and Moerman (2008). For the Eurozone, Eiling et al. (2012) find that industry effects prevail after 1999 as a result of the progressive increase in European integration. We add to these studies by evaluating the influence of industrial structure and country effects on higher-moments in the portfolio return distribution. To our knowledge, our paper is the first to look beyond variance in the country-industry diversification debate working on a comprehensive international dataset. You and Daigler (2010) considers the impact of skewness on the international diversification benefits, but their contribution is limited to the *across-countries* dimension only. In a similar vein, Chollete et al. (2011) find different degrees of downside risk between G5 and Latin and Asian countries.

A second stream of research looks at the impact of higher-order moments on the cross-section of expected returns, prompted by the three-moment CAPM model of Kraus and Litzenberger (1976) and its extensions by Harvey and Siddique (2000) and Smith (2007). In their framework, investors have a preference for positive skewness and assets that make portfolio returns left-skewed should command higher expected returns. Besides co-skewness, a growing literature has explored the impact of individual-stock skewness on prices spurred by empirical evidence that retail and institutional investors are often not fully diversified (Goetzmann and Kumar, 2008). Theoretical models that provide a foundation for preferences for individual skewness include Mitton and Vorkink (2007), Barberis and Huang (2008), and Dahlquist et al. (2017). Consistently with the predictions of these theoretical models, a number of empirical contributions document a negative correlation between idiosyncratic skewness and expected returns.[1] We add to this discussion by examining how taking skewness

[1] A partial list includes: Bali et al. (2011), who proxy skewness with the maximum daily return over the past one month; Conrad et al. (2013), who extrapolate ex-ante higher order moments of the risk neutral distribution from option prices; and Xing et al.

into account affect the mix between country versus industry allocation.

Finally, an emerging literature investigates how skewness aggregates in the cross-section of stock returns. A notable contribution in this direction is Albuquerque (2012), who provides a theoretical model that reconciles the negative skewness in aggregate stock returns with the positive skewness in firm-level returns by relating aggregate skewness to the cross-sectional heterogeneity in the timing of earnings announcement events. We contribute to this literature by studying how the effects of aggregation impact the decision to diversify internationally.

The remainder of the paper is structured as follows. In section 4.2, we thoroughly describe the international dataset we use. Section 4.3 summarizes the country versus industry decomposition and our application to skewness. Section 4.3.3 describes the bootstrapping simulation approach and discusses the empirical results. Section 4.4 presents a portfolio allocation problem that exploits time-variation in skewness. Section 4.5 concludes.

4.2 Data

Our dataset consists of the following 19 developed countries: Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, the Netherlands, Norway, Singapore, South Korea, Spain, Sweden, Switzerland, the United Kingdom, and the United States. Unlike Griffin et al. (2010), we avoid including emerging countries in the sample and restrict our attention to diversification benefits between developed markets only. For each country, we gather from Thomson Reuters Datastream the comprehensive constituent lists of all equities traded in the country. We make sure the lists contain both active and delisted (dead) stocks to avoid that results being driven by survivorship bias.

For each stock, we collect local-currency denominated and U.S.-dollar denominated return indices (RI), market capitalization (MV), price to book ratios (PTBV), and share prices (P). The time span of the sample is from January, 1990 to December, 2020 and the frequency of

(2010), who use the shape of stocks' volatility smirks. A negative impact on prices by firm-specific skewness is also highlighted by Brunnermeier et al. (2007), Zhang (2006) and Lin and Liu (2018).

the data is monthly. As highlighted in Griffin and Karolyi (1998), given the international nature of our dataset, working with higher frequency data such as daily would introduce a bias due to the asynchronous trading hours across different countries and continents, making it difficult to analyse return comovements. We perform an extensive pre-processing of the dataset, following other studies that use Thomson Reuters Datastream. All details are collected in Appendix 4.A.

To keep a balanced sample between countries and industries, we classify industries according to the "ICB/Sector Datastream Level 4" definition, which assigns firms to one of the following 19 distinct industries: Automobiles and Parts, Banks, Basic Resources, Chemicals, Construction and Materials, Financial Services, Food and Beverage, Healthcare, Personal and, Household goods, Industrial Goods and Services, Insurance, Media, Oil and Gas, Real Estate, Retail, Technology, Telecommunications, Travel and Leisure and Utilities. Due to limited data availability, we decided to incorporate Real Estate with Financials, leading to 18 industries in total. Other studies such as Griffin and Karolyi (1998) and Brooks and Del Negro (2004) use more granular industry classifications in order to avoid excessive diversifed industry portfolios that might dampen the industry effects. We avoid this for three reasons. First, our sample mainly consist of large developed markets and the coverage of our sample within a country is on average larger than theirs. Second, we want to keep a reasonably balanced number of countries and industries (19 vs. 18). Aggregating the data at smaller levels (e.g. ICB/Sector Datastream Level 5) would possibly distort our inference. Finally, when constructing portfolios in our bootstrap procedure outlined above we consider up to 40 stocks. A more granular industry classification would make it impossible to build such portfolios for some industries, especially in the earlier years of the sample when we have limited cross-sectional coverage.

Table 4.1 presents the total number of stocks divided by countries and industries after the cleaning procedure. Our final working sample contains 33'311 individual stocks distributed

across 19 countries and 18 industries over a 31-year sample period.[2] The largest and smallest country subsamples correspond to the United States (9'378 stocks) and Austria (150 stocks). Moreover, three countries – United States, Japan and Canada – account for slightly about 54% of the total number of stocks. In addition, the industrial composition of countries is far from being uniformly distributed, as the number of stocks in a given industry differs considerably. For example, Australia and Canada are heavily oriented towards the Basic Resources industry, which accounts for about half of the total number of stocks within the two countries. Turning to industries, at the two extreme industry subsamples we find Industrial Goods and Services (5'703 stocks) and Telecommunications (394 stocks). Compared to countries, the three largest industries only account for about 39% of the stocks in the sample.

Table 4.2 presents summary statistics for the final sample disaggregated by country (Panel A) and industry (Panel B). Reported are mean, standard deviation and skewness for value-weighted (VW) monthly indices manually constructed from the universe of individual stocks within each country/industry subsample. Table 4A.1 in the Appendix is constructed similarly for equally-weighted (EW) indices. Returns are monthly and measured in U.S. Dollars. The two last rows present a simple average and a market-cap based (computed as the average in-sample market capitalization of a country or industry) average across countries (Panel A) or industries (Panel B) of the first three moments. Regarding countries, Austria and Italy are the worst indices in terms of average performance, with an average VW (EW) monthly return that is about half (one quarter) compared to the top performer, i.e. Hong Kong (Canada). Countries differ also substantially in terms of volatility, with South Korea that is notably about twice as volatile as the average across countries. We also note that Asian countries are mostly positively skewed while all the other countries are largely negatively skewed. Finally, equally-weighted indices are more positively skewed than their value-weighted counterparts as they put more weight on small-cap firms that are well-known to be on average positively skewed (Bali et al., 2011; Langlois, 2020). Turning to industries,

[2]Our coverage is noticeably larger in both time series and cross-section compared to previous studies such as Heston and Rouwenhorst (1994), Griffin and Karolyi (1998) and Cavaglia et al. (2000).

the average return performance is slightly lower compared to countries. The average standard deviation of industries is about 1% smaller than the one of countries, suggesting a more homogeneous volatility distribution across industries. In terms of skewness, VW indices have an average skewness similar to VW countries (around -0.3), while EW indices of industries are on average more negatively skewed than their countries' counterparts. More precisely, all skewness values are negative except the VW Auto index and the EW Healthcare index which are nevertheless very close to zero.

The last columns of Table 4.2 report the proportion of the average stock market capitalization in sample. The United States make on average almost 50% of the total market cap over the sample period. Other large countries such as Japan (12.90%) and the United Kingdom (7.23%) have a much lower weight in the sample. Five countries (Austria, Belgium, Denmark, Norway and Singapore) are smaller than 1%. Turning to the industries, the proportions are considerably more balanced. The industry with the largest capitalization is Personal and Household goods which corresponds to 12.44% of the average total market cap, closely followed by Technology (11.26%) and Banks (10.38%). All the industries are greater than 2% of the total average market capitalization.

4.3 Disentangling country and industry effects

4.3.1 Framework

Our goal is to analyze the influence of industrial structure on the cross-section of variance and higher-moments risk. This involves isolating country and industry effects and quantifying their contribution to both the variance and skewness of the aggregate indices. International stock returns can vary because of common variation with the country return where the firm is located, because of common variation with the industry the firm belongs to as well as to other idiosyncratic sources uncorrelated with country or industry effects.[3]

[3]Since we measure returns into a common currency, i.e. U.S. dollars, we omit exchange-rate variation as an additional source of returns.

The popular model of Heston and Rouwenhorst (1994) isolates such effects by estimating a dummy-regression framework on stock-level data. The dummy estimates allow us to decompose the country and industry contributions to the *actual* aggregate country or industry indices. With this model, we first show that the benefits of international diversification in variance terms have decreased. In this sense, diversifying portfolios *across* countries or *across* industries gives analogous variance reduction benefits. In a second step, we extend this approach to a higher-moments setting and analyze the impact on aggregate skewness related to the country and industry effects.

The model can be summarized as follows. We assume that the return in month t associated to stock i, which belongs to industry j and country k, depends linearly on a global common component captured by α_t, an industry-related factor β_{jt}, a country-related factor γ_{kt} and a firm-specific disturbance ϵ_{it}:

$$R_{it} = \alpha_t + \beta_{jt} + \gamma_{kt} + \epsilon_{it}. \tag{4.1}$$

Equation (4.1) can be further elaborated and reformulated in a dummy-variable format as follows:

$$R_{it} = \alpha_t + \beta_{1t}I_{1i} + \beta_{2t}I_{2i} + ... + \beta_{18t}I_{18i} + \gamma_{1t}C_{1i} + \gamma_{2t}C_{2i} + ... + \gamma_{19t}C_{19i} + \epsilon_{it}, \tag{4.2}$$

where the dummy variable I_{ji} (C_{ki}) is equal to one if stock i belongs to industry j (country k) and zero otherwise.

We estimate equation (4.2) with a panel regression approach for each month t of the entire sample period. Since we have perfect multicollinearity between the dummies, it is not feasible to estimate this cross-sectional regression directly, as we would fall into the dummy variable trap – i.e., the dummies add up to one across firms. Following Heston and Rouwenhorst (1994), we thus impose two linear constraints that allow us to interpret the dummy variables as cross-sectional differences between countries/industries relative to the

world equally-weighted market portfolio:

$$\sum_{j=1}^{18} n_{j,t}\beta_{j,t} = 0 \qquad \& \qquad \sum_{k=1}^{19} m_{k,t}\gamma_{k,t} = 0\,, \tag{4.3}$$

where $n_{j,t}$ and $m_{k,t}$ are the number of stocks in industry j and country k in month t. In this specification, the intercept can be interpreted as the return on the World equally-weighted global portfolio.

The monthly panel regressions return time series of *i)* the global equally-weighted portfolio $\hat{\alpha}$, *ii)* the pure industry effects relative to the global portfolio $\hat{\beta}_j$, and *iii)* the pure country effects relative to the global portfolio $\hat{\gamma}_k$.

With these time series of estimated coefficients, we can then decompose the *actual* equally-weighted country portfolio R_k^{ew} into a the return of the world global factor $\hat{\alpha}$, a pure country effect $\hat{\gamma}_k$ and a weighted average of the industry effects $\hat{\beta}_j$ as follows:

$$R_k^{ew} = \hat{\alpha} + \frac{1}{m_k}\sum_i \sum_{j=1}^{18} \hat{\beta}_j I_{ij} + \hat{\gamma}_k. \tag{4.4}$$

Analogously, the *actual* equally weighted industry return R_j^{ew} is decomposed into the return of the world global factor $\hat{\alpha}$, a weighted-average of the country effects $\hat{\gamma}_k$ and a pure industry effect $\hat{\beta}_j$:

$$R_j^{ew} = \hat{\alpha} + \hat{\beta}_j + \frac{1}{n_j}\sum_i \sum_{k=1}^{19} \hat{\gamma}_k C_{ik}. \tag{4.5}$$

A similar framework can be applied to the *actual* value-weighted country and industry indices R_k^{vw} and R_j^{vw} (Griffin and Karolyi, 1998):

$$R_k^{vw} = \hat{\alpha} + \sum_{j=1}^{18} x_{k,j}\hat{\beta}_j I_{k,j} + \hat{\gamma}_k \tag{4.6}$$

and

$$R_j^{vw} = \hat{\alpha} + \hat{\beta}_j + \sum_{k=1}^{19} \eta_{k,j}\hat{\gamma}_k C_{k,j}. \tag{4.7}$$

where $x_{k,j}$ ($\eta_{k,j}$) is the proportion of total market capitalization of industry group j (country k) into country k (industry j). Equation (4.6) and (4.7) are again estimated month-by-month with a WLS approach under the following linear constraints:

$$\sum_{j=1}^{18} w_{j,t}\beta_{j,t} = 0 \qquad \& \qquad \sum_{k=1}^{19} v_{k,t}\gamma_{k,t} = 0 \tag{4.8}$$

where $w_{j,t}$ and $v_{k,t}$ are the weights of industry j and country k in the world value-weighted market index in month t. In this case, the dummy coefficients can be interpreted as the deviations with respect to the global value-weighted portfolio return.

Table 4.3 presents the empirical results of the Heston and Rouwenhorst (1994) decomposition in terms of the second moment for the value-weighted (VW) indices of equations 4.6 and 4.7 for the entire 1990-2020 sample period. We report analogous results for the equally-weighted (EW) indices R_k^{ew} and R_j^{ew} in Appendix Table (4A.2). For country indices, we display the variance of the pure country effects, $\sigma^2(\hat{\gamma}_k)$, and of the weighted sum of 18 industry effects, $\sigma^2(\frac{1}{m_k}\sum_i \sum_{j=1}^{18} x_{k,j}\hat{\beta}_j I_{ij})$, along with their ratio with respect to the variance of the excess country index, $\sigma^2(R_k^{vw} - \hat{\alpha})$. Similarly, for industry indices we report the variance of the pure industry effects, $\sigma^2(\hat{\beta}_j)$, and of the weighted sum of 19 country effects, $\sigma^2(\frac{1}{n_j}\sum_i \sum_{k=1}^{19} \eta_{k,j}\hat{\gamma}_k C_{ik})$, and their ratio with respect to the variance of the excess industry index, $\sigma^2(R_j^{vw} - \hat{\alpha})$.

We note that, for excess country value-weighted indices ($R_k^{vw} - \hat{\alpha}$), the largest contribution to variance comes from the pure country effects, which are 16.35%-squared on average across countries. The contribution of the weighted sum of pure industry effects is remarkably small, being as little as 0.98%-squared on average. When we compare this result with the excess industry value-weighted indices $R_j^{vw} - \hat{\alpha}$, we see that the contribution of the pure industry effects to the variance is a half of that of pure country effects on excess country value-weighted indices, being barely 8.38%-squared on average.[4] Overall, we confirm the findings in Heston

[4]For the EW indices, the results are in line with their VW counterparts, although in this case the cross-country average of the pure country effects in excess country value-weighted indices is four times larger the cross-industry average of the pure industry effects in excess industry value-weighted indices. Moreover, only Basic Resources, Oil and Gas, Technology

and Rouwenhorst (1994) that, in variance terms, pure country effects are on average larger than pure industry effects.

To understand whether these findings extend to the whole sample, we re-estimate the decomposition separately during the two subsamples before and after the 2007-2008 Financial Crisis, and report the results in Table 4.4. The leftmost panels are for the 1990-2006 subsample while the rightmost ones for the 2009-2020 subsample. Interestingly, we uncover time-variation in the importance of country effects in country indices that is hidden by the full sample estimates. In fact, when we compare the pre-crisis subsample with the post-crisis one, the contribution to the variance of excess country indices that comes from the pure country effects passes from 21.109%-squared to 8.941%-squared, while at the same time the contribution to the variance that comes from the pure industry effects in excess industry indices passes from 9.068%-squared to 6.751%-squared – a sensibly lower reduction for the latter ones. Moreover, the proportion between the ratios relative to the market of the pure country (industry) effects and the weighted sum of industry (country) effects in excess country (industry) indices are more homogeneous in the post-Crisis panel compared to the pre-Crisis one. The main message from this table is that, after the Financial Crisis, a trend in variance convergence has taken place in developed markets.

Table 4.5 presents the country indices corrected for industry composition and industry indices corrected for country composition.[5] Heston and Rouwenhorst (1994) state that more uniform volatilities and average returns after industry correction are to be expected if the industrial structure of countries is important. Moreover, they also assert that country correlations should increase after industry correction if industry effects are relevant. Therefore, any difference between the upper (lower) panel of Table 4.5 and Table 4.2 is given by the exclusion of return variation due to the industrial (country) composition of country (industry) indices.

and Telecommunications pure industry effects variances are larger than the smallest pure country effect in excess country equally-weighted indices, i.e. Sweden.

[5] Appendix Table 4A.3 reports the results for EW indices.

Comparing the two tables, it is easy to see that the country indices adjusted for the effect of industry composition and the industry indices adjusted for the effect of country composition appear quite similar to the raw indices.[6] Overall, the takeaway is that in terms of variance the differences between countries and industries in developed markets have become negligible.

