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# Monetary Policy and Interest Rate Products

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## *Abstract*

My PhD thesis consists of three papers which study how interest rate products' prices react to both the central bank's policy goals and communication. As tool I make use of various econometric techniques such as affine models, general method of moments or Haar like filtering.

The first chapter studies government bond excess term premia. I show that their predictability is driven by monetary policy. The long term impact of the central bank actions on risk free bonds returns are examined via a study of one year holding period for bond excess returns. The analysis demonstrates that the premia predictability increases for the bond maturities closer to respective central bank policy goals. I decompose macroeconomic data into transitory and persistent components of various frequencies to model monetary policy. I accommodate two effects in the single $\mathcal{MP}$ factor: slow persistent long term relation and short exogenous shocks, which produce a significant predictive power of bond excess returns.

The second chapter focuses on the direct impact of Federal Open Market Committee meetings and policy announcements on the corporate bond market. In the case of FOMC announcements we obtain the probability of a good state, using 30-day Fed Funds futures transaction prices. We find that market makers protect themselves by adjusting the bid and offer prices depending on this probability. Additionally, we document very different behaviour across buy and sell sides in relation to mid prices.

The last chapter shows how future monetary policy uncertainty, measured as the 30 day Fed funds futures signal to microstructure noise ratio, variation throughout a FOMC cycle (time period between two consecutive and scheduled meetings) leads to changes in returns and liquidity of the US corporate bond market. It shows that the FOMC communication generates two distinct corporate bond return regimes. I advocate that the cycle pattern, large and statistically significant excess bond returns only in even weeks, can be partially explained by a substantial difference in transaction costs between the two periods. My study demonstrates that the excess returns patterns coincide with liquidity regimes. I document that they are related to uncertainty about future monetary policy and describe a mechanism which can explain the empirical facts.

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# Chapter 1

# Introduction

LATELY, monetary policy studies have gained popularity among financial economists as it was shown that the policy has much greater impact on financial markets than previously thought. In my PhD thesis I try to answer how interest rate products' prices react to both the central bank's policy goals and communication.

I start with a study of government bond term premia. I show that their predictability is driven by monetary policy. The long term impact of the policy and the central bank actions on risk free bonds returns are examined via a study of one year holding period for bond excess returns. The analysis of four economies (US, UK, Switzerland and Japan) demonstrates that the premia predictability increases for the bond maturities closer to respective central bank policy goals.

I decompose macroeconomic data into transitory and persistent components of various frequencies to model monetary policy. Expected inflation, unemployment and output gap are filtered since these variables play a key role for policy makers, and are thus important indicators of the state of economy. I accommodate two effects in the single $\mathcal{MP}$ factor: slow persistent long term relation and short exogenous shocks, which produce a significant predictive power of bond excess returns. They confirm that changes in the monetary policy ingredients have not only short, but also long term impact on the economy. This factor can predict between 32% and 74% of the variation of excess bond risk premia in the sample.

Additionally, the factor unveils differences in monetary policy between countries through a variation in predictability across maturities. It also provides further evidence that the macroeconomic variables are important predictors for the term premia. This factor is highly correlated with other factors from previous studies yet it provides additional information to what is already captured by them. The high predictability likely comes from the commitment of the central bank to its goals. Lastly, the out of sample tests suggest the time varying relation between the variables in question. The test also

indicates that the more committed is the central bank to its goals, the better are the forecasts.

The following two chapters of my thesis focus on the direct impact of Federal Open Market Committee [FOMC] meetings and policy announcements on the corporate bond market. I focus on this market because both bond prices' dependence on interest rates and the over the counter structure are suitable to study the impact of future policy uncertainty.

In my joint work with Alessio Ruzza, using 30 day Fed funds futures prices and applying Glosten and Milgrom (1985) model, we extract the market expectations about the policy and test the participants reaction during five days around the FOMC meetings. The policy announcements are known to affect asset prices in several ways: not only by setting the level of the short term rate, but also by signaling future policy thus affect the longer part of the risk free curve.

In the case of FOMC announcements we are able to obtain the probability of a good state (high payoff), $\theta$, using 30-day Fed Funds futures transaction prices. We find that market makers protect themselves by adjusting the bid and offer prices depending on the $\theta$. Additionally, we document very different behaviour across buy and sell sides in relation to mid prices.

While theory predicts larger spread before an announcement, we observe the opposite effect in the data. This raises several questions about the behaviour of market participants. We discover a rise in volume ahead of the FOMC meetings. Such increase is caused by agents with heterogeneous beliefs. Our tests confirm that even though there is information asymmetry among participants, the inventory risk aversion is the key driver of the results. A GMM model confirms that the market makers do not face large adverse selection costs around the FOMC meetings, but decrease their order processing costs in order to adjust their inventories accordingly.

Furthermore, the dealers are able to compute the corridor of the post announcement price and to adjust the spread accordingly. Due to large inventory risk aversion, the dealers tend to decrease the bid prices before announcements. Moreover, the intermediaries also provide a discount, albeit smaller, at the ask in order to reduce their exposure to the unexpected monetary policy change. This effect is even more pronounced for counter-cyclical sectors, which can further translate to similar premiums as in the stock market. Secondly, our results support the hypothesis that there is a flow of information from the 30 day Fed funds futures market ahead of the monetary committee meetings. In particular, the dealers use prices and adjust bond spreads such that it is impossible to trade on this information in the corporate bond market.

In the last chapter, I study how future monetary policy uncertainty, measured as the 30 day Fed funds futures signal to microstructure noise ratio, variation throughout a FOMC cycle (time period between two consecutive and scheduled meetings) leads to

changes in returns and liquidity of the US corporate bond market. I show that the FOMC communication generates two distinct corporate bond return regimes. They correspond to odd and even FOMC cycle weeks with significantly different loads on risk factors and my measure of uncertainty.

Moreover, I advocate that the cycle pattern, large and statistically significant excess bond returns only in even weeks, can be partially explained by a substantial difference in transaction costs between the two periods. My study demonstrates that the excess returns patterns coincide with liquidity regimes. I document that they are related to uncertainty about future monetary policy and describe a mechanism which can explain the empirical facts. This is consistent with previous research on liquidity risk.

The effective half spreads (a half of difference in bid and ask transaction prices), computed using more than 60 million trades, are from 3 to 25 bps smaller in odd weeks due to increased levels of risk and a drop in financial intermediaries' inventory capacity. My results show that it is considerably cheaper to trade in weeks ahead of announcements due to disagreement about upcoming fundamental news.

The difference is the largest for low credit quality bonds and retail size trades. Since large transactions are often being prearranged thus allow liquidity providers to manage their inventory, funding capital and risk more efficiently. Relative differences in costs vary from about 15% to more than 70%. The significant disparity in transaction costs, notably for small transactions, suggests that the OTC market participants are impacted by upcoming monetary policy news as they create shifts in risk aversion and inventory capacity capabilities of financial intermediaries.

# Chapter 2

# Monetary Policy and Bond Risk Premia in the US and the UK

MONETARY policy can affect interest rates in various ways, for instance, setting the short term interest rate ("funds rate" in the US and "bank rate" in the UK) or through the adjustment in the supply of government bonds (e.g. (Greenwood and Vayanos 2014) or (Kuttner 2006)). These operations are supposed to indirectly control inflation, employment and output. As each country sets different monetary policy goals, one of the important questions in finance and economics is to determine whether monetary policy has also an impact on the variation of expected returns of government bonds.