How do changes in the relative importance of country and industry effects impact diversification benefits? To address this question we display in Figure 4.1 the evolution of the portfolio variance for an increasing number of stocks as a percentage of the variance of the average stock in sample.[7]. The plot shows that an investor that randomly picks and allocates stocks into progressively larger portfolios can reduce portfolio variance up to 6% of the variance of the typical stock in sample. The limit to diversification of forming portfolios within an industry across countries is 8%, quite comparable to that of combining stocks into large portfolio within a country but across industries at 10%. Overall, in terms of variance reduction, the two strategies deliver quite similar variance reduction, and are much closer to the theoretical limit compared to the Heston and Rouwenhorst (1994) sample.

4.3.2 Application to skewness

The previous analysis shows that portfolio benefits in terms of variance reduction have tapered off over time. We now shift our attention to skewness in order to assess what are the benefits of international diversification at the industry- versus country-level when taking the third moment into account. We rely again on the Heston and Rouwenhorst (1994) model to disentangle industry and country effects and trace the origins of downside risk. Rearranging equation (4.6) for the value-weighted country indices and bringing the global component

[6]This is also reinforced by the correlation between the raw indices and between the corrected indices reported in Appendix Table 4A.4, which are very similar in the upper and lower part of the correlation matrix.

[7]The plot is constructed as in Figure 1 of Heston and Rouwenhorst (1994)

common to all countries $\hat{\alpha}$ to the left hand side, we obtain:

$$R_k^{vw} - \hat{\alpha} = \frac{1}{m_k} \sum_i \sum_{j=1}^{18} x_{k,j} \hat{\beta}_j I_{ij} + \hat{\gamma}_k. \tag{4.9}$$

As a consequence, the skewness of the excess country index $R_k^{vw} - \hat{\alpha}$ is equal to the skewness of the sum of the pure country effect $\hat{\gamma}_k$ and the weighted sum of the pure industry effects $\frac{1}{m_k} \sum_i \sum_{j=1}^{18} x_{k,j} \hat{\beta}_j I_{ij}$:

$$Skew(R_k^{vw} - \hat{\alpha}) = Skew\left(\frac{1}{m_k} \sum_i \sum_{j=1}^{18} x_{k,j} \hat{\beta}_j I_{ij} + \hat{\gamma}_k\right). \tag{4.10}$$

The skewness of the right hand side of the equation is not equal to the sum of the skewness of the two terms, but rather involves six coskewness terms. However, accurate estimates of the Coskewness matrix for a linear combination of random variables is not a straightforward task. We therefore rely on the multivariate approach with shrinkage estimates of the coskewness matrix developed by Boudt et al. (2020), which is based on an unbiased estimate of the MSE loss function. Boudt et al. (2020) define the (Unadjusted) skewness $\hat{\phi}_v$ of a linear combination of random variables as:

$$\hat{\phi}_v^k := \mathbf{v}' \hat{\mathbf{\Phi}}_k (\mathbf{v} \otimes \mathbf{v}). \tag{4.11}$$

In our case, since $\mathbf{v} = (1, 1)'$, the unadjusted skewness $\hat{\phi}_v^k$ of the excess country index $R_k^{vw} - \hat{\alpha}$ is just the sum of the eight Coskewness Matrix elements of $\hat{\mathbf{\Phi}}$. The Coskewness Matrix of $R_k^{vw} - \hat{\alpha}$ is a 2x4 matrix with the following elements:

$$\hat{\mathbf{\Phi}} = \begin{bmatrix} \phi_{III} & \phi_{IIC} & \phi_{CII} & \phi_{CIC} \\ \phi_{ICI} & \phi_{ICC} & \phi_{CCI} & \phi_{CCC} \end{bmatrix}, \tag{4.12}$$

where the subscript I indicates the weighted sum of industry effects and the subscript C indicates the pure country fixed effects. Therefore, after applying the Heston and Rouwenhorst (1994) methodology and decomposing the actual value-weighted country indices, we can

compute for each country k the Coskewness Matrix $\hat{\mathbf{\Phi}}_{\mathbf{k}}$ with the two series $\frac{1}{m_k}\sum_i \sum_{j=1}^{18} x_{k,j}\hat{\beta}_j I_{ij}$ and $\hat{\gamma}_k$ and trace the origins of downside risk from the Coskewness Matrix.[8]

Unlike variance, skewness can be both negative and positive, making it impossible to compare the direct proportion of a coskewness terms with respect to the total skewness in a similar fashion to the ratios of variances we displayed in tables 4.3. Therefore, to compare the relative importance of each coskewness term, we first compute for each element ϕ_h^k of the Coskewness Matrix Φ the absolute deviation from the total unadjusted skew $\hat{\phi}_v^k$ which we label as ϵ_h^k:

$$\epsilon_h^k = |\phi_h^k - \hat{\phi}_v^k|, \tag{4.13}$$

where $h = III, IIC, CII, CIC, ICI, ICC, CCI, CCC$ are all the combinations of country (C) and industry (I) elements. We then compare the absolute error ϵ_h^k to the total sum of absolute errors $\sum_{h=1}^{8} \epsilon_h^k$:

$$\psi_h^k = \frac{\epsilon_h^k}{\sum_{h=1}^{8} \epsilon_h^k}. \tag{4.14}$$

A small skewness error ratio ψ_h^k indicates a higher weight of the Coskewness Matrix component ϕ_h^k on the total unadjusted skewness $\hat{\phi}_v$ of equation 4.11. Table 4.6 reports, for country indices, the skewness of pure country effects ϕ_{CCC} and ψ_{CCC}^k together with the skewness of the weighted average of industry effects ϕ_{III} and ψ_{III}^k. For industry indices, ϕ_{CCC} and ψ_{CCC}^k are related to the weighted sum of pure country effects and ϕ_{III} and ψ_{III}^k are related to the pure industry effects. The full results of the Coskewness matrices for excess country and industry indices are presented in Appendix Table 4A.5, while the skewness ratio are collected in Table 4.6 and in Appendix Table 4A.6 for the EW indices.

As specified, we consider *excess* country or industry indices, meaning that we neglect the impact of the global component $\hat{\alpha}$[9]. Therefore, the skewness is driven by the pure skewness of the country effects, the pure skewness of the industry effects and all the coskewness terms,

[8]The same reasoning applies to the value-weighted industry indices R_j^{vw}. In that case, the weighted country indices, we can then calculate for each country k the Coskewness Matrix $\hat{\mathbf{\Phi}}_{\mathbf{j}}$ is constructed from the two series $\hat{\beta}_j$ and $\sum_{k=1}^{19} \eta_{k,j}\hat{\gamma}_k C_{k,j}$.

[9]The global component $\hat{\alpha}$ by itself has an adjusted skewness of -0.58 and an unadjusted skewness of -51.73

which are relatively small. From the upper panel of table 4.6, we notice that the median cross-country unadjusted skew of the pure country effects is about -10.74[10]. This corresponds to a median error relative to the sum of skewness errors of only 0.46%. This very small error suggests that the final skewnewss of the excess index is very close to the median skew. On the other hand turning to the industry indices, we see that the cross-industries unadjusted skew of the pure industry effects is -0.15, which correpsonds to 1.79% of the sum of the skewness errors. This value is 3.9 times larger than the corresponding one for the country indices. This large difference indicates that for industry indices a larger part of the unadjusted skewness of the index is made up of the sum of the other 7 elements of the Coskewness Matrix. So for VW indices, we conclude that country effects are stronger in driving the excess skewness of the indices compared to industry effects. Table 4A.6 in the Appendix is constructed similarly but for the EW indices[11]. For EW indices, the results are even stronger. The difference in medians is about 6.7 times. Moreover, the sign of the cross-country median unadjusted skewness of the pure country effects is positive.

4.3.3 Bootstrap

We seek to quantify how country- versus industry aggregation of stocks impacts higher-order moments of portfolio returns. To deal with the issue of skewness aggregation, we rely on empirical estimates from a stratified bootstrap approach. The goal of this bootstrap exercise is to evaluate how portfolio distribution and performance – as measured by the average return, variance, skewness, certainty equivalent for a CRRA power utility investor with relative risk aversion $\gamma = 5$), and Value at Risk – varies with the degrees of diversification (i.e. portfolios with different total number of stocks N) for portfolios that are either a) concentrated within an industry (and hence diversified across countries), or b) concentrated within a country (and hence diversified across industries).

As shown above and in accordance with Roll (1992), aggregate equity country returns are

[10]The unadjusted skewness values in the tables have been multiplied by 1'000'000 for easiness of representation

[11]In this case the unadjusted skewness of the global component $\hat{\alpha}$ is -63.13 and its adjusted skewness is -0.53

affected by differences in the industrial structure of countries, which make some countries less diversified than others, and by the fact that some industries are intrinsically less volatile than others. Therefore, countries that load more on riskier industries would have more volatile aggregate country indices. This fact implies that a bootstrap with an unconditional re-sampling procedure would potentially deliver country portfolios that are excessively concentrated in some highly represented industries, thereby confounding country and industry effects akin to what observed in Table 4.2 and distorting our inference. For example, Canada has a very large proportion of stocks in the Basic resources industry, since the country is rich in mineral resources with hundreds of public companies active in that industry. If we were to create unconditional bootstrap portfolios for Canada, we would end up with a very high probability of picking up stocks belonging to the Basic Resources industry and forming portfolios excessively concentrated in that industry. Similarly, unconditionally bootstrapped industry portfolios diversified across countries would be over-represented by those countries that are highly specialized in those industries (e.g., most of the Technology stocks in sample are based in the United States), making it impossible to isolate country and industry effects.

To overcome these issues, we adopt a “conditional sampling" bootstrap strategy, where we “force" the bootstrapped portfolios to achieve the maximum diversification across industries/countries that is feasible while at the same time preserving the randomness which lies at the foundation of the bootstrap approach. Section 4.3.3.1 details the bootstrap implementation, Section 4.3.3.2 presents the unconditional results, while in Section 4.3.4 we carry the bootstrap on rolling windows of data.

4.3.3.1 Description

In detail, suppose we want to construct a portfolio of N random stocks from country k that is highly diversified across the industries present in country k, with the N stocks that are resampled once every year t in January and kept constant throughout the year. When we select the N random stocks to fill the portfolio we face two possible situations.

The first scenario is when $N \leq I_{0,k,t}$ where $I_{0,k,t}$ is the total number of industries available to an investor in country k at the start of the year t. In this case, we first select N random industries without replacement among the $I_{0,k,t}$ possible and then we select one random stock within each sampled industry.

The second situation is where $N > I_{0,k,t}$, i.e. when we have to select more stocks than the total number of industries available to an investor in country k at the start of the year t. In this case, we adopt the following iterative process to create the portfolio. We start selecting all $I_{0,k,t}$ industries and pick a random stock from each of the $I_{0,k,t}$ industries without replacement. In this way, we start filling the portfolio with $n_{1,k,t}$ stocks, where $n_{1,k,t}$ is the total number of stocks chosen in the first round of selection in year t for country k [12]. After this first round of selection, we then check how many stocks are still needed to be selected to fill the N stocks, i.e. we check whether $N - n_{1,k,t} > I_{1,k,t}$, where $I_{1,k,t}$ is the total number of industries available to be selected after the first round of selection[13]. Again, if $N - n_{1,k,t} > I_{1,k,t}$ we select a random stock from each of the $I_{1,k,t}$ industries without replacement. This, leads us after the second round of selection to have picked out $n_{1,k,t} + n_{2,k,t}$ stocks out of N. We then define $I_{2,k,t}$ the total number of industries still available to be selected after the first two rounds of selection and $N - (n_{1,k,t} + n_{2,k,t})$ the total number of stocks still needed to fill the portfolio of N stocks. We continue the algorithm iteratively until after q rounds of selection we have reached the point where the number of stocks left to fill the portfolio of N stocks, $N - (n_{1,k,t} + .. + n_{q,k,t})$, is smaller than the total number of industries available after the qth round of selection, i.e. when we get $N - (n_{1,k,t} + ... + n_{q,k,t}) < I_{q,k,t}$. In that case, we select randomly without replacement $N - (n_{1,k,t} + ... + n_{q,k,t})$ industries and randomly select one stock from each industry.

In sum, this conditional sampling procedure allows us to select N random stocks and at the same time “forcing" industry diversification in a way that avoids the excessive concentration

[12] Clearly $n_{1,k,t} = I_{0,k,t}$ since we pick a single stock from each of the $I_{0,k,t}$ industries

[13] $I_{1,k,t}$ might differ from $I_{0,k,t}$ since after each round of selection some industries might be "exhausted" because we select stocks without replacement.

of stocks in few industries from which an unconditional bootstrap might suffer.

We repeat this procedure at the begin of every year t, and build value-weighted portfolio monthly returns of the N stocks $R^p_{k,t,\tau}$, with the portfolios p that are kept fixed within each year t:

$$R^p_{k,t,\tau} = \sum_{n=1}^{N} \lambda_{n,t,\tau} r_{n,t,\tau}, \tag{4.15}$$

where τ denotes a given month in year t and p is a value-weighted portfolio with weights $\lambda_{n,t,\tau} = \frac{MV_{n,t}}{\sum_{n=1}^{N} MV_{n,t}}$.

We construct these monthly portfolios for the period January 1990 to December 2020, and compute for each run the first three sample moments as well as the certainty equivalent (CE) for a power utility investor with relative risk aversion coefficient γ equal to 5. To quantify tail risk we also rely on the VaR measure developed by Favre and Galeano (2002) that, unlike the traditional VaR, also takes portfolio skewness and kurtosis into account . The four-moment modified VaR has the following form:

$$VaR = W(\mu - (z_c + \frac{1}{6}(z_c^2 - 1)SK + \frac{1}{24}(z_c^3 - 3z_c)K - \frac{1}{36}(2z_c^3 - 5z_c)SK^2)\sigma), \tag{4.16}$$

where μ is the average return, σ the portfolio volatility, SK is the portfolio skewness, K is the excess kurtosis, z_c is the quantile of the normal distribution associated with a certain degree of confidence level of the VaR, and W is the portfolio value. We set $W = 100\$$, and report the VaR at the 95% confidence level. We also keep track of the average number of stocks within the portfolio p, as delistings that occur within a year may temporarily reduce the number of stocks in a portfolio before the new resampling takes place at the begin of the subsequent year.

We follow an analogous procedure when forming portfolios of N stocks for a given industry j that are “forced" to be diversified across countries. We replicate this bootstrap exercise 1’000 times over the entire sample period T for each of the 19 countries and for each of the 18 industries and we average across simulations and countries/industries the estimates of

the i) first three portfolio moments, $(\widehat{\mu}, \widehat{\sigma}^2, \widehat{SK})$, ii) the certainty equivalent, $\widehat{CE}$, and iii) four-moment VaR, $\widehat{VaR}$. For each of these statistics, call them $\widehat{m}$, we then compute:

$$\widehat{m}_{J,T} = \frac{1}{1000} \sum_{s=1}^{1000} \sum_{j=1}^{18} \omega_{j,T} \widehat{m}_{j,s,T} \qquad \widehat{m}_{K,T} = \frac{1}{1000} \sum_{s=1}^{1000} \sum_{k=1}^{19} \upsilon_{k,T} \widehat{m}_{k,s,T}$$

where s is the sth bootstrapped portfolio out of 1'000 in industry j/country k, and T indicates that the statistics are computed over the entire sample period from Jan. 1990 to Dec. 2020. For example, $SK_{J,T}$ is a market-cap weighted average across all $J = 18$ industries of the skewness of industry portfolios diversified across countries and $\sigma^2_{K,T}$ is a market-cap weighted average variance across the $K = 19$ countries of bootstrap country portfolios that are diversified across industries.[14] We construct portfolios with increasing degrees of diversification, i.e. for $N = \{1, 5, 10, 20, 40\}$. To guarantee a common benchmark for the portfolios diversified across countries and across industries, we use as a starting point for both cases a portfolio with $N = 1$ that is selected with an *unconditional* random sampling. In other words, in January of every year t we randomly select a single stock across the entire universe available to an investor at that point in time and we keep that stock for an entire year before a resampling of another stock happens in January of the subsequent year.

4.3.3.2 Empirical results

Table 4.7 reports the results of the bootstrap simulation for the VW bootstrapped portfolios over the full sample. Panel A is for the strategy in which the investor diversifies *across* industries *within* the same country, while Panel B is for the strategy in which the investor diversifies *across* countries *within* the same industry.

First, we note that the benchmark portfolio with a single stock, selected with an unconditional random sampling, has a monthly average return of 1.16%. This portfolio is clearly

[14] To build the market-cap weights $\upsilon_{k,T}$ and $\omega_{j,T}$ used for the aggregation across countries/industries, we take the average total market capitalization of each industry j (country k) in the whole sample period and we create the industry weights as $\omega_{j,T} = \frac{AvgMktCap_{j,1990\to2020}}{\sum_{j=1}^{18} AvgMktCap_{j,1990\to2020}}$ and country weights $\upsilon_{k,T} = \frac{AvgMktCap_{k,1990\to2020}}{\sum_{k=1}^{19} AvgMktCap_{k,1990\to2020}}$.

very risky, with a sizeable average monthly variance of about 2.81%. The strategy is largely positively skewed, with an impressive +2.17. The high risk of this benchmark is reflected by the average monthly certainty equivalent which is a negative -8.28%.