The broad literature on the subject specifies two distinctive groups. One is the yield curve itself which can successfully explain the variation in risk premia (e.g. (Cochrane and Piazzesi 2005)); the other is macroeconomic activity such as expected inflation, business cycles or the impact of monetary policy (e.g. (Buraschi, Carnelli and Whelan 2014)). This analysis will build up on the monetary policy literature and employ the (Ang, Boivin, Dong and Loo-Kung 2011) result, who show some evidence that monetary policy is affected by variations in the unemployment rate. It should improve the understanding of bond risk premia as monetary policy has a direct impact on the government bond prices. Additionally, unemployment, as an observable variable, should enhance the understanding of macroeconomic policy shocks driving the business cycles and consequently bond excess returns. The recent bond premia literature only marginally focuses on macroeconomic variables (e.g. (Ludvigson and Ng 2009)). Moreover, in many cases no strong connection between macroeconomic factors and bond risk premia has been shown. However, in contrast to the empirical findings, (Galí, Smets and Wouters 2012) highlight that the unemployment rate is an important variable used by central banks in the process of monetary policy making. Empirically, an addition of unemployment significantly improves modelling of central banks' monetary policy and variation in macroeconomic

data such as the output gap or inflation.

In this study I will model monetary policy using persistent "scales" filtered out of the series of interest as depicted by (Bandi, Perron, Tamoni and Tebaldi 2019). The authors show that one frequency shock is not necessarily a function of other frequency shocks. As a result it is pertinent to disentangle those effects in order to capture all relevant information from expected inflation, unemployment and output gap to model monetary policy. Additionally, this procedure should enhance the predictive power of the information as a significant fraction of irrelevant information will be removed thanks to filtering. To my knowledge, this has not been performed before. The combination of the three macro series in the model should create high predictability factor of bond returns at all maturities. At the short end of yield curve shocks to the unemployment rate play a pivotal role in changes to the risk premia while in the long run excess returns predictability should be captured by the change in the output gap and adjustments in the equilibrium inflation rate.

Historically, there have been several studies showing evidence of correlation between business cycles and bond returns (e.g. (Fama and Bliss 1987)). In this study, I try to decompose the three series by removing noise and keeping the long term persistent equilibrium components. Regressing a spectrum of frequencies allows to extract the equilibrium relations from the shocks. Residuals represent shocks to long term relationship between each of the three series and bond yields. Using this relationship, I aim to obtain a single component which can explain variability in yields through business cycles. This approach leads to significant results of bond excess returns predictability. They confirm that changes in the monetary policy ingredients have not only short, but also long term impact on the macro-economy. Moreover, the residuals are combined and composed into a single monetary policy factor $\mathcal{MP}_t$. The $\mathcal{MP}_t$ can predict between 52% and 66% of bond excess returns within the US sample and between 32% and 74% in the UK sample. The high predictability comes from the substantial importance of the unemployment rate, the output gap and the inflation target in determining monetary policy actions. These variables play a key role for monetary policy makers, and are thus important indicators of the state of economy. They also directly impact changes in bond yields through, for instance, a variation in the funds or bank rate.

In this paper I also examine factors from two other studies conducted by (Cochrane and Piazzesi 2005) and (Cieslak and Povala 2015). The findings confirm that the $\mathcal{MP}_t$ factor has superior predictive power within the sample. All regressors display cyclical dynamics and are highly correlated (all correlations above 0.65). Furthermore, due to a variety of underlying explanatory variables taken from the monetary policy modelling itself, the $\mathcal{MP}_t$ variable contains extra information not captured by the other two. This additional short term uncertainty dynamics is connected with expectations about the short term state of the economy. This in turn has an effect on the bond risk premia

especially in the shorter part of the yield curve. The results confirm that the factor successfully captures both long and short features of variability in bond excess returns. Nevertheless the difference in the adjusted coefficient of determination $R^2$ across the maturities varies in line with the respective monetary policy goals. Within the US sample, the highest predictability is achieved at long-term maturities which is consistent with the FOMC goal of long run stability. On the other hand, in the UK the highest predictability lies around 10 year tenor as the Bank of England goals are tied to medium term goals.

The rest of the chapter is organised as follows. In 2.1 a brief history and insight into the monetary policy and bond risk premia research areas is outlined. The data, summary statistics and preliminary analysis is presented in 2.2. The methods used to estimate a single factor for the excess return predictability are summarised in 2.3. Empirical results of the predictive models and robustness tests are provided in 2.4 and 2.5, while 2.6 concludes.

## 2.1 Literature review

There has been a major stream of research focused on monetary policy modelling and its ingredients. This field is dominated by New Keynesian models with inflation as a key variable of monetary policy. (Bansal and Shaliastovich 2013) document the link between long run expected growth and inflation risks and bond risk premia. As monetary policy indirectly impacts the two variables, it may lead to a variation in bond returns notably on the longer horizon. Additionally, (Storm, Naastepad et al. 2012) (p.4) describe inflation as *the outcome of a conflict over income distribution between workers (labor unions) and capitalists (firms).* This conflict leads to variations in either the unemployment rate or in inflation. Empirically, the inverse relationship between inflation and unemployment was first discovered by (Phillips 1958) and soon became widely accepted amongst policy makers and economists. Nonetheless, (Friedman 1968) argues that although a short run Phillips Curve [PC] may exist, there is no such relationship in the long run, which indicates that unemployment should be a factor in monetary policy modelling; otherwise the long run response of the policy may not be fully efficient.

Another argument is brought by (Gowland 1991), who states that it is possible to reduce real wages without reducing the unemployment rate. In addition, (Fender 2012) revises many existing empirical studies and concludes that the dynamics of unemployment and inflation are equivocal, and thus that PC performance is not as clear as presented by (Phillips 1958). (Kitov 2007) also finds that PC assumptions are not supported by the empirical evidence. He argues that trade-off between inflation and other macroeconomics variables vary over time. His argument is supported by (Galí and Gertler 1999), (Stock and Watson 2002), (Stock and Watson 2003) and (Ball 2000), who each discovered sim-

ilar behaviour linking inflation and other variables. This paper will try to address the issue of time varying behaviour and will assess the PC relationship via both short and long maturity excess returns predictability regressions.

Historically, unemployment was not an essential variable from the perspective of the New Keynesian model. I can infer such unimportance from the activities of central banks, who did not have to respond to unemployment fluctuations when designing monetary policy. However, recently there has been a growing interest in unemployment and labour market imperfections showing its importance for the policy making (Galí 2011). The author shows some evidence that central banks put more value in unemployment than previously thought. It has been also noted that despite its value, unemployment is generally absent in the New Keynesian general equilibrium models used for macroeconomic analysis (Galí et al. 2012). (Blanchard and Galí 2010) and (Thomas 2008) further support the importance of unemployment and labor market inefficiency in designing the monetary policy by providing evidence of inefficient responses to shocks when the variable is omitted. For instance, in the case of the US, the Federal Reserve Act of 1977 specified two key monetary policy goals: maximum output and employment and stable prices. This research will try to consider these arguments and to include an assessment of the unemployment rate and its effects on monetary policy, in order to create an efficient predictor of bond excess returns.

(Fender 2012) adds that since policy makers cannot directly impact inflationary expectations, they need to consider higher unemployment rates before acting to lower the inflation rate. (Gowland 1991) emphasises that inflationary expectations play an important role in the formation of business cycles. He argues that monetary transactions signal the state of economy which can impact both growth and unemployment. Moreover, speculation leads to persistent unemployment during recessions and gives a strong indication of the variable being cyclical. This argument strongly supports the addition of the unemployment rate to the monetary policy factor.

In a recent study, (Cieslak and Povala 2015) find a cycle factor extracted from core CPI. The factor explains around 50% of the variation of annual bond returns. Furthermore, building on the link between bond risk premia and business cycles, (Duffee 2011) highlights that there is a hidden factor in the yield curve which is related to economic activity and investors' expectations of future interest rates. Following the cyclicality and PC relationship, there is more evidence for the importance of monetary policy in general. (Sherman 2014) provides evidence of a strong relationship between national income and sticky employee compensation, which is a good predictor of business cycles. In addition, he highlights the impact of monetary policy on the discount rate and on available credit by open market operations. (Fontaine and Garcia 2012) investigate the link between liquidity risk and future risk premia. The authors find that change in liquidity largely impacts the U.S. bonds and the size of liquidity premia is negatively correlated with

money supply. As a result, a strong relationship between risk premia and monetary policy is very likely to exist. However, (Storm et al. 2012) point out that fiscal and monetary policies are inefficient in moving the unemployment rate from its equilibrium in the long run. Thus, the inclusion of unemployment into the monetary policy model is likely to substantially improve the short term bond excess predictability.