As we increase the number of stocks N in the portfolio, both the strategy that diversifies across industries and the one that diversifies across countries provide variance reduction, as the diversification principle implies, as well as more negative skewness as the portfolio size increases, consistent with Albuquerque (2012). The effect on variance and skewness are marginally decreasing as N becomes larger.

Regarding variance, for large N, we obtain similar portfolio variance when diversifying across countries compared to across industries diversification. For example, for $N = 40$ the monthly portfolio variance is in both cases 0.40%. This result is consistent with evidence in Figure 4.1 that country diversification benefits for mean-variance investors have declined substantially in recent years.

Strikingly, the patterns in skewness are considerably different. As the number of stocks selected increases, country portfolios diversified across industries are more positively skewed for all N, with the difference compared to industry portfolios (diversified across countries) that reaches 0.1 for large N. In this respect, country portfolios (diversified across industries) present more upside potential compared to industry portfolios (diversified across countries) accompanied by analogous portfolio variances. Yet, both strategies have negative skewness when stocks are aggregated into large portfolios, in agreement with what previously observed by Albuquerque (2012) and Ghysels et al. (2016b).

Normally, there is a positive relationship between standard deviation and skewness (You and Daigler, 2010). Both the Certainty Equivalent and the four-moment VaR measures try to quantify this trade-off between standard deviation and skewness in relation to the benefits of international diversification. We see that the higher skewness of country portfolios translates into a difference of 15 basis points in terms of Certainty Equivalent in favour of country portfolios. Regarding the other trade-off measure, the VaR, we see that this difference

corresponds to approximately 0.61$ difference at the 95% confidence level for an arbitrary 100$ investment.

4.3.4 Rolling window analysis

To get a graphical overview of the dynamics of the bootstrapped portfolio returns over the entire sample period, we compute the statistics over 10-year rolling windows focusing on the most diversified portfolio of $N = 40$ stocks.

Specifically, we look at the difference in variance, skewness, certainty equivalent, and four-moment VaR between an average portfolio diversified across industries (within country) and an average portfolio diversified across countries (within industry) for an expanding sample. The first sample corresponds to the period from Jan1990 to Dec1999, and then shifts the entire window forward by one year, keeping fixed its 10-year window length.[15]

Figure 4.2a collects the corresponding results. Over the expanding sample, we observe a reduction in the variance difference between the two dimensions of diversification. Remarkably, the difference starts from about 1% in the early years of the sample and converges to zero by sample end. This is consistent with the idea that country effects have decreased in importance over time (Cavaglia et al., 2000; Brooks and Del Negro, 2004; Ferreira and Ferreira, 2006; Eiling et al., 2012).

On the other hand, when looking at the difference in skewness in Figure 4.2b, the skewness of countries is increasing in the first decade of the years 00s and then remains constantly higher compared to the one of industries, with a peak around the Great Financial Crisis. Turning to the two trade-off measures, when we look at the Certainty Equivalent in Figure 4.2c we notice that starting from a position more favourable for the industry portfolios the plots display a slightly increasing trend toward the positive side, meaning that in the later part of the sample the benefits for diversification across countries decrease in importance. Similarly, in terms of four-moment the VaR (Figure 4.2d) the difference between country and

[15]The weights used to average the statistics are based on the market cap in the corresponding sample.

industry portfolios almost halves over the sample period.[16]

To evaluate whether our results are driven by a given industry performance over the period, Figure 4.6 shows the end-of-sample difference between the skewness of the country portfolios diversified across industries minus the skewness of the industry portfolios diversified across countries for the bootstrapped portfolios with $N = 40$ stocks, where in each row we report which industry that has been excluded from the bootstrap. It is clear that the difference remains positive in favour of country portfolios irrespective of the industry that is excluded from the sample.

The overall takeaway is that, in the static setting, the benefits of international diversification across countries or across industries in terms variance have become similar while a substantial difference remains in terms of downside risk, with the industry-concentrated portfolios diversified across countries that are more negatively skewed than the within-country concentrated portfolios diversified across industries.

4.4 Conditional skewness

Until now, we have taken a static perspective on the third moment. However, there is mounting evidence that the asymmetry in the returns distribution is time-varying (Ghysels et al., 2016b). Despite this fact, an accurate modelling of conditional skewness does not come without any difficulty. First, realized past skewness has been found to be a poor predictor of future skewness given the sensitivity of the standard moment-based estimator to outliers. Indeed, researchers have tried to proxy conditional skewness with either firm-based characteristics (e.g. Boyer et al. (2010)), the lottery-like behavior of stocks (see, e.g., Bali et al., 2011; Lin and Liu, 2018), or options data (Bakshi et al., 2003; Xing et al., 2010; Conrad et al., 2013). Second, incorporating skewness into portfolio choice analysis is a challenging endeavor, unless we are willing to accept restrictive distributional assumptions, which are often rejected by the data and are not suitable for a large number of assets. Third, recent

[16] Working on expanding windows delivers similar, although more stale, plots; see Appendix Figures 4A.1a–4A.1d.

studies have shown that skewness is not a short-lived phenomenon. Indeed, as documented by Engle and Mistry (2014) and Neuberger (2012) for the U.S. market, the skewness of aggregate stock returns persists or even amplifies (i.e., becomes more negative) over longer horizons. Finally, the average skewness of individual stock returns is positive, which suggests that further investigation is needed to understand how positively skewed shocks in individual stocks returns interact to generate negative skewness at the aggregate level.

In this section, we take a conditional skewness approach to investigate the differences in time-varying returns asymmetries across countries and industries. More precisely, we seek to quantify whether these differences can be exploited and translated into substantial utility gains to international investors that are facing the choice to allocate capital across countries or across industries. In Section 4.4.1 we discuss the conditional skewness measure we use and provide summary statistics, and Section 4.4.2 describes the asset allocation framework and its results.

4.4.1 Description and estimates

We use the conditional skewness measure of Ghysels et al. (2016b), which was used to estimate the international diversification benefits differences across developed and emerging markets. Namely, we compute a *conditional* version of the robust coefficient of asymmetry $CA_{INT,t-1}$ of Groeneveld and Meeden (1984), which does not depend on a specific quantile of the returns distribution:

$$CA_{INT,t-1}(r_{t,n}) = \frac{\int_{0.5}^{1}\{[q_{\alpha,t-1}(r_{t,n}) - q_{0.50,t-1}(r_{t,n})] - [q_{0.50,t-1}(r_{t,n}) - q_{1-\alpha,t-1}(r_{t,n})]\}d\alpha}{\int_{0.5}^{1}[q_{\alpha,t-1}(r_{t,n}) - q_{1-\alpha,t-1}(r_{t,n})]d\alpha}, \tag{4.17}$$

where $q_{\alpha,t-1}(r_{t,n})$ is the conditional quantile of the n-horizon return distribution associated with the α confidence level. We then exploit a combination of this coefficient of asymmetry with the Cornish and Fisher (1938) approximation, which allows us to rescale $CA_{INT,t-1}$ and

convert it into a conditional moment-based skewness measure $SK_{INT,t-1}$:

$$SK_{INT,t-1}(r_{t,n}) = 6 \cdot CA_{INT,t-1}(r_{t,n}) \frac{\int_{0.5}^{1} q_\alpha(z) d\alpha}{\int_{0.5}^{1} q_\alpha^2(z) d\alpha}. \tag{4.18}$$

The advantage of this methodology is that is robust to outliers unlike standard moment based estimators, assuming we obtain reliable estimates of the conditional quantiles of the returns distribution. To estimate the conditional quantiles $q_{\alpha,t-1}(r_{t,n})$, we make use of conditional MIDAS (Mixed-Data Sampling) quantile regressions. Specifically, we relate the conditional quantile of the n-horizon distribution $r_{t,n}$ to a MIDAS element composed of the past daily absolute returns:

$$q_{\alpha,t-1}(r_{t,n}; \theta_{\alpha,n}) = \beta_{\alpha,n}^0 + \beta_{\alpha,n}^1 Z_{t-1}(\kappa_{\alpha,n}), \tag{4.19}$$

where $\theta_{\alpha,n} = (\gamma_{\alpha,n}, \delta_{\alpha,n}, \kappa_{\alpha,n})$ are the unknown parameters to be estimated and $Z_{t-1}(\kappa_{\alpha,n})$ is a sequence of daily absolute returns $x_t = |r_t|$ embedded into a MIDAS structure with weights ϕ_d characterized by the two-dimensional parameters vector $\kappa_{\alpha,n}$:

$$Z_{t-1}(\kappa_{\alpha,n}) = \sum_{d=0}^{D} \phi_d(\kappa_{\alpha,n}) x_{t-1-d}. \tag{4.20}$$

Consistently with Ghysels et al. (2006), we choose the weights of the MIDAS element to follow “Beta" polynomial

$$\phi_d(\kappa_{\alpha,n}) = \frac{f(\frac{d}{D}, \kappa_{1,\alpha,n}, \kappa_{2,\alpha,n})}{\sum_{d=0}^{D} f(\frac{d}{D}, \kappa_{1,\alpha,n}, \kappa_{2,\alpha,n})}, \tag{4.21}$$

with $f(z, a, b) = \frac{z^{a-1}(1-z)^{b-1}}{\beta(a,b)}$ and $\beta(a, b) = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)}$, where $\Gamma(x)$ is the Gamma function. Similarly to Ghysels et al. (2016b), we impose a downward-sloping MIDAS weighting scheme by setting $\kappa_{1,\alpha,n} = 1$ and $\kappa_{2,\alpha,n} > 1$ and we estimate the conditional quantiles using the past $D = 250$ absolute returns.

Unfortunately, the large nature of our dataset does not allow us to estimate the conditional skewness measure at the stock-level. Moreover, skewness aggregation is particularly problematic since the portfolio skewness is the sum of the average firm-skewness and all coskewness terms which grow at the third power. To this end, we estimate the conditional skewness measures at the aggregate index level directly. We thus gather U.S. dollar-denominated daily return series (RI) for the aggregate Country and Industry indices from Datastream.[17] The advantages of this approach are multiples. First, we do not have to deal with the aggregation of the skewnesses of the individual stocks, which is hard to model, and at the same time we can safely diversify most of the effects related to the differences in industrial (country) structure for country (industry) portfolios. Second, the MIDAS quantile measure is based on the past returns only and we do not have to deal with options data to extract a skewness measure as in Bakshi et al. (2003) or Conrad et al. (2013) among others. Finally, unlike standard sample estimators, this conditional asymmetry measure is robust to outliers.

Table 4.8 reports summary statistics about the end-of-month sampled MIDAS conditional skewness estimates SK_{INT} for each country k and industry j, at the monthly horizon ($n = 22$). Reported are the average conditional skewness, its standard deviation and both the minimum and the maximum over the sample period 1990-2020. Some results are worth mentioning. All industries have a negative average conditional skewness SK_{INT} over the sample period, with Telecommunications which is the only one close to the positive territory. The equally-weighted average across industries is -0.43 and the value-weighted one is also very close with a value of -0.44. Turning to countries, we note that all of them except South Korea display a negative average conditional skewness. South Korea and Austria are also the countries that feature the greatest variability, as highlighted by the large standard deviation. The equally-weighted SK_{INT} average across countries is -0.33 while the VW one is even more negative at -0.49, however this last value is clearly heavily influenced by the United States which is the country with the largest negative skewness as well as the country with both the largest market

[17] See Appendix Table 4A.7 for the exact Datastream Codes.

capitalization, which corresponds to almost half of the total sample market capitalization.

Figure 4.3 shows the difference between the MIDAS conditional skewness across countries and the conditional skewness across industries over time. The average conditional asymmetry of countries is consistently less negative compared to the average of the industry ones. In the next section, we assess whether this persistently higher skewness of country-portfolios can be exploited in an international asset allocation setting.

4.4.2 Conditional portfolio allocation

In this section we consider the benefits of integrating the conditional skewness measure SK_{INT} in a portfolio allocation problem where an investor must decide which proportion of capital he has to assign to countries and industries respectively. As a preliminary analysis, Figure 4.4 displays the average correlation of monthly returns and of conditional skewness across countries and industries computed over rolling windows of 24 months each. We see that the average rolling correlation in monthly returns is increasing over the sample period, for both countries and industries, consistent with the process of financial market integration (Baele and Inghelbrecht, 2009; Eiling et al., 2012). On the other hand, the patterns in skewness correlation reveal that the average correlation between countries and industries is very small, in the tune of 0.1 to 0.2 over the sample period, which suggests there is scope for diversification in third moments.

We decompose the portfolio return $r_{t,p} = \sum_{j=1}^{J} w_{t-1,j} r_{j,t} + \sum_{k=1}^{K} w_{t-1,k} r_{k,t}$ into a benchmark $r_{t,p}^{B}$ and a skewness-specific portfolio $r_{t,p}^{SK}$ which is dependent on a Country part $r_{t,Count}^{SK}$ and an Industry specific part $r_{t,Ind}^{SK}$ with weights $w_{t-1,Count}^{SK}$ and $w_{t-1,Ind}^{SK}$ as:

$$r_{t,p} = r_{t,p}^{B} + r_{t,p}^{SK} = r_{t,p}^{B} + r_{t,Count}^{SK} + r_{t,Ind}^{SK}. \tag{4.22}$$

Portfolio weights follow the parametric approach developed by Brandt et al. (2009). These weights are modelled as a linear function of the country/industry index specific information

and, for the skewness-augmented version, also of the conditional skewness measure SK_{INT}:

$$w_{t-1,i} = \overline{w}_{t-1,i} + \lambda_Z' \frac{1}{N_{t-1}} \widetilde{Z}_{t-1,i} + \lambda_{SK} \frac{1}{N_{t-1}} \widetilde{SK}_{t-1,i}(r_{t,i}). \tag{4.23}$$

We use the following index-specific information for both countries and industries for the conditioning information set $\widetilde{Z}$: the log Dividend Yield, DY; the log Book to Price value, BP; the log Price to Earnings ratio, PE; the log Price to Cash Flow ratio, PC; the Momentum return of the index (Mom); and MIDAS conditional volatility, Vol (Ghysels et al., 2006). The 'tilde' indicates that all variables are cross-sectionally standardized with mean 0 and variance 1. We then maximize the expected utility with respect to the λ_Z and λ_{SK} parameters for a power utility investor with a coefficient of relative risk aversion that, in the baseline case, we set equal to $\gamma = 5$:

$$\max_{\lambda_Z, \lambda_{SK}} \frac{1}{T} \sum_{t=1}^{T-1} \frac{(1 + r_{t,p})^{1-\gamma}}{1-\gamma}. \tag{4.24}$$

The parameter λ_{SK} captures the direction of tilt in international asset allocation as a function of an index conditional skewness. We are interested in its sign and statistical significance, and in the performance implication of the tilt.

Baseline results

Table 4.9 summarizes the baseline results. The VW portfolio splits almost equally the proportion between countries and industries, with an average weight to countries of about 53.2%. The average annualized portfolio return is 8.9% and both countries and industries contribute almost equally with average returns of 4.7% and 4.2%, respectively. The resulting optimal portfolio return is negatively skewed, consistent with the evidence we reported above, and the certainty equivalent is a modest 2.4% per year.

In the benchmark column *bench*, we let the weights to be dependent on the index-specific variables but not on conditional skewness. Although the average allocation to countries is very close to the previous case, the portfolio performance differs considerably when we let the

weights vary over time. The portfolio return almost doubles in magnitude (16.5%), at the cost of a small increase in volatility (16.5% vs. 15.6%). As a result, the certainty equivalent grows to 8.8%, and the portfolio becomes less exposed to downside risk, with a skewness of -0.25. Regarding the predictors, the portfolio weights are strongly and statistically related to Momentum.

In the third column, we add conditional skewness to the set of predictors. The loading on SK_{INT} is positive and significant at the 10% level. When we exploit time-variation in skewness, the average allocation to countries grows by 15% with respect to the benchmark, reaching an average of 66.5%. Notably, its addition delivers an average 2% return to the benchmark, and makes the optimal portfolio less negatively skewed at -0.13. The certainty equivalent exceeds 10%, with an annual α with respect to the benchmark of 2.5%.

When looking at the contribution of the skewness-managed components, we notice that loading on skewness gives a 4.2% returns that comes from the countries and a -2.3% contrubution related to the industries, confirming that exploiting the more positively skewed behaviour of countries is beneficial to investors. Figure 4.5 plots the time series of the monthly skewness related weights w_t^{SK} related to countries and industries. Due to the monthly nature of the weights, both time series are quite noisy. Still, the tilt towards countries is consistent during the entire sample period, with just few short-lived exceptions where the countries get shorted in favour of industry portfolios.

Sensitivity to varying risk aversion coefficient

In the first two columns of Table 4.10, we re-estimate the allocation for different levels of relative risk aversion $\gamma = \{3, 10\}$. Several results are worth mentioning. The coefficient on conditional skewness measure SK_{INT} decreases for larger values of relative risk aversion but remains significant at the 10% level or less. The optimized portfolios that consider SK_{INT} into their weights always deliver higher average returns, lower volatility, and more positive skewness compared to their benchmark counterparts. The certainty equivalent gains are substantial, especially for low level of risk aversion. For $\gamma = 3$, the annual certainty equivalent

increases from 12.8% of the benchmark to 14.6% simply by adding SK_{INT} into the portfolio weights. Finally, in both specifications, conditioning on skewness raises the tilt towards the more positively skewed countries, especially for lower level of γ.

Transaction costs

In the last two columns of table 4.10, we consider the impact of transaction costs on portfolio allocation. Following Brandt et al. (2009), we model portfolio turnover as the sum of absolute changes in the weights assigned to each asset over two successive periods:

$$T_{t-1} = \sum_{i=1}^{N} |w_{i,t-2} - w_{i,t-1}|. \tag{4.25}$$

The optimized portfolio return after taking into account transaction costs then becomes:

$$r_{p,t} = \sum_{i=1}^{N} w_{i,t-1} r_{i,t} - c_{t-1} \times T_{t-1}, \tag{4.26}$$

where c_{t-1} are the trading costs than can be modelled in several ways. We consider two scenarios. The first one is a constant case where $c_t = c$. Given the fact that our sample only consider liquid developed markets and major industries we assume a transaction cost estimate of $c_{t-1} = 0.10\%$. A second scenario models the transaction costs inversely proportional to both the liquidity and to the size of the country/industry. Analogously to Ghysels et al. (2016b), we express the transaction costs as a linear specification $c_{t-1,i} = 0.0040 - 0.0030 \times MktCap_{t-1,i}$, where the market capitalization $MktCap_{t-1,i}$ is cross-sectionally standardized.

A few results stand out. In both scenarios, conditioning on SK_{INT} tilts the average weight assigned to countries to about 60%, still larger then their benchmarks. The α with respect to the benchmark is clearly reduced after transaction cost, but still positive at about 1%. Finally, the portfolio becomes less negatively skewed after adding SK_{INT} and the average portfolio return is about 1% higher, obtaining CE increases in the range of about 0.6% compared to the benchmarks. Overall, although smaller in magnitude, the economic value of

conditional skewness and the tilt toward country indices appear to persist after accounting for transaction costs.

4.5 Concluding remarks

We revisit the vivid debate whether differences in industry composition across countries are responsible for the cross-sectional differences in the level risk, but unlike previous studies that consider only variance, we expand the discussion by looking at the implications for downside risk, as measured by skewness.

We find that the benefits in variance reduction across countries and across industries have decreased in recent years, consistent with the country and industry convergence process in developed markets. However, we provide evidence that there are still substantial differences in terms of skewness. First, combining the Heston and Rouwenhorst (1994) framework with the Boudt et al. (2020) coskewness shrinkage estimator approach, we decompose the skewness of country and industry indices, and show that the country effects are mostly responsible in driving the skewness of the indices. Armed with this evidence, we show by means of a stratified bootstrap approach that country portfolios diversified across industries have more upside potential compared to industry portfolios diversified across countries. In the static setting, this translates into a higher certainty equivalent and lower four-moment VaR.

Finally, we consider also the potentials from time-variation in the return distribution within an international asset allocation strategy when an investor chooses the proportion of capital to allocate to country and industry indices. We find that timing for skewness leads to a higher proportion of capital allocated to the more positively skewed countries, which translates into an economically large annual certainty equivalent and a more positively skewed portfolio. This result is robust to several level of risk aversion as well as after reasonable transaction costs estimates.

Our study sheds new light on the risks implied by the differences in the industrial structure

of countries and is of great relevance for the financial industry. For example, it offers asset managers a new perspective on the country versus industry diversification benefits, eventually allowing them to diversify away downside risks more efficiently.

Figure 4.1: Portfolio variance for increasing number of stocks in the portfolio

This figure replicates Figure 1 of Heston and Rouwenhorst (1994) with our sample. It shows portfolio variance as a percentage of the variance of a typical stock in sample as a function of the number of stocks N in the portfolio. The orange line is the variance of the portfolio that diversifies across industries (limit is 10%). The grey line the portfolio that diversifies across countries (limit is 8%). The blue line is the theoretical limit of a portfolio that diversifies across countries and industries (limit is 6%). Time span of the sample is Jan. 1990 - Dec. 2020

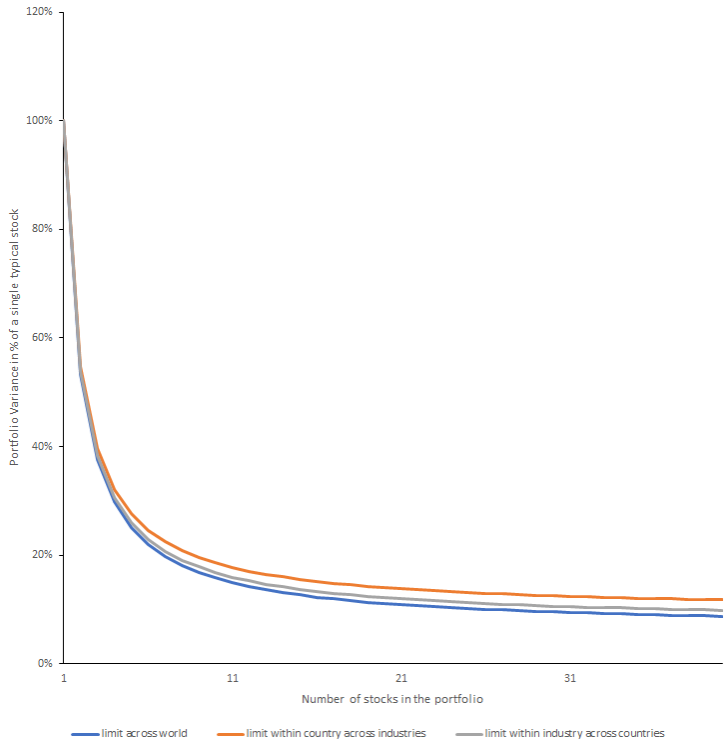
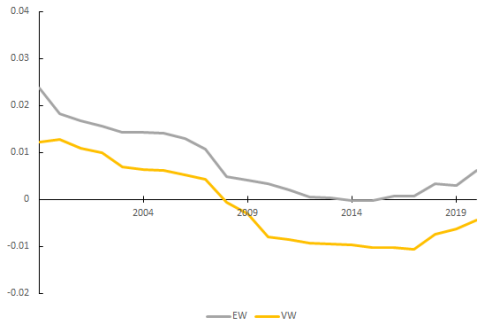
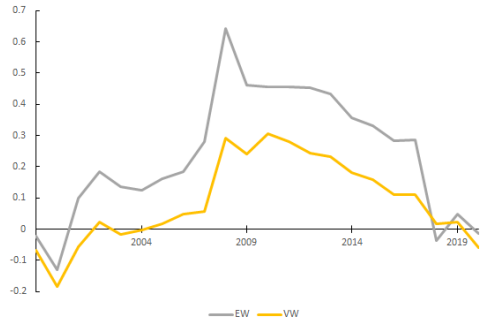


Figure 4.2: Rolling sample bootstrap

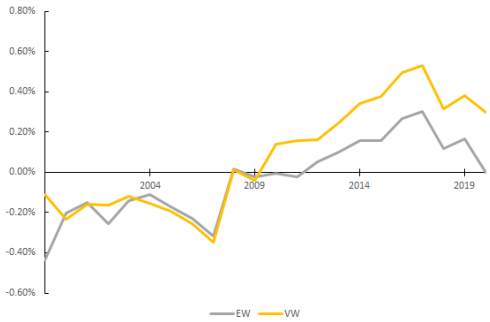
This figure shows the difference between the variance (4.2a), skewness (4.2b), CE (4.2c), VaR95 (4.2d) of the country portfolios diversified across industries minus the variance, skewness, CE, VaR95 of the industry portfolios diversified across countries for the bootstrapped portfolios with $N = 40$ stocks. The yellow (grey) line refers to the VW (EW) bootstrapped portfolios. The first sample is January 1990 - December 1999 and then we move the entire window one year forward in an rolling fashion until the end of the sample in December 2020.



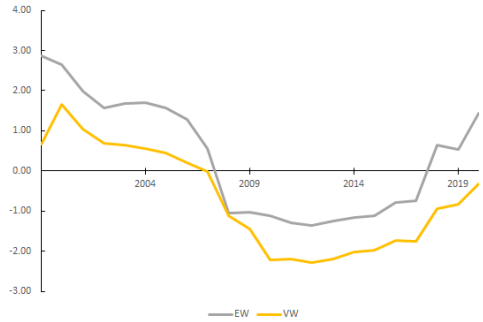
(a) Variance difference



(b) Skewness difference



(c) CE difference



(d) VaR95 difference

Figure 4.3: Difference in average SK_{INT} between countries and industries

This figure displays the time-series of the difference between the average MIDAS robust integrated conditional skewness SK_{INT} across countries and the MIDAS robust integrated conditional skewness SK_{INT} across industries. Time span is January 1990 - December 2020

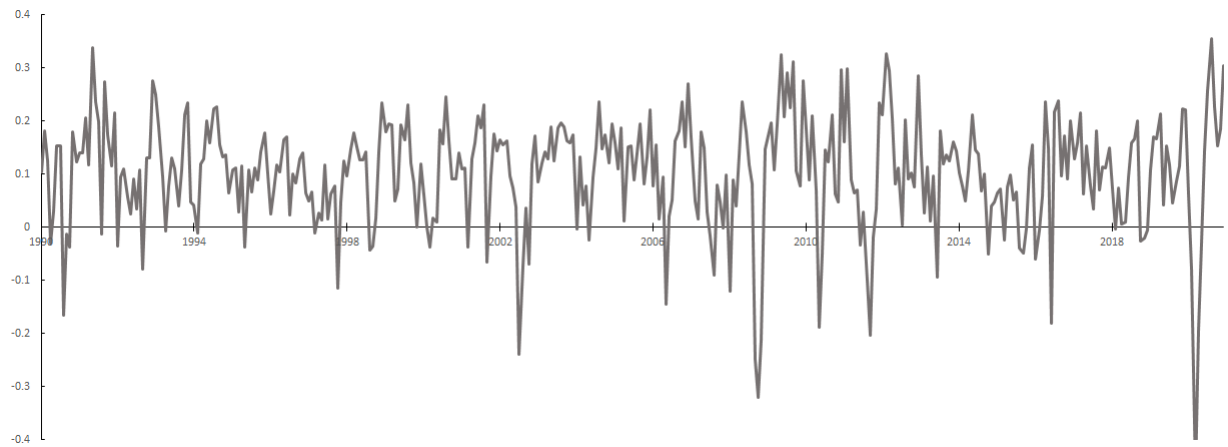
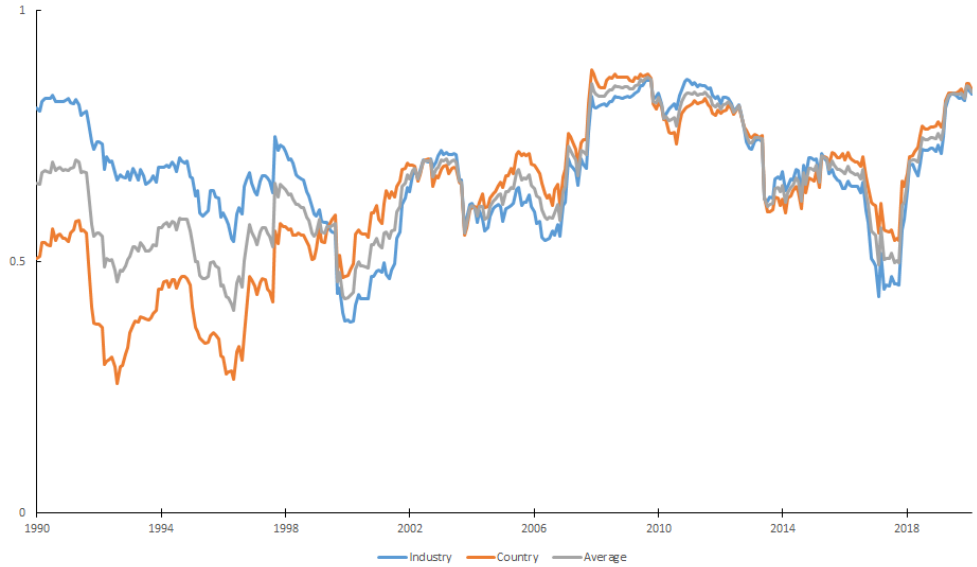
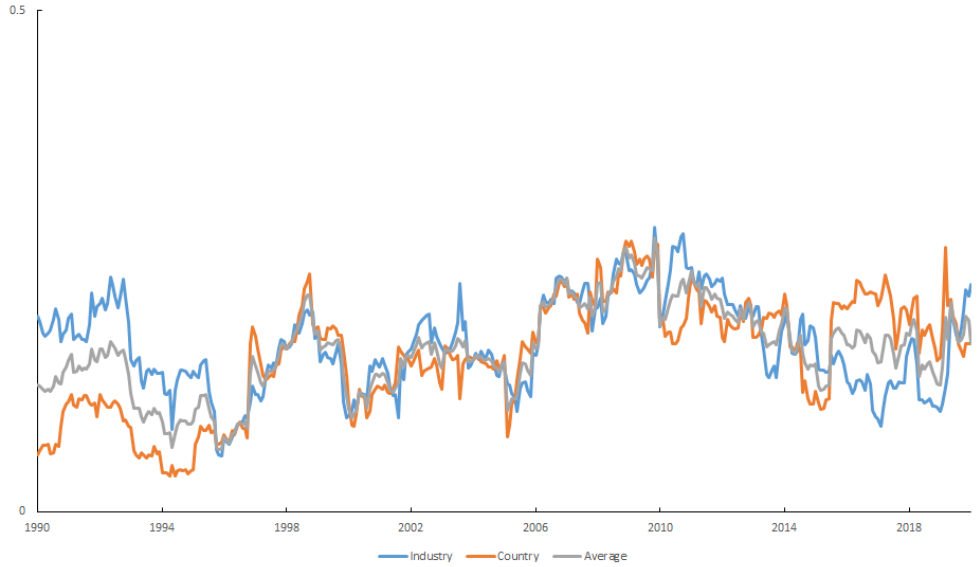


Figure 4.4: Correlations in international returns and conditional skewness

This figure displays the average correlation in monthly returns across countries (orange line) and across industries (blue line) and between countries and industries (grey line) calculated over rolling windows of 24 months from the aggregate DS country and industry indices summarized in Appendix 4A.7. Time span is January 1990 - December 2020



(a) Returns



(b) SK_{INT}

Figure 4.5: Skewness managed portfolio weights w_{count}^{SK} vs. w_{ind}^{SK}

This figure displays the time series of the monthly optimal portfolio weights related to the conditional skewness measure SK_{INT} for both countries (orange line) and industries (blue line). Time span is Jan. 1990 - Dec. 2020

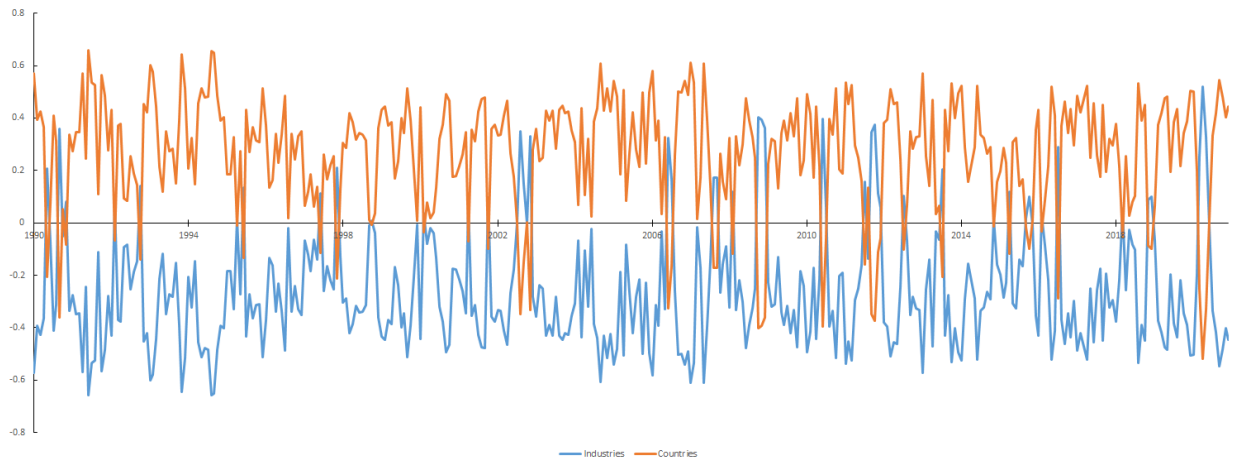


Figure 4.6: Skewness difference excluding one industry at a time

(Preliminary) This figure plots the difference between the skewness of the country portfolios diversified across industries minus the skewness of the industry portfolios diversified across countries for the bootstrapped portfolios with $N = 40$ stocks. Each row indicates the industry that has been excluded from the bootstrap. Time span of the sample is Jan. 1990 - Dec. 2020

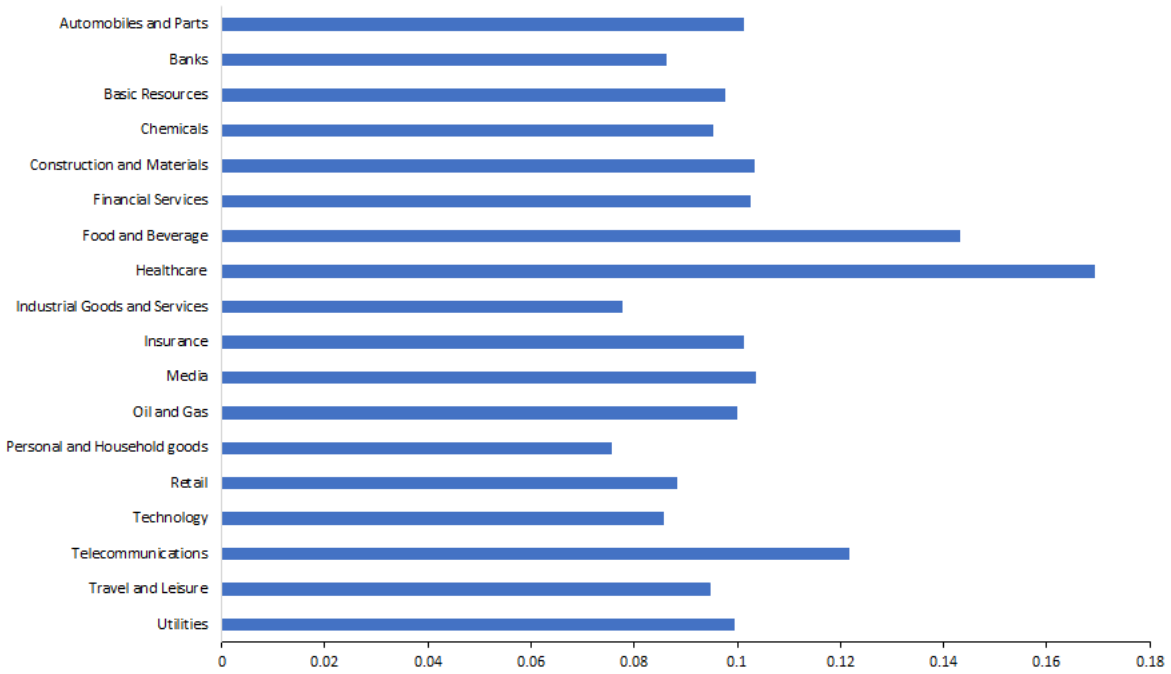


Table 4.1: Number of stocks by country and industry

This table presents the total number of stocks available in our international sample divided by country and industry. Time span is January, 1990 to December, 2020.