This paper will also contribute to the works on bond risk premia. In many cases, the literature in the field provides arguments against pure expectations hypothesis. For instance, (Fama and Bliss 1987) find a relationship between bond risk premia and business cycles. From the theoretical point of view, (Evans 1994) in his analysis develops a model which highlights the necessity for macro forces driving risk premia. (Ludvigson and Ng 2009) show empirically that 132 macroeconomic variables have some predictive power for bond risk premia. They find that macroeconomic activity exhibits not only statistical but also economic significance.

Another strand in the literature focuses on policy implications and its effect on bond risk premia. (Palazzo and Nobili 2010) argue that the overall macroeconomic environment is an important factor driving bond risk premia. They also point out that monetary policy credibility and economic indicators, such as a rate of employment, lead to lower risk premia. Similarly, (Ang et al. 2011) highlight a relationship between monetary policy, yield curve and unemployment. With their model, the authors show that monetary policy affects the entire term structure. They add that shifts in monetary policy create uncertainty. Consequently, higher uncertainty leads to time variation of bond risk premia. On the other hand, (Christoffel, Jaccard and Kilponen 2011) point out that fiscal policy is positively related to risk premia and increases bond volatility. They also argue that monetary policy can only effectively counteract pro-cyclical fiscal policy at the cost of greater bond risk premia. (Palomino 2012) finds a positive correlation between policy credibility and bond risk premia and volatility. Similarly, (Arnold and Vrugt 2010) document that the bond volatility across all maturities is affected by monetary policy. They also point out that uncertainty about the monetary policy shocks comes from expectations about inflation and economic activity including unemployment.

There is also a stream of literature related to the monetary policy announcements shocks (e.g. (Gürkaynak, Sack and Swanson 2005b) or (Kuttner 2001)). Nevertheless, in this paper the focus will remain on the long term implications of monetary policy on bond returns and the monetary policy uncertainty shocks issue will not be addressed here. This study will aim to implement findings from both macroeconomics and fixed income strands of research in order to better understand bond risk premia predictability.

## 2.2 Data

### 2.2.1 US

Data used in this paper runs from July 1977 until September 2014 which gives 447 observations. I use end of month yield data downloaded from the Federal Reserve statistical release H.15. The bond maturities covered in this analysis are one, two, three, five, seven, ten and twenty years. The CMT yields are assumed par yields and are used in order to interpolate zero coupon curve. The unemployment (ID: LNS14000000) and CPI (ID: CUUR0000SA0L1E) data comes from Bureau of Labor Statistics. The CPI core series is used, as core CPI is seen as a tool for monetary policy makers as is not as volatile as all items CPI. In line with (Laubach and Williams 2003), the expected average inflation over the next year has been obtained using an autoregressive model of order 3 [AR(3)] of the CPI estimated on past 40 quarters. The GDP (ID: GDPC96) data is downloaded from U.S Department of Commerce: Bureau of Economic Analysis. The series is seasonally adjusted and expressed in 2005 Dollars so the inflation effect is not accounted for twice in the analysis. As the data is released in quarterly frequency, monthly observations have been spline interpolated after the application of Hodrick-Prescott filter on the log series.