Coun/Ind	AUTO	BANK	BASI	CHEM	CONS	FINA	FOOD	HEAL	PERS	INDU	INSU	MEDI	OIL	RETA	TECH	TELE	TRAV	UTIL	Total
AUS	15	18	1058	31	69	183	114	194	262	24	68	202	58	97	191	43	78	35	2740
AUT	7	8	10	6	15	10	14	2	32	6	5	3	12	1	5	2	8	4	150
BEL	3	10	8	8	9	21	19	22	32	2	8	1	10	10	26	2	6	8	205
CAN	16	14	1557	39	48	358	68	146	250	18	67	661	58	78	201	27	57	50	3713
DEN	3	56	3	3	28	14	13	25	57	7	6	3	24	8	26	2	16	6	300
FRA	30	36	31	27	44	81	86	124	309	24	93	32	126	88	237	17	52	26	1463
GER	38	27	30	45	38	127	44	67	207	27	59	37	83	55	194	17	22	37	1154
HKG	35	24	99	42	165	164	90	99	318	9	69	45	308	125	187	20	120	35	1954
ITA	17	58	9	14	29	52	20	22	113	24	35	12	62	18	54	12	21	34	606
JPN	167	131	152	236	385	198	224	223	1146	32	177	35	413	522	651	25	255	39	5011
NED	1	11	5	11	12	11	15	11	65	5	10	6	18	17	36	8	3	2	247
NOR	2	44	15	4	9	18	26	22	110	7	12	90	14	9	52	5	17	4	460
SGP	7	7	41	34	73	38	66	41	271	5	15	42	76	47	89	5	51	10	918
KOR	64	29	81	87	99	93	61	55	188	14	20	13	129	28	58	6	19	17	1061
ESP	3	28	22	6	29	12	23	16	40	4	12	10	10	16	14	7	11	18	281
SWE	10	8	36	16	28	46	15	140	191	6	20	31	46	39	158	12	33	8	843
SUI	3	36	9	10	17	24	17	46	79	11	5	2	15	16	24	2	19	16	351
UK	14	16	165	55	64	205	83	164	530	57	170	141	159	164	247	30	174	38	2476
USA	81	1212	211	163	162	409	212	1399	1503	270	286	494	408	462	1395	152	344	215	9378
Total	516	1773	3542	837	1323	2064	1210	2818	5703	552	1137	1860	2029	1800	3845	394	1306	602	33311

Table 4.2: Summary Statistics by country and industry

This table reports summary statistics of our data by country (Panel A) and industry (Panel B). We report the first three moments of returns to the aggregate value-weighted (VW) indices constructed from the individual stock simple returns for each of the 19 countries in our sample. The last three columns report the average firm size within a country in Mn of US$, the average number of stocks per month within a country, and the proportion between the average market-cap of the country compared to the total average market cap of the world sample. The two bottom rows present the results of the first three moments of the indices aggregated across countries with equal-weights or with the average market-cap weights.

Panel A: Country indices

Country	Mean	Std. Dev.	Skewness	Average Firm Size (Mn US$)	Average Monthly # of stocks	Average Market Cap-Weight
Australia	0.94%	6.13%	-0.54	386.4	962	2.40%
Austria	0.62%	6.50%	-0.62	822.1	65	0.25%
Belgium	0.70%	5.59%	-0.82	1436.5	98	0.72%
Canada	0.89%	5.58%	-0.62	383.4	1303	3.22%
Denmark	1.02%	5.16%	-0.57	877.5	141	0.56%
France	0.83%	5.63%	-0.40	1326.9	611	4.66%
Germany	0.71%	5.79%	-0.41	1459.3	526	3.98%
Hong Kong	1.18%	6.65%	-0.05	1115.2	720	3.77%
Italy	0.58%	6.84%	-0.05	1425.9	210	1.71%
Japan	0.32%	5.66%	0.30	996.9	2873	12.90%
Netherlands	0.87%	5.63%	-0.79	3148.3	114	1.58%
Norway	0.92%	7.15%	-0.51	641.5	146	0.55%
Singapore	0.73%	6.44%	-0.10	358.0	376	0.77%
South Korea	0.85%	9.88%	1.03	860.5	533	1.97%
Spain	0.71%	6.50%	-0.09	2612.4	118	1.70%
Sweden	1.08%	7.10%	-0.15	564.3	267	1.10%
Switzerland	0.95%	4.70%	-0.43	3082.3	194	3.07%
United Kingdom	0.69%	4.81%	-0.30	1142.2	955	7.23%
United States	0.99%	4.36%	-0.59	2299.5	3614	47.89%
EW Average	0.82%	6.11%	-0.30			
VW Average	0.84%	5.14%	-0.36			

Panel B: Industry indices

Industry	Mean	Std. Dev.	Skewness	Average Firm Size (Mn US$)	Average Monthly # of stocks	Average Market Cap-Weight
Automobiles and Parts	0.74%	5.77%	0.18	1990.3	277	2.86%
Banks	0.60%	5.75%	-0.51	2271.1	781	10.38%
Basic Resources	0.66%	7.07%	-0.33	369.6	1334	2.81%
Chemicals	0.74%	5.25%	-0.36	1297.0	445	2.48%
Construction and Materials	0.53%	5.67%	-0.24	601.6	670	1.94%
Financial Services	0.78%	6.12%	-0.41	1015.6	758	4.03%
Food and Beverage	0.79%	3.58%	-0.43	1573.5	580	4.46%
Healthcare	0.99%	3.86%	-0.33	1559.9	1004	9.88%
Personal and Household goods	0.83%	4.05%	-0.33	1130.9	913	12.44%
Industrial Goods and Services	0.74%	5.10%	-0.55	909.4	2610	4.57%
Insurance	0.71%	5.09%	-0.70	3465.8	237	2.65%
Media	0.79%	5.24%	-0.40	1163.6	434	6.44%
Oil and Gas	0.72%	6.22%	-0.19	1512.8	659	6.01%
Retail	0.88%	4.11%	-0.19	1376.0	766	5.79%
Technology	1.16%	6.74%	-0.32	1499.0	1395	11.26%
Telecommunications	0.62%	4.75%	0.00	5826.4	131	5.04%
Travel and Leisure	0.56%	4.90%	-0.40	1096.3	532	2.84%
Utilities	0.67%	3.75%	-0.50	2803.2	298	4.14%
EW Average	0.75%	5.17%	-0.33			
VW Average	0.79%	5.17%	-0.36			

Table 4.3: Variance decomposition country and industry portfolios

This table presents the variance of the pure country (industry) components and the variance of the weighted sum of 18 (19) industry (country) effects of the excess value-weighted country (industry) index returns decomposed using the Heston and Rouwenhorst (1994) methodology. The top panel shows the decomposition of variance of Eq.4.6. The lower panel shows the decomposition of variance of Eq.4.7. The variance of each country k (industry j) is also presented as a ratio with respect to the excess country (industry) return $R_k^{vw} - \hat{\alpha}$ (respectively $R_j^{vw} - \hat{\alpha}$). Returns are monthly and U.S. dollar-denominated. The time span is Jan. 1990 - Dec. 2020.

	Pure country effect		Sum of 18 industry effects	
Country	Variance	Ratio relative to the market	Variance	Ratio relative to the market
Australia	13.254	0.855	1.399	0.090
Austria	18.016	0.856	1.745	0.083
Belgium	12.072	0.911	1.757	0.133
Canada	8.222	0.802	1.173	0.114
Denmark	12.191	1.014	1.225	0.102
France	9.013	1.033	0.151	0.017
Germany	9.777	0.976	0.452	0.045
Hong Kong	25.243	1.039	0.485	0.020
Italy	23.060	1.030	0.973	0.043
Japan	16.640	1.064	0.188	0.012
Netherlands	8.777	0.979	1.149	0.128
Norway	18.102	0.778	2.595	0.111
Singapore	19.797	1.031	0.590	0.031
South Korea	66.468	1.001	0.381	0.006
Spain	17.033	1.000	1.067	0.063
Sweden	16.666	0.906	0.860	0.047
Switzerland	7.328	0.782	1.766	0.189
United Kingdom	5.214	0.864	0.527	0.087
United States	3.873	1.012	0.148	0.039
EW average	16.355	0.944	0.981	0.072
VW average	7.451	0.987	0.387	0.048

	Sum of 19 country effects		Pure industry effect	
Industry	Variance	Ratio relative to the market	Variance	Ratio relative to the market
Automobiles and Parts	3.370	0.324	12.298	1.183
Banks	0.390	0.045	9.048	1.046
Basic Resources	0.639	0.031	17.843	0.860
Chemicals	0.427	0.082	4.929	0.945
Construction and Materials	1.605	0.221	5.047	0.696
Financial Services	0.793	0.118	5.613	0.834
Food and Beverage	0.324	0.039	7.824	0.932
Healthcare	0.805	0.091	7.804	0.881
Personal and Household goods	0.307	0.091	3.283	0.974
Industrial Goods and Services	0.154	0.084	1.703	0.934
Insurance	0.653	0.098	6.288	0.942
Media	0.743	0.127	4.961	0.848
Oil and Gas	1.165	0.064	17.608	0.973
Retail	0.244	0.046	4.704	0.898
Technology	0.496	0.031	16.128	1.002
Telecommunications	0.492	0.049	9.991	0.988
Travel and Leisure	0.575	0.103	5.115	0.914
Utilities	0.332	0.033	10.622	1.064
EW average	0.751	0.093	8.378	0.940
VW average	0.628	0.079	8.564	0.952

Table 4.4: Variance decomposition Pre- and Post- Financial Crisis

This table presents the variance of the pure country (industry) components and the variance of the weighted sum of 18 (19) industry (country) effects of the excess value-weighted country (industry) index returns decomposed using the Heston and Rouwenhorst (1994) methodology on the two sample periods before and after the Global Financial Crisis. The top panel shows the decomposition of variance of Eq.4.6. The lower panel shows the decomposition of variance of Eq. (4.7). The variance of each country k (industry j) is also presented as a ratio with respect to the excess country (industry) return $R_k^{vw} - \hat{\alpha}$ (respectively $R_j^{vw} - \hat{\alpha}$) as well as the ratio between the two ratios relative to the market. Returns are monthly and U.S. dollar-denominated.

	1990-2006					2009-2020				
	Pure country effect		Sum of 18 industry effects			Pure country effect		Sum of 18 industry effects		
Country	Variance	Ratio relative to the market	Variance	Ratio relative to the market	Ratio of the ratios	Variance	Ratio relative to the market	Variance	Ratio relative to the market	Ratio of the ratios
Australia	15.390	0.888	1.433	0.083	10.736	10.457	0.857	1.150	0.094	9.092
Austria	21.995	0.872	2.035	0.081	10.807	10.708	0.803	1.358	0.102	7.885
Belgium	13.026	0.891	2.194	0.150	5.938	8.147	0.906	1.023	0.114	7.965
Canada	10.096	0.892	0.751	0.066	13.436	5.190	0.674	1.535	0.199	3.382
Denmark	13.464	1.003	1.259	0.094	10.697	9.449	1.000	1.216	0.129	7.771
France	10.262	1.010	0.119	0.012	86.363	7.294	1.076	0.181	0.027	40.305
Germany	12.651	1.013	0.487	0.039	25.962	5.480	0.855	0.341	0.053	16.070
Hong Kong	34.644	1.036	0.658	0.020	52.688	11.370	1.042	0.168	0.015	67.734
Italy	28.309	1.083	1.103	0.042	25.657	16.770	0.915	0.729	0.040	22.996
Japan	21.674	1.050	0.173	0.008	125.000	9.294	1.098	0.186	0.022	49.975
Netherlands	11.075	1.066	1.402	0.135	7.898	4.968	0.890	0.568	0.102	8.744
Norway	21.337	0.861	2.295	0.093	9.299	10.707	0.648	2.341	0.142	4.575
Singapore	25.777	1.049	0.519	0.021	49.647	10.542	0.960	0.665	0.061	15.847
South Korea	100.656	1.011	0.482	0.005	209.038	15.946	0.916	0.241	0.014	66.214
Spain	16.071	1.068	1.315	0.087	12.221	17.844	0.919	0.661	0.034	27.006
Sweden	22.814	0.896	1.340	0.053	17.030	7.553	0.958	0.190	0.024	39.797
Switzerland	9.681	0.792	2.395	0.196	4.042	3.736	0.745	0.758	0.151	4.929
United Kingdom	6.528	0.865	0.715	0.095	9.134	3.196	0.883	0.247	0.068	12.922
United States	5.612	1.023	0.208	0.038	26.932	1.226	0.927	0.063	0.047	19.620
EW average	21.109	0.967	1.099	0.069	13.951	8.941	0.899	0.717	0.076	11.876
VW average	6.468	1.002	0.302	0.046	21.998	4.832	0.933	0.281	0.055	16.994

	Sum of 19 country effects		Pure industry effect			Sum of 19 country effects		Pure industry effect		
Industry	Variance	Ratio relative to the market	Variance	Ratio relative to the market	Ratio of the ratios	Variance	Ratio relative to the market	Variance	Ratio relative to the market	Ratio of the ratios
Automobiles and Parts	4.585	0.551	9.764	1.173	2.130	1.426	0.115	14.000	1.130	9.815
Banks	0.473	0.076	6.999	1.122	14.788	0.254	0.023	10.459	0.964	41.168
Basic Resources	0.584	0.035	14.677	0.872	25.122	0.683	0.031	19.060	0.866	27.890
Chemicals	0.436	0.068	6.259	0.970	14.362	0.361	0.115	2.875	0.917	7.961
Construction and Materials	2.315	0.254	6.229	0.682	2.690	0.526	0.140	3.038	0.807	5.778
Financial Services	1.239	0.141	6.962	0.794	5.621	0.149	0.044	3.275	0.968	21.967
Food and Beverage	0.494	0.048	9.358	0.916	18.960	0.082	0.014	5.470	0.966	66.826
Healthcare	1.254	0.125	8.529	0.851	6.799	0.127	0.019	6.354	0.963	50.149
Personal and Household Goods	0.403	0.107	3.721	0.988	9.244	0.176	0.068	2.452	0.953	13.930
Industrial Goods and Services	0.226	0.112	1.718	0.849	7.594	0.049	0.035	1.492	1.063	30.725
Insurance	1.077	0.131	7.679	0.932	7.133	0.067	0.017	3.853	0.962	57.543
Media	1.174	0.159	6.073	0.824	5.175	0.133	0.035	3.387	0.899	25.400
Oil and Gas	1.826	0.103	17.909	1.009	9.809	0.190	0.012	15.281	0.930	80.453
Retail	0.336	0.056	5.322	0.893	15.855	0.097	0.024	3.674	0.918	38.031
Technology	0.487	0.020	24.392	1.009	50.096	0.423	0.088	4.545	0.941	10.737
Telecommunications	0.488	0.044	11.191	1.009	22.928	0.408	0.051	7.568	0.944	18.556
Travel and Leisure	0.799	0.136	5.082	0.867	6.358	0.245	0.048	5.029	0.995	20.534
Utilities	0.262	0.025	11.359	1.068	43.306	0.372	0.041	9.701	1.064	26.093
EW average	1.025	0.122	9.068	0.935	7.684	0.320	0.051	6.751	0.958	18.736
VW average	0.833	0.101	9.528	0.959	9.496	0.268	0.047	6.347	0.957	20.276

Table 4.5: Indices corrected for country/industry composition

This table presents the country indices corrected for industry composition $\hat{\alpha} + \hat{\gamma}_k$ (upper panel) and the industry indices corrected for country composition $\hat{\alpha} + \hat{\beta}_j$ (lower panel) using the Heston and Rouwenhorst (1994) decomposition. Reported are the monthly mean, standard deviation and skewness for the value-weighted corrected indices. The time span of the sample is Jan. 1990 - Dec. 2020.

Panel A: Country indices corrected for industry composition ($\hat{\alpha} + \hat{\gamma}_k$)

Country	Mean	Std. Dev	Skewness
Australia	1.03%	5.80%	-0.45
Austria	0.79%	6.33%	-0.66
Belgium	0.73%	5.88%	-0.72
Canada	0.98%	5.09%	-0.61
Denmark	1.01%	5.59%	-0.52
France	0.85%	5.81%	-0.38
Germany	0.68%	5.82%	-0.43
Hong Kong	1.22%	6.83%	-0.04
Italy	0.66%	6.97%	-0.01
Japan	0.29%	5.72%	0.32
Netherlands	0.88%	5.68%	-0.64
Norway	1.05%	6.72%	-0.55
Singapore	0.79%	6.52%	-0.12
South Korea	0.84%	9.94%	1.06
Spain	0.82%	6.74%	-0.07
Sweden	1.06%	6.76%	-0.17
Switzerland	0.94%	5.02%	-0.46
United Kingdom	0.76%	4.86%	-0.30
United States	0.96%	4.34%	-0.61
EW Average	0.86%	6.13%	-0.28
VW Average	0.84%	5.15%	-0.36

Panel B: Industry indices corrected for country composition ($\hat{\alpha} + \hat{\beta}_j$)

Industry	Mean	Std. Dev.	Skewness
Automobiles and Parts	1.00%	5.95%	0.11
Banks	0.64%	5.63%	-0.53
Basic Resources	0.65%	6.78%	-0.30
Chemicals	0.83%	5.18%	-0.37
Construction and Materials	0.68%	5.20%	-0.45
Financial Services	0.85%	5.93%	-0.50
Food and Beverage	0.73%	3.67%	-0.35
Healthcare	0.89%	4.04%	-0.26
Personal and Household goods	0.90%	4.01%	-0.43
Industrial Goods and Services	0.79%	5.10%	-0.62
Insurance	0.68%	5.15%	-0.61
Media	0.70%	5.36%	-0.37
Oil and Gas	0.57%	6.30%	-0.08
Retail	0.84%	4.21%	-0.20
Technology	1.11%	6.88%	-0.30
Telecommunications	0.62%	4.80%	0.10
Travel and Leisure	0.64%	4.90%	-0.52
Utilities	0.68%	3.69%	-0.39
EW Average	0.77%	5.15%	-0.34
VW Average	0.80%	5.12%	-0.34

Table 4.6: Skewness decomposition of country and industry indices

This table reports for the value-weighted excess country indices $R^k_{vw} - \hat{\alpha}$ the unadjusted skewness of the pure country effects ϕ_{CCC} and of the weighted sum of the 18 industry effects ϕ_{III} (Panel A) and for the value-weighted excess industry indices $R^j_{vw} - \hat{\alpha}$ the unadjusted skewness of the pure industry effects ϕ_{III} and of the weighted sum of 19 country effects ϕ_{CCC} (Panel B). The second columns report ψ_h, i.e. the ratio between the absolute deviation from the total unadjusted skew ϵ_h over the sum of absolute errors $\sum_{h=1}^{8} \epsilon_h$. At the end of the panel are reported the equally and market cap-based weighted average and the median across countries (Panel A) or industries (Panel B). The Coskewness matrix is estimated with Boudt et al. (2020)'s shrinkage approach.

	Pure country effect		Sum of 18 industry effects	
Country	Unadj Skew	Ratio relative to sum of skew errors	Unadj Skew	Ratio relative to sum of skew errors
Australia	-29.30	4.08%	-0.76	14.02%
Austria	-24.87	0.22%	-0.39	14.06%
Belgium	-38.22	0.25%	0.67	14.47%
Canada	-5.85	9.25%	-1.15	13.29%
Denmark	-14.68	2.16%	0.81	14.55%
France	-3.51	0.04%	0.01	14.32%
Germany	7.45	13.68%	-0.08	10.62%
Hong Kong	-49.19	0.76%	-0.33	14.20%
Italy	-11.84	0.35%	-0.29	13.94%
Japan	10.16	0.00%	0.00	14.29%
Netherlands	-16.24	0.35%	0.39	14.53%
Norway	-48.98	3.34%	-1.13	14.03%
Singapore	-37.35	0.45%	-0.47	13.97%
South Korea	43.98	16.73%	0.08	9.46%
Spain	-10.74	0.46%	-0.35	13.83%
Sweden	-10.20	0.73%	-0.55	13.56%
Switzerland	-6.71	2.09%	0.89	15.78%
United Kingdom	8.15	0.32%	0.19	13.97%
United States	2.05	0.04%	-0.01	14.32%
EW average	-12.42	2.91%	-0.13	13.75%
VW average	-0.80	1.47%	-0.04	14.02%
Median	-10.74	0.46%	-0.08	14.03%

	Sum of 19 country effects		Pure industry effect	
Industry	Unadj Skew	Ratio relative to sum of skew errors	Unadj Skew	Ratio relative to sum of skew errors
Automobiles and Parts	1.29	14.47%	-19.37	3.22%
Banks	-0.09	14.19%	-12.88	0.10%
Basic Resources	-0.13	14.24%	-35.53	2.56%
Chemicals	0.04	14.05%	2.35	0.24%
Construction and Materials	0.04	14.52%	-1.83	0.32%
Financial Services	-0.27	13.26%	-3.57	1.02%
Food and Beverage	0.08	13.24%	5.99	2.88%
Healthcare	0.13	12.55%	0.72	4.34%
Personal and Household goods	-0.05	14.54%	2.38	3.28%
Industrial Goods and Services	0.01	14.21%	-1.03	0.87%
Insurance	0.57	9.21%	1.03	5.07%
Media	0.57	10.54%	1.60	3.75%
Oil and Gas	0.64	14.64%	-17.16	4.78%
Retail	0.05	12.09%	1.43	5.53%
Technology	0.06	14.30%	-39.86	0.02%
Telecommunications	-0.03	14.31%	15.07	0.03%
Travel and Leisure	0.10	14.39%	-9.19	0.15%
Utilities	-0.07	14.35%	12.15	0.08%
EW average	0.16	13.50%	-5.43	2.12%
VW average	0.12	13.57%	-6.72	2.23%
Median	0.04	14.23%	-0.15	1.79%

Table 4.7: Bootstrap results

This table shows the results of the stratified bootstrap with 1'000 VW bootstraped portfolios for each country or industry in the sample. Panel A shows the diversification benefits of an investor that invests in stocks across industries in the same country. Panel B shows the diversification benefits of an investor that invests in stocks across countries within the same industry. Reported are for each portfolio size N the monthly mean μ (%) , variance σ^2 (%), skewness, certainty equivalent (%) for a power utility investor with $\gamma = 5$, four-moment VaR ($) at the 95 confidence level for an arbitrary 100$ investment and the average number of stocks in a portfolio (slightly lower than N due to possible delistings). We aggregate the final results by using the VW weights equal to the average aggregate market cap of the countries (Panel A) or the industries (Panel B). Each column reports the results for a portfolio made of N stocks. For $N = 1$ we use a bootstrap approach with unconditional random sampling in order to have a common benchmark for all portfolios.

Panel A: Diversification across industries within the same country

Statistics	N=1	N=5	N=10	N=20	N=40
μ (%)	1.16	0.95	0.91	0.88	0.86
σ^2 (%)	2.81	0.74	0.57	0.46	0.40
SK	2.17	0.33	0.13	-0.02	-0.08
CE (%)	-8.28	-1.26	-0.78	-0.43	-0.19
VaR95 ($)	14.43	18.30	16.80	15.44	14.26
Avg. Stocks	0.99	4.92	9.84	19.68	39.35

Panel B: Diversification across countries within the same industry

Statistics	N=1	N=5	N=10	N=20	N=40
μ (%)	1.16	0.87	0.85	0.82	0.78
σ^2 (%)	2.81	0.73	0.58	0.48	0.40
SK	2.17	0.28	0.05	-0.11	-0.18
CE (%)	-8.28	-1.47	-1.01	-0.64	-0.33
VaR95 ($)	14.43	18.56	17.32	16.20	14.87
Avg. Stocks	0.99	4.93	9.86	19.72	39.43

Table 4.8: Robust conditional skewness SK_{INT}, summary statistics

This table reports summary statistics of the end-of month MIDAS Conditional Skewness measure SK_{INT} estimated on the aggregate DS indices summarized in Appendix 4A.7 and used in the dynamic portfolio allocation problem of section 4.4.2. Reported are the mean, standard deviation, minimum and maximum for each country and industry in our sample. Time span is January 1990 - December 2020.

Country	Mean	Std	Min	Max
Australia	-0.443	0.208	-1.073	0.510
Austria	-0.048	0.317	-1.211	0.785
Belgium	-0.440	0.224	-1.281	0.208
Canada	-0.518	0.109	-0.913	-0.212
Denmark	-0.296	0.207	-1.135	0.205
France	-0.402	0.173	-0.954	0.157
Germany	-0.515	0.089	-0.733	-0.231
Hong Kong	-0.241	0.091	-0.438	0.047
Italy	-0.069	0.080	-0.422	0.091
Japan	-0.106	0.203	-0.636	0.594
Netherlands	-0.640	0.229	-1.412	0.188
Norway	-0.362	0.236	-1.100	0.179
Singapore	-0.435	0.251	-0.981	0.184
South Korea	0.051	0.267	-0.660	0.918
Spain	-0.203	0.050	-0.313	-0.014
Sweden	-0.274	0.200	-1.065	0.231
Switzerland	-0.398	0.119	-0.792	-0.094
United Kingdom	-0.345	0.162	-1.233	-0.024
United States	-0.711	0.159	-1.370	-0.334
EW Average	-0.337	0.178	-0.933	0.178
VW Average	-0.494	0.161	-1.088	-0.051

Industry	Mean	Std	Min	Max
Automobiles and Parts	-0.244	0.240	-0.919	0.590
Banks	-0.392	0.255	-1.137	0.420
Basic Resources	-0.268	0.258	-1.312	0.169
Chemicals	-0.557	0.175	-1.068	0.075
Construction and Materials	-0.424	0.235	-1.140	0.475
Financial Services	-0.534	0.240	-0.961	0.413
Food and Beverages	-0.576	0.349	-1.692	1.032
Healthcare	-0.479	0.308	-1.312	1.139
Industrial Goods and Services	-0.667	0.198	-1.433	0.037
Insurance	-0.481	0.080	-0.773	-0.236
Media	-0.575	0.154	-1.001	-0.193
Oil and Gas	-0.314	0.135	-0.713	0.414
Personal and Household goods	-0.532	0.100	-0.869	-0.191
Retail	-0.381	0.077	-0.624	-0.200
Technology	-0.336	0.191	-0.855	0.424
Telecommunications	-0.154	0.171	-0.635	0.610
Travel and Leisure	-0.517	0.223	-1.384	0.251
Utilities	-0.358	0.162	-0.898	0.015
EW Average	-0.433	0.197	-1.040	0.291
VW Average	-0.441	0.200	-1.053	0.330

Table 4.9: Portfolio allocation, baseline results

This table reports the results of the dynamic portfolio allocation problem between countries and industries at the monthly horizon over the entire sample period Jan. 1990 - Dec. 2020. Column (1) VW is a value-weighted portfolio across countries and industries. Column (2) *bench* is a benchmark portfolio for a power utility investor with relative risk aversion $\gamma = 5$ in which the investor conditions the portfolio weights on index-specific information only: MIDAS conditional volatility (Vol), Momentum (Mom), log Dividend Yield (DY), log Book-to-Price ratio (BP), log Price-Earnings ratio (PE) and log Price-to-Cash Flow ratio (PC). In Column (3) the investor conditions the portfolio on both the above-specified index-specific information as well as on the MIDAS robust integrated conditional skewness SK_{INT}. For each variable we report both the optimal loadings λ as well as their p-values in parentheses. We also report detailed results for the Optimal Portfolios. $\overline{w}_{count}$, $\overline{w}^{SK}_{count}$ and $se(\overline{w}^{SK}_{count})$ are the average weights on countries, the average weights on countries related to conditional skewness and its standard error respectively. $\overline{r}_p$, σ_p, $S(r_p)$, $CE(r_p)$ and $\alpha(r_p)$ are the annualized return, standard deviation, skewness, certainty equivalent and α with respect to the benchmark of the optimized portfolio p. $\overline{r}_{count}$, $\overline{r}_{ind}$ and $\rho(r_{count}, r_{ind})$ are the average return and their correlation of the country and industry returns of the optimal portfolio p. The last three rows are similar but for the Skewness managed parts SK.

	(1) VW	(2) *bench*	(3) SK
SK_{INT}			2.520
			(0.069)
Vol		-1.324	-1.744
		(0.223)	(0.130)
Mom		2.592	2.504
		(0.002)	(0.003)
DY		-0.473	-0.021
		(0.801)	(0.991)
BP		1.239	2.223
		(0.571)	(0.325)
PE		-2.835	-3.183
		(0.143)	(0.103)
PC		-0.922	-1.232
		(0.611)	(0.505)
$p - val$		0.006	0.001
Optimal Portfolio Properties			
$\overline{w}_{count}$ (%)	53.019	51.023	66.547
$\overline{w}^{SK}_{count}$ (%)			26.451
$se(\overline{w}^{SK}_{count})$			14.551
$\overline{r}_p$	0.089	0.165	0.184
σ_p	0.156	0.173	0.181
$S(r_p)$	-0.638	-0.249	-0.138
$CE(r_p)$	0.024	0.088	0.101
$\alpha(r_p)$ *wrt bench*			0.025
$\overline{r}_{count}$	0.047	0.086	0.116
$\overline{r}_{ind}$	0.042	0.079	0.068
$\rho(r_{count}, r_{ind})$	0.998	0.110	-0.092
$\overline{r}^{SK}_{count}$			0.042
$\overline{r}^{SK}_{ind}$			-0.023
$\rho(r^{SK}_{count}, r^{SK}_{ind})$			-0.477

Table 4.10: Portfolio allocation results, robustness analysis

This table reports the results of the dynamic portfolio allocation problem between countries and industries at the monthly horizon over the entire sample period Jan. 1990 - Dec. 2020. Panel reports the results for different levels of relative risk aversion γ. Panel B reports the results for two different estimates of transaction costs and for a power utility investor with relative risk aversion $\gamma = 5$. Columns (1) and (2) under *Constant* refer to a constant trasaction cost estimate of $c_{t-1,i} = 0.10\%$. Columns (3) and (4) under *Linear* refer to a linear trasaction cost estimate based on the inverse of the market capitalization of the index according to $c_{t-1,i} = 0.0040 - 0.0030 \times MV_{t-1,i}$ similarly to Ghysels et al. (2016b). The investor conditions the portfolio weights on index-specific information (MIDAS conditional volatility (Vol), Momentum (Mom), log Dividiend Yield (DY), log Book-to-Price ratio (BP), log Price-Earnings ratio (PE) and log Price-to-Cash Flow ratio (PC)) in the benchmarks (1), (3), (5) and (7) as well as on the MIDAS robust integrated conditional skewness SK_{INT} in specifications (2), (4), (6) and (8). For each variable we report both the optimal loadings λ as well as their p-values in parentheses. We also report detailed results for the Optimal Portfolios. $\overline{w}_{count}$, $\overline{w}^{SK}_{count}$ and $se(\overline{w}^{SK}_{count})$ are the average weights on countries, the average weights on countries related to conditional skewness and its standard error respectively. $\overline{r}_p$, σ_p, $S(r_p)$, $CE(r_p)$ and $\alpha(r_p)$ are the annualized return, standard deviation, skewness, certainty equivalent and α with respect to the benchmark of the optimized portfolio p. $\overline{r}count$, $\overline{r}ind$ and $\rho(r_{count}, r_{ind})$ are the average return and their correlation of the country and industry returns of the optimal portfolio p. The last three rows are similar but for the Skewness managed parts SK.