### 2.2.2 UK

As the Bank of England became fully independent only in June 1998, the UK data runs from June 1998 until September 2014 - 195 observations. The yield curve data is downloaded from the Bank of England statistical release Government Liability Curve. The release covers the whole spot curve from 1 month to 25 years. Nonetheless, this study will focus on the same maturities as in the US case. There were periods with missing data for yields beyond 17 years. Those have been replaced with the change in the next available maturity and the previous available rate. The unemployment rate "16-64" (ID: LF2Q), "long term indicator of prices of consumer goods and services" (ID: CDKO) and GDP (ID: ABMI) series come from Office for National Statistics. The GDP is seasonally adjusted and expressed in chained Pounds. Similarly to the US case, monthly observations have been spline interpolated after the application of Hodrick-Prescott filter on the log series and the expected inflation has been obtained through the (Laubach and Williams 2003) procedure.

It is necessary to point out that for all the explanatory variables to extract the frequency factors a significant number of additional observations is necessary (up to 256 for the 8th scale). Additionally, in order to generate the expected inflation extra 10 years of data is required to apply the (Laubach and Williams 2003)'s method. For instance, to obtain the 8th scale on June 1998 I need data to run from February 1977. Furthermore,

in case of expected inflation I run the AR(3) model from February 1967. For these reasons the data time period used to filter the series is actually much larger than the one used for predictive regressions. The exact filtering procedure will be explained in the methodology section.

The yield curve is spline interpolated only in the US sample as the Bank of England data provides enough curve points at each point in time.

### 2.2.3 Preliminary Analysis

The one year holding period for bond excess returns is examined. The one year holding period excess log return from buying a $n$-year bond at time $t$ is equal to

$$rx_{t+12}^{(n)} = p_{t+12}^{(n-1)} - p_t^{(n)} - y_t^{(1)}, \tag{2.1}$$

where $p_t^{(n)}$ is the log price of a zero coupon bond and $y_t^{(1)}$ is the one year continuously compounded rate and time $t$ is expressed in months. The one-year forward rate at time $t$ for the period between $t + (n - 1)$ and $t + n$ is denoted by

$$f_t^{(n)} = p_t^{(n-1)} - p_t^{(n)}. \tag{2.2}$$

Summary statistics of bond yields and excess returns are in Tables 2.1 and 2.2. Bond yields exhibit a typical behaviour with monotonically increasing mean and low standard deviation. The yields are highly persistent with first autoregression coefficients AR(1) above 0.99 in both countries. Moreover, the UK yields are negatively skewed with kurtosis between 1.4 and 3.4. On the other hand, the US yields are positively skewed with relatively constant kurtosis between 2.8 and 3.0. The mean excess returns increase with maturity and the reported values are consistent with previous research. All excess returns horizons fail the test for normality. US bond excess returns are highly persistent with AR(1) equal to 0.94 for all maturities and between 0.89 and 0.96 in the UK, this is due to overlapping horizon of 11 months. Nevertheless, there is a difference between the two countries. The average excess returns are steeper and more correlated across maturities in the US than in the UK.

**Table 2.1:** Summary statistics of the US bond excess returns.
The table presents summary statistics of bond yields and excess returns and correlation between excess returns across maturities. The data runs from July 1977 until September 2014 - 447 observations. The yields and excess returns are reported in percent.