	Panel A: Different γ				Panel B: Transaction costs			
	$\gamma = 3$		$\gamma = 10$		Constant		Linear	
	(1) *bench*	(2)	(3) *bench*	(4)	(5) *bench*	(6)	(7) *bench*	(8)
SK_{INT}		3.919		1.518		1.428		1.487
		(0.086)		(0.035)		(0.293)		(0.274)
Vol	-1.220	-1.988	-1.291	-1.443	-1.164	-1.434	-1.193	-1.412
	(0.495)	(0.285)	(0.029)	(0.022)	(0.280)	(0.205)	(0.270)	(0.213)
Mom	4.058	3.998	1.484	1.363	2.356	2.370	2.388	2.407
	(0.004)	(0.005)	(0.001)	(0.002)	(0.005)	(0.005)	(0.004)	(0.004)
DY	-1.115	-0.523	0.049	0.448	-0.274	-0.049	-0.281	0.002
	(0.717)	(0.866)	(0.962)	(0.660)	(0.883)	(0.979)	(0.880)	(0.999)
BP	1.304	2.826	1.341	1.942	1.333	1.800	1.302	1.854
	(0.719)	(0.452)	(0.245)	(0.099)	(0.541)	(0.422)	(0.551)	(0.409)
PE	-3.870	-4.396	-2.064	-2.295	-2.660	-2.791	-2.676	-2.802
	(0.223)	(0.170)	(0.050)	(0.029)	(0.168)	(0.150)	(0.166)	(0.148)
PC	-1.806	-2.375	-0.220	-0.315	-0.843	-1.052	-0.824	-1.039
	(0.541)	(0.429)	(0.826)	(0.758)	(0.641)	(0.567)	(0.649)	(0.572)
$p - val$	0.043	0.008	0.000	0.000	0.007	0.005	0.006	0.001
Optimal Portfolio Properties								
$\overline{w}_{count}$ (%)	75.033	96.166	33.983	46.217	52.336	60.755	51.868	61.800
$\overline{w}^{SK}_{count}$ (%)		41.137		15.933		14.989		15.615
$se(\overline{w}^{SK}_{count})$		23.926		7.573		14.248		14.268
$\overline{r}_p$	0.209	0.241	0.132	0.142	0.149	0.157	0.151	0.159
σ_p	0.233	0.254	0.142	0.141	0.166	0.169	0.167	0.170
$S(r_p)$	0.020	0.278	-0.517	-0.496	-0.316	-0.240	-0.310	-0.227
$CE(r_p)$	0.128	0.146	0.021	0.032	0.078	0.084	0.079	0.085
$\alpha(r_p)$ *wrt bench*		0.034		0.017		0.010		0.010
$\overline{r}_{count}$	0.135	0.179	0.050	0.070	0.084	0.101	0.084	0.103
$\overline{r}_{ind}$	0.074	0.062	0.082	0.072	0.075	0.070	0.076	0.069
$\rho(r_{count}, r_{ind})$	-0.055	-0.267	0.261	0.217	0.169	0.049	0.162	0.041
$\overline{r}^{SK}_{count}$		0.065		0.025		0.024		0.025
$\overline{r}^{SK}_{ind}$		-0.035		-0.014		-0.013		-0.013
$\rho(r^{SK}_{count}, r^{SK}_{ind})$		-0.477		-0.477		-0.477		-0.477

Appendix 4.A Data cleaning and filters

We first identify equities which are both primary quoted and major securities and we only focus on stocks that are listed on the countries' major exchanges, where we define as the major exchange the one in which the majority of the stocks are traded. For few countries in the sample we have multiple major exchanges (Deutsche Borse and Xetra for Germany, Tokyo and Osaka for Japan, NYSE, Nasdaq and Amex for the United States). We also manually check and remove all stocks traded in foreign exchanges and we focus only on stocks that are quoted in local currency.

We eliminate stocks with missing stock prices or missing market capitalization and we winsorize the left tail of the price to book ratio to zero. To be included in the sample, we require a stock to have a valid price to book ratio and have at least one year of observations available.

We calculate monthly US $ total simple returns and we winsorize returns at the 99.9^{th} percentile within a country. As common practice in the literature (Ince and Porter, 2006; Griffin et al., 2010; Lee, 2011), to reduce the impact of errors in the data we control for extreme returns that are reversed the following day. More specifically, if the monthly returns r_t or r_{t-1} are greater then 300% and $(1 + r_t)(1 + r_{t-1}) - 1 < 50\%$ then we set both r_t and r_{t-1} to missing. To mitigate the impact of very small stocks that trade infrequently, we filter penny stocks by removing stocks whose price falls in the lowest 10th percentile in a given year in a given country.

Datastream repeats the last stale value when a company ceases to exist, however this stale value converted in US$ can vary due to exchange rate fluctuations, potentially misleading the analysis. To this end, we control with the local currency denominated return that once a firm stops trading or gets delisted is excluded from the sample from that point onwards.

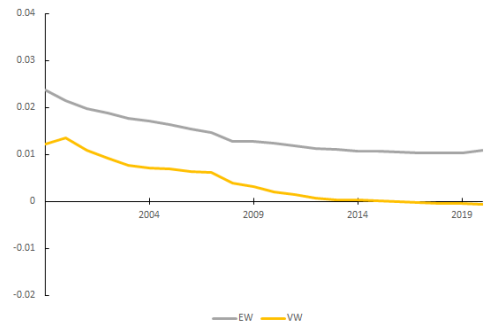
The screening of common ordinary stocks is far from being a straightforward task in Datastream due to the lack of a separate specific security-type information. The only way to extract common stocks from the constituent lists is to rely on text-specific filters applied to

the name field of the security (Ince and Porter, 2006; Griffin et al., 2010). To this end, we clean the data by following the same multistage filtering process described in Griffin et al. (2010), which includes both global filters as well as country-specific filters. This procedure allows us to eliminate all non-common ordinary stocks such as preferred stock, warrants, unit or investment trusts, mutual funds, unit trusts, certificates, notes and rights.

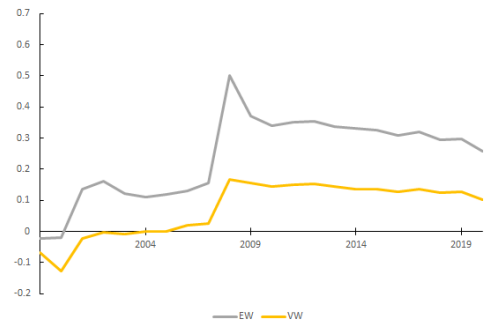
Appendix 4.B Additional Tables and Figures

Figure 4A.1: Expanding sample bootstrap

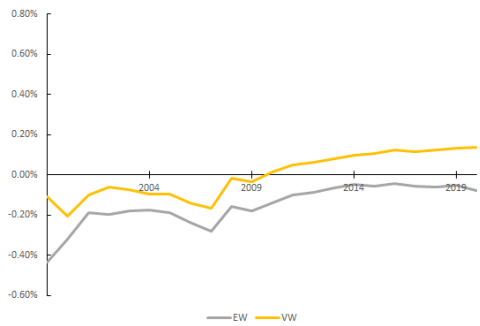
This figure shows the difference between the variance (4A.1a), skewness (4A.1b), CE (4A.1c), VaR95 (4A.1d) of the country portfolios diversified across industries minus the variance, skewness, CE, VaR95 of the industry portfolios diversified across countries for the bootstrapped portfolios with $N = 40$ stocks. The yellow (grey) line refers to the VW (EW) bootstrapped portfolios. The first sample is January 1990 - December 1999 and then we add one year of data in an expanding fashion until the end of the sample in December 2020.



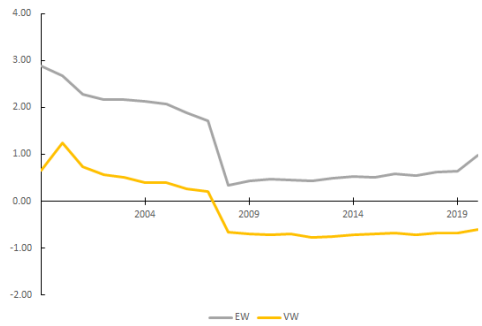
(a) Variance difference



(b) Skewness difference



(c) CE difference



(d) VaR95 difference

Table 4A.1: Summary Statistics EW indices

This table reports summary statistics of our data by country (Panel A) and industry (Panel B). We report the first three moments of returns to the aggregate equally-weighted (EW) indices constructed from the individual stock simple returns for each of the 19 countries in our sample. The last three columns report the average firm size within a country in Mn of US$, the average number of stocks per month within a country, and the proportion between the average market-cap of the country compared to the total average market cap of the world sample. The two bottom rows present the results of the first three moments of the indices aggregated across countries with equal-weights or with the average market-cap weights.

Panel A: Country indices

Country	Mean	Std. Dev.	Skewness
Australia	1.47%	7.70%	-0.23
Austria	0.76%	5.39%	-0.33
Belgium	0.81%	4.87%	-0.39
Canada	2.01%	7.49%	-0.20
Denmark	0.92%	4.89%	-0.19
France	1.05%	5.16%	-0.38
Germany	0.81%	5.29%	-0.28
Hong Kong	1.34%	8.14%	0.23
Italy	0.49%	6.59%	-0.03
Japan	0.59%	6.38%	0.42
Netherlands	0.96%	5.70%	-0.47
Norway	1.10%	6.95%	-0.33
Singapore	1.06%	8.14%	0.99
South Korea	1.25%	10.40%	0.73
Spain	0.77%	5.86%	-0.18
Sweden	1.23%	7.08%	-0.09
Switzerland	0.92%	4.72%	-0.54
United Kingdom	0.88%	5.64%	-0.34
United States	1.49%	5.33%	-0.46
EW Average	1.05%	6.41%	-0.11
VW Average	1.21%	5.87%	-0.24

Panel B: Industry indices

Industry	Mean	Std. Dev.	Skewness
Automobiles and Parts	0.98%	5.61%	-0.12
Banks	0.96%	3.68%	-0.99
Basic Resources	1.68%	8.01%	-0.04
Chemicals	1.02%	5.15%	-0.18
Construction and Materials	0.87%	5.14%	-0.13
Financial Services	1.22%	5.06%	-0.59
Food and Beverage	0.90%	3.67%	-0.35
Healthcare	1.55%	5.60%	0.05
Personal and Household goods	0.93%	4.52%	-0.43
Industrial Goods and Services	1.07%	4.91%	-0.53
Insurance	1.05%	4.19%	-0.84
Media	0.97%	5.22%	-0.56
Oil and Gas	1.42%	7.34%	-0.38
Retail	1.01%	4.16%	-0.28
Technology	1.57%	6.79%	-0.08
Telecommunications	1.45%	5.92%	-0.13
Travel and Leisure	0.92%	4.41%	-0.59
Utilities	1.01%	3.43%	-0.88
EW Average	1.14%	5.16%	-0.39
VW Average	1.19%	5.17%	-0.40

Table 4A.2: Variance decomposition country and industry portfolios, EW indices

This table presents the variance of the pure country (industry) components and the variance of the weighted sum of 18 (19) industry (country) effects of the excess equally-weighted country (industry) index returns decomposed using the Heston and Rouwenhorst (1994) methodology. The top panel shows the decomposition of variance of Eq.4.4. The lower panel shows the decomposition of variance of Eq.4.5. The variance of each country k (industry j) is also presented as a ratio with respect to the excess country (industry) return $R_k^{ew} - \hat{\alpha}$ (respectively $R_j^{ew} - \hat{\alpha}$). Returns are monthly and U.S. dollar-denominated. The time span is Jan. 1990 - Dec. 2020.

	Pure country effect		Sum of 18 industry effects	
Country	Variance	Ratio relative to the market	Variance	Ratio relative to the market
Australia	18.812	0.859	1.110	0.051
Austria	15.533	0.901	0.445	0.026
Belgium	9.867	0.917	0.254	0.024
Canada	12.817	0.645	2.028	0.102
Denmark	11.456	0.889	0.799	0.062
France	9.636	0.987	0.191	0.020
Germany	9.592	0.951	0.189	0.019
Hong Kong	41.340	1.013	0.108	0.003
Italy	20.700	0.981	0.536	0.025
Japan	22.526	0.968	0.178	0.008
Netherlands	10.282	1.001	0.213	0.021
Norway	17.074	0.930	0.379	0.021
Singapore	35.293	1.001	0.074	0.002
South Korea	71.078	1.002	0.129	0.002
Spain	14.711	0.931	0.509	0.032
Sweden	19.032	0.946	0.384	0.019
Switzerland	8.391	0.902	0.358	0.038
United Kingdom	9.023	1.003	0.051	0.006
United States	8.078	0.912	0.241	0.027
EW average	19.223	0.934	0.430	0.027
VW average	8.758	0.930	0.172	0.024

	Sum of 19 country effects		Pure industry effect	
Industry	Variance	Ratio relative to the market	Variance	Ratio relative to the market
Automobiles and Parts	3.279	0.581	3.973	0.703
Banks	1.805	0.170	8.483	0.798
Basic Resources	2.830	0.143	10.245	0.518
Chemicals	2.142	0.547	1.540	0.393
Construction and Materials	2.239	0.416	2.421	0.450
Financial Services	0.443	0.276	1.430	0.892
Food and Beverage	0.402	0.093	3.326	0.770
Healthcare	0.902	0.119	5.924	0.781
Personal and Household goods	0.644	0.318	1.268	0.626
Industrial Goods and Services	0.236	0.289	0.456	0.558
Insurance	1.506	0.195	6.284	0.812
Media	0.963	0.244	2.683	0.678
Oil and Gas	2.492	0.141	14.543	0.821
Retail	0.637	0.197	2.078	0.642
Technology	0.415	0.032	11.571	0.904
Telecommunications	1.832	0.144	10.252	0.808
Travel and Leisure	0.368	0.116	2.717	0.858
Utilities	1.011	0.127	7.833	0.981
EW average	1.341	0.230	5.390	0.722
VW average	1.153	0.200	5.891	0.746

Table 4A.3: EW Indices corrected for country/industry composition

This table presents the country indices corrected for industry composition $\hat{\alpha}+\hat{\gamma}_k$ (upper panel) and the industry indices corrected for country composition $\hat{\alpha}+\hat{\beta}_j$ (lower panel) using the Heston and Rouwenhorst (1994) decomposition. Reported are the monthly mean, standard deviation and skewness for the equally-weighted corrected indices. The time span of the sample is Jan. 1990 - Dec. 2020

Panel A: Country indices corrected for industry composition ($\hat{\alpha}+\hat{\gamma}_k$)

Country	Mean	Std. Dev.	Skewness
Australia	1.41%	7.18%	-0.29
Austria	0.87%	5.55%	-0.34
Belgium	0.84%	5.09%	-0.41
Canada	1.89%	6.51%	-0.38
Denmark	1.02%	5.34%	-0.25
France	1.08%	5.23%	-0.41
Germany	0.85%	5.30%	-0.29
Hong Kong	1.39%	8.26%	0.22
Italy	0.58%	6.89%	-0.05
Japan	0.61%	6.43%	0.42
Netherlands	0.98%	5.72%	-0.47
Norway	1.19%	6.89%	-0.32
Singapore	1.08%	8.18%	0.98
South Korea	1.25%	10.44%	0.75
Spain	0.83%	6.14%	-0.21
Sweden	1.19%	6.87%	-0.13
Switzerland	0.97%	5.05%	-0.52
United Kingdom	0.90%	5.59%	-0.32
United States	1.51%	5.47%	-0.46
EW Average	1.08%	6.43%	-0.13
VW Average	1.23%	5.93%	-0.24

Panel B: Industry indices corrected for country composition ($\hat{\alpha}+\hat{\beta}_j$)

Industry	Mean	Std. Dev.	Skewness
Automobiles and Parts	1.22%	5.57%	-0.34
Banks	0.86%	3.62%	-0.82
Basic Resources	1.41%	6.89%	-0.07
Chemicals	1.19%	5.00%	-0.46
Construction and Materials	1.12%	4.96%	-0.47
Financial Services	1.21%	4.94%	-0.52
Food and Beverage	1.01%	3.67%	-0.47
Healthcare	1.44%	5.46%	0.09
Personal and Household goods	1.05%	4.57%	-0.54
Industrial Goods and Services	1.17%	5.03%	-0.62
Insurance	0.98%	4.16%	-0.73
Media	0.97%	5.35%	-0.52
Oil and Gas	1.11%	6.91%	-0.20
Retail	1.10%	4.45%	-0.36
Technology	1.54%	6.84%	-0.12
Telecommunications	1.36%	5.79%	-0.12
Travel and Leisure	0.99%	4.60%	-0.59
Utilities	0.94%	3.52%	-0.61
EW Average	1.15%	5.07%	-0.42
VW Average	1.16%	5.11%	-0.39

Table 4A.4: Correlation Matrix VW indices

This table shows the correlation matrix for the value-weighted (VW) indices. The lower diagonal elements refer to the correlations between the actual VW country (industry) indices returns R_k^{vw} (R_j^{vw}). The upper diagonal element refer to the correlations between the country (industry) indices adjusted for industry (country) composition $\hat{\alpha} + \hat{\gamma}_k$ ($\hat{\alpha} + \hat{\beta}_j$).

Panel A: Countries

	AUS	AUT	BEL	CAN	DEN	FRA	GER	HKG	ITA	JPN	NED	NOR	SGP	KOR	ESP	SWE	SUI	GBR	USA
AUS	1.00	0.64	0.68	0.75	0.63	0.69	0.69	0.64	0.58	0.48	0.69	0.70	0.69	0.55	0.66	0.68	0.69	0.74	0.70
AUT	0.65	1.00	0.77	0.66	0.72	0.77	0.81	0.57	0.68	0.47	0.76	0.72	0.63	0.42	0.73	0.66	0.72	0.72	0.62
BEL	0.63	0.74	1.00	0.69	0.78	0.85	0.82	0.53	0.73	0.44	0.86	0.76	0.60	0.44	0.77	0.70	0.77	0.80	0.72
CAN	0.77	0.65	0.63	1.00	0.68	0.72	0.72	0.69	0.62	0.42	0.73	0.74	0.68	0.48	0.65	0.68	0.71	0.75	0.83
DEN	0.59	0.69	0.74	0.63	1.00	0.78	0.78	0.53	0.69	0.47	0.80	0.76	0.56	0.43	0.72	0.77	0.76	0.77	0.66
FRA	0.67	0.75	0.82	0.70	0.76	1.00	0.90	0.60	0.79	0.47	0.90	0.78	0.62	0.47	0.84	0.79	0.83	0.85	0.76
GER	0.67	0.77	0.78	0.70	0.76	0.90	1.00	0.62	0.76	0.46	0.89	0.75	0.65	0.47	0.81	0.79	0.82	0.81	0.76
HKG	0.63	0.53	0.47	0.68	0.48	0.59	0.60	1.00	0.50	0.40	0.61	0.58	0.79	0.47	0.59	0.58	0.58	0.64	0.62
ITA	0.57	0.66	0.68	0.62	0.67	0.79	0.75	0.47	1.00	0.44	0.75	0.67	0.54	0.45	0.81	0.69	0.66	0.68	0.60
JPN	0.49	0.45	0.41	0.45	0.47	0.49	0.45	0.40	0.44	1.00	0.46	0.43	0.47	0.50	0.51	0.48	0.54	0.51	0.43
NED	0.70	0.76	0.82	0.74	0.78	0.89	0.88	0.61	0.75	0.48	1.00	0.76	0.64	0.48	0.80	0.79	0.84	0.84	0.78
NOR	0.72	0.70	0.69	0.76	0.71	0.73	0.70	0.56	0.64	0.43	0.76	1.00	0.62	0.44	0.71	0.75	0.74	0.79	0.72
SGP	0.70	0.62	0.56	0.68	0.53	0.62	0.64	0.77	0.53	0.49	0.65	0.62	1.00	0.51	0.61	0.61	0.60	0.67	0.65
KOR	0.55	0.39	0.39	0.49	0.40	0.46	0.45	0.46	0.43	0.50	0.46	0.43	0.52	1.00	0.46	0.43	0.50	0.50	0.49
ESP	0.63	0.70	0.72	0.62	0.70	0.84	0.78	0.55	0.80	0.49	0.78	0.66	0.59	0.42	1.00	0.76	0.74	0.77	0.67
SWE	0.67	0.61	0.64	0.69	0.74	0.78	0.79	0.59	0.69	0.51	0.78	0.71	0.61	0.46	0.74	1.00	0.76	0.76	0.70
SUI	0.63	0.67	0.75	0.61	0.71	0.78	0.76	0.52	0.62	0.51	0.78	0.64	0.55	0.44	0.69	0.69	1.00	0.81	0.73
GBR	0.74	0.73	0.77	0.74	0.74	0.83	0.79	0.62	0.68	0.52	0.83	0.77	0.67	0.47	0.75	0.74	0.76	1.00	0.80
USA	0.69	0.58	0.67	0.81	0.62	0.75	0.76	0.63	0.61	0.46	0.76	0.67	0.65	0.50	0.65	0.73	0.67	0.76	1.00

Panel B: Industries

	AUTO	BANK	BASI	CHEM	CONS	FINA	FOOD	HEAL	PERS	INDU	INSU	MEDI	OIL	RETA	TECH	TELE	TRAV	UTIL
AUTO	1.00	0.77	0.68	0.82	0.78	0.78	0.61	0.53	0.77	0.82	0.75	0.74	0.62	0.74	0.64	0.51	0.79	0.50
BANK	0.76	1.00	0.65	0.79	0.81	0.88	0.68	0.62	0.77	0.82	0.89	0.75	0.65	0.74	0.58	0.55	0.80	0.59
BASI	0.70	0.66	1.00	0.85	0.81	0.73	0.60	0.56	0.72	0.82	0.67	0.68	0.76	0.68	0.58	0.51	0.71	0.57
CHEM	0.84	0.80	0.84	1.00	0.90	0.85	0.79	0.70	0.87	0.92	0.83	0.77	0.77	0.82	0.64	0.59	0.86	0.67
CONS	0.80	0.79	0.79	0.90	1.00	0.85	0.77	0.69	0.86	0.92	0.84	0.78	0.74	0.83	0.64	0.59	0.88	0.70
FINA	0.80	0.87	0.72	0.84	0.84	1.00	0.70	0.71	0.83	0.91	0.86	0.86	0.67	0.80	0.75	0.68	0.84	0.63
FOOD	0.62	0.70	0.58	0.77	0.72	0.68	1.00	0.78	0.86	0.74	0.78	0.63	0.63	0.77	0.45	0.57	0.78	0.78
HEAL	0.53	0.63	0.49	0.66	0.62	0.67	0.75	1.00	0.77	0.73	0.71	0.67	0.56	0.72	0.58	0.59	0.71	0.65
PERS	0.79	0.78	0.72	0.87	0.86	0.83	0.83	0.73	1.00	0.90	0.82	0.79	0.67	0.85	0.70	0.64	0.86	0.70
INDU	0.85	0.83	0.80	0.92	0.91	0.91	0.71	0.69	0.90	1.00	0.86	0.89	0.74	0.85	0.80	0.69	0.89	0.66
INSU	0.73	0.90	0.63	0.81	0.79	0.82	0.78	0.69	0.80	0.83	1.00	0.76	0.66	0.80	0.59	0.62	0.85	0.72
MEDI	0.72	0.75	0.63	0.74	0.71	0.81	0.60	0.65	0.75	0.85	0.76	1.00	0.62	0.79	0.82	0.77	0.80	0.56
OIL	0.63	0.66	0.76	0.75	0.69	0.65	0.60	0.50	0.66	0.72	0.65	0.60	1.00	0.60	0.48	0.47	0.67	0.62
RETA	0.74	0.75	0.63	0.79	0.77	0.79	0.75	0.70	0.83	0.83	0.79	0.77	0.58	1.00	0.69	0.66	0.85	0.63
TECH	0.64	0.59	0.55	0.61	0.60	0.73	0.42	0.56	0.67	0.78	0.59	0.81	0.46	0.67	1.00	0.70	0.64	0.38
TELE	0.54	0.56	0.51	0.60	0.59	0.67	0.54	0.55	0.64	0.68	0.60	0.74	0.45	0.63	0.70	1.00	0.63	0.56
TRAV	0.80	0.79	0.70	0.86	0.87	0.84	0.75	0.66	0.86	0.89	0.80	0.75	0.64	0.82	0.62	0.60	1.00	0.70
UTIL	0.54	0.64	0.59	0.69	0.73	0.65	0.77	0.62	0.72	0.68	0.71	0.55	0.61	0.61	0.39	0.56	0.71	1.00

Table 4A.5: Coskewness matrices, VW indices

This table reports the full results by country (upper part) and industry (lower part) of all 8 coskewness elements of the Coskewness Matrix Φ for the excess value-weighted country indices $R^k_{ew} - \hat{\alpha}$ and for the excess value-weighted industry indices $R^j_{ew} - \hat{\alpha}$ estimated using Boudt et al. (2020)'s shrinkage approach.

	AUS	AUT	BEL	CAN	DEN	FRA	GER	HKG	ITA	JPN	NED	NOR	SGP	KOR	ESP	SWE	SUI	GBR	USA
ϕ_{III}	-0.76	-0.39	0.67	-1.15	0.81	0.01	-0.08	-0.33	-0.29	0.00	0.39	-1.13	-0.47	0.08	-0.35	-0.55	0.89	0.19	-0.01
ϕ_{IIC}	-0.76	0.00	0.00	-0.77	-0.05	0.00	0.09	0.59	0.00	0.00	0.00	-0.22	-0.02	-0.06	0.00	0.00	0.00	0.00	0.00
ϕ_{CII}	-0.76	0.00	0.00	-0.77	-0.05	0.00	0.09	0.59	0.00	0.00	0.00	-0.22	-0.02	-0.06	0.00	0.00	0.00	0.00	0.00
ϕ_{CIC}	-2.90	0.00	0.00	-2.43	0.45	0.00	-1.47	-1.41	0.00	0.00	0.00	-4.40	0.55	-9.31	0.00	0.00	0.00	0.00	0.00
ϕ_{ICI}	-0.76	0.00	0.00	-0.77	-0.05	0.00	0.09	0.59	0.00	0.00	0.00	-0.22	-0.02	-0.06	0.00	0.00	0.00	0.00	0.00
ϕ_{ICC}	-2.90	0.00	0.00	-2.43	0.45	0.00	-1.47	-1.41	0.00	0.00	0.00	-4.40	0.55	-9.31	0.00	0.00	0.00	0.00	0.00
ϕ_{CCI}	-2.90	0.00	0.00	-2.43	0.45	0.00	-1.47	-1.41	0.00	0.00	0.00	-4.40	0.55	-9.31	0.00	0.00	0.00	0.00	0.00
ϕ_{CCC}	-29.30	-24.87	-38.22	-5.85	-14.68	-3.51	7.45	-49.19	-11.84	10.16	-16.24	-48.98	-37.35	43.98	-10.74	-10.20	-6.71	8.15	2.05

	AUTO	BANK	BASI	CHEM	CONS	FINA	FOOD	HEAL	PERS	INDU	INSU	MEDI	OIL	RETA	TECH	TELE	TRAV	UTIL
ϕ_{III}	-19.37	-12.88	-35.53	2.35	-1.83	-3.57	5.99	0.72	2.38	-1.03	1.03	1.60	-17.16	1.43	-39.86	15.07	-9.19	12.15
ϕ_{IIC}	1.21	0.00	-2.24	0.00	0.00	0.00	-0.44	-0.04	0.17	0.02	0.00	0.00	-2.43	-0.14	0.00	0.00	0.00	0.00
ϕ_{CII}	1.21	0.00	-2.24	0.00	0.00	0.00	-0.44	-0.04	0.17	0.02	0.00	0.00	-2.43	-0.14	0.00	0.00	0.00	0.00
ϕ_{CIC}	-0.39	0.00	-0.30	0.00	0.00	0.00	0.06	0.10	0.08	-0.01	0.00	0.00	-0.66	-0.02	0.00	0.00	0.00	0.00
ϕ_{ICI}	1.21	0.00	-2.24	0.00	0.00	0.00	-0.44	-0.04	0.17	0.02	0.00	0.00	-2.43	-0.14	0.00	0.00	0.00	0.00
ϕ_{ICC}	-0.39	0.00	-0.30	0.00	0.00	0.00	0.06	0.10	0.08	-0.01	0.00	0.00	-0.66	-0.02	0.00	0.00	0.00	0.00
ϕ_{CCI}	-0.39	0.00	-0.30	0.00	0.00	0.00	0.06	0.10	0.08	-0.01	0.00	0.00	-0.66	-0.02	0.00	0.00	0.00	0.00
ϕ_{CCC}	1.29	-0.09	-0.13	0.04	0.04	-0.27	0.08	0.13	-0.05	0.01	0.57	0.57	0.64	0.05	0.06	-0.03	0.10	-0.07

Table 4A.6: Skewness decomposition, EW indices

This table reports for the equally-weighted excess country indices $R^k_{ew} - \hat{\alpha}$ the unadjusted skewness of the pure country effects ϕ_{CCC} and of the weighted sum of the 18 industry effects ϕ_{III} (Panel A) and for the equally-weighted excess industry indices $R^j_{ew} - \hat{\alpha}$ the unadjusted skewness of the pure industry effects ϕ_{III} and of the weighted sum of 19 country effects ϕ_{CCC} (Panel B). The second columns report ψ_h, i.e. the ratio between the absolute deviation from the total unadjusted skew ϵ_h over the sum of absolute errors $\sum_{h=1}^{8} \epsilon_h$. At the end of the panel are reported the equally and market cap-based weighted average and the median across countries (Panel A) or industries (Panel B). The Coskewness matrix is estimated with Boudt et al. (2020)'s shrinkage approach.

	Pure country effect		Sum of 18 industry effects	
Country	Unadj Skew	Ratio relative to sum of skew errors	Unadj Skew	Ratio relative to sum of skew errors
Australia	6.31	5.74%	0.80	13.20%
Austria	24.24	0.25%	-0.41	14.46%
Belgium	-4.99	2.49%	-0.03	14.21%
Canada	15.45	8.89%	1.83	13.65%
Denmark	-7.34	2.19%	-0.15	14.03%
France	1.82	1.25%	-0.01	14.39%
Germany	1.47	0.20%	-0.02	14.43%
Hong Kong	37.59	0.63%	-0.02	14.11%
Italy	45.83	0.12%	-0.39	14.37%
Japan	39.96	0.02%	-0.05	14.30%
Netherlands	-2.82	12.99%	0.02	10.70%
Norway	4.94	1.03%	-0.11	14.34%
Singapore	330.39	0.00%	-0.01	14.29%
South Korea	750.74	0.42%	-0.02	14.16%
Spain	6.82	5.40%	-0.28	13.49%
Sweden	8.91	6.57%	0.21	14.10%
Switzerland	-4.99	0.25%	-0.09	14.04%
United Kingdom	-6.57	0.01%	0.00	14.28%
United States	-1.95	0.20%	-0.03	14.09%
EW average	65.57	2.56%	0.07	13.93%
VW average	24.10	1.03%	0.04	14.07%
Median	6.31	0.63%	-0.02	14.16%

	Sum of 19 country effects		Pure industry effect	
Industry	Unadj Skew	Ratio relative to sum of skew errors	Unadj Skew	Ratio relative to sum of skew errors
Automobiles and Parts	4.18	2.23%	4.17	2.24%
Banks	-0.02	3.08%	-2.32	42.16%
Basic Resources	2.13	13.76%	27.61	7.47%
Chemicals	2.30	17.04%	-0.26	12.39%
Construction and Materials	2.04	1.21%	1.50	4.64%
Financial Services	-0.09	17.12%	0.39	3.97%
Food and Beverage	0.07	6.62%	0.06	7.66%
Healthcare	0.00	14.28%	36.14	0.00%
Personal and Household goods	0.21	18.88%	-0.22	9.35%
Industrial Goods and Services	0.03	16.66%	-0.06	9.32%
Insurance	-0.29	13.88%	-10.34	0.09%
Media	-0.54	16.99%	2.43	3.78%
Oil and Gas	-2.29	15.87%	13.96	4.49%
Retail	0.12	14.86%	-1.85	1.40%
Technology	0.03	14.28%	46.27	2.11%
Telecommunications	-1.03	14.80%	23.26	2.64%
Travel and Leisure	-0.16	13.27%	-2.14	1.01%
Utilities	-0.16	7.22%	-0.16	7.07%
EW average	0.36	12.34%	7.69	6.77%
VW average	0.07	13.02%	11.16	8.43%
Median	0.02	14.28%	0.23	4.23%

Table 4A.7: Aggregate Indices DS Codes

This Table shows the Thomson Reuters Datastream DS Codes for each aggregate country and industry in our sample.

Description	Code
Australia	*TOTMKAU*
Austria	*TOTMKOE*
Belgium	*TOTMKBG*
Canada	*TOTMKCN*
Denmark	*TOTMKDK*
France	*TOTMKFR*
Germany	*TOTMKBD*
Hong Kong	*TOTMKHK*
Italy	*TOTMKIT*
Japan	*TOTMKJP*
Netherlands	*TOTMKNL*
Norway	*TOTMKNW*
Singapore	*TOTMKSG*
South Korea	*TOTMKKO*
Spain	*TOTMKES*
Sweden	*TOTMKSD*
Switzerland	*TOTMKSW*
United Kingdom	*TOTMKUK*
United States	*TOTMKUS*
Automobiles and Parts (Developed Countries)	*AUTMBDV*
Banks (Developed Countries)	*BANKSDV*
Basic Resources (Developed Countries)	*BRESRDV*
Chemicals (Developed Countries)	*CHMCLDV*
Construction and Materials (Developed Countries)	*CNSTMDV*
Financial Services (Developed Countries)	*FINSVDV*
Food and Beverage (Developed Countries)	*FDBEVDV*
Healthcare (Developed Countries)	*HLTHCDV*
Personal and Household goods (Developed Countries)	*PERSGDV*
Industrial Goods and Services (Developed Countries)	*INDGSDV*
Insurance (Developed Countries)	*INSURDV*
Media (Developed Countries)	*MEDIADV*
Oil and Gas (Developed Countries)	*OILINDV*
Real Estate (Developed Countries)	*RLESTDV*
Retail (Developed Countries)	*RTAILDV*
Technology (Developed Countries)	*TECNODV*
Telecommunications (Developed Countries)	*TELCMDV*
Travel and Leisure (Developed Countries)	*TRLESDV*
Utilities (Developed Countries)	*UTILSDV*

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