| Bond yields | | | | | | |
|---|---|---|---|---|---|---|
| | $y^{(1)}$ | $y^{(2)}$ | $y^{(5)}$ | $y^{(7)}$ | $y^{(10)}$ | $y^{(20)}$ |
| Mean | 5.48 | 5.79 | 6.30 | 6.55 | 6.73 | 7.10 |
| $\sigma$ | 3.82 | 3.75 | 3.44 | 3.29 | 3.12 | 2.86 |
| Skewness | 0.52 | 0.43 | 0.47 | 0.51 | 0.58 | 0.64 |
| Kurtosis | 2.91 | 2.72 | 2.72 | 2.71 | 2.73 | 2.86 |
| AR(1) | .994 | .995 | .996 | .996 | .997 | .997 |
| **Bond excess returns** | | | | | | |
| | $rx^{(2)}$ | $rx^{(5)}$ | $rx^{(7)}$ | $rx^{(10)}$ | $rx^{(15)}$ | $rx^{(20)}$ |
| Mean | 0.78 | 2.02 | 2.54 | 2.74 | 3.25 | 5.79 |
| $\sigma$ | 1.98 | 6.46 | 8.97 | 12.38 | 18.21 | 24.28 |
| Skewness | −0.28 | −0.25 | −0.19 | −0.09 | −0.01 | 0.03 |
| Kurtosis | 4.42 | 3.84 | 3.86 | 3.83 | 4.02 | 4.34 |
| AR(1) | 0.94 | 0.94 | 0.94 | 0.94 | 0.93 | 0.94 |
| **Correlation between excess returns** | | | | | | |
| | $rx^{(2)}$ | $rx^{(5)}$ | $rx^{(7)}$ | $rx^{(10)}$ | $rx^{(15)}$ | $rx^{(20)}$ |
| $rx^{(2)}$ | 1.00 | | | | | |
| $rx^{(5)}$ | 0.95 | 1.00 | | | | |
| $rx^{(7)}$ | 0.91 | 0.99 | 1.00 | | | |
| $rx^{(10)}$ | 0.88 | 0.98 | 0.99 | 1.00 | | |
| $rx^{(15)}$ | 0.86 | 0.95 | 0.97 | 0.98 | 1.00 | |
| $rx^{(20)}$ | 0.84 | 0.94 | 0.97 | 0.98 | 0.98 | 1.00 |
| **Correlation with respective UK excess returns** | | | | | | |
| | $rx^{(2)}$ | $rx^{(5)}$ | $rx^{(7)}$ | $rx^{(10)}$ | $rx^{(15)}$ | $rx^{(20)}$ |
| | 0.41 | 0.49 | 0.50 | 0.50 | 0.42 | 0.32 |

**Table 2.2:** Summary statistics of the UK bond excess returns.
The table presents summary statistics of bond yields and excess returns and correlation between excess returns across maturities.The data runs from June 1998 until September 2014 - 195 observations. The yields and excess returns are reported in percent.

| Bond yields | | | | | | |
|---|---|---|---|---|---|---|
| | $y^{(1)}$ | $y^{(2)}$ | $y^{(5)}$ | $y^{(7)}$ | $y^{(10)}$ | $y^{(20)}$ |
| Mean | 3.14 | 3.27 | 3.69 | 3.88 | 4.07 | 4.25 |
| $\sigma$ | 2.14 | 2.02 | 1.58 | 1.33 | 1.04 | 0.58 |
| Skewness | −0.28 | −0.31 | −0.50 | −0.63 | −0.87 | −1.13 |
| Kurtosis | 1.38 | 1.49 | 1.90 | 2.17 | 2.61 | 3.35 |
| AR(1) | .995 | .996 | .995 | .993 | .987 | .968 |
| Bond excess returns | | | | | | |
| | $rx^{(2)}$ | $rx^{(5)}$ | $rx^{(7)}$ | $rx^{(10)}$ | $rx^{(15)}$ | $rx^{(20)}$ |
| Mean | 0.57 | 1.96 | 2.49 | 2.99 | 3.46 | 3.72 |
| $\sigma$ | 1.12 | 3.81 | 5.24 | 6.97 | 9.02 | 10.76 |
| Skewness | 0.57 | −0.18 | −0.01 | 0.35 | 0.80 | 0.92 |
| Kurtosis | 3.83 | 2.67 | 2.71 | 2.87 | 3.40 | 3.61 |
| AR(1) | 0.96 | 0.94 | 0.93 | 0.92 | 0.90 | 0.89 |
| Correlation between excess returns | | | | | | |
| | $rx^{(2)}$ | $rx^{(5)}$ | $rx^{(7)}$ | $rx^{(10)}$ | $rx^{(15)}$ | $rx^{(20)}$ |
| $rx^{(2)}$ | 1.00 | | | | | |
| $rx^{(5)}$ | 0.87 | 1.00 | | | | |
| $rx^{(7)}$ | 0.78 | 0.99 | 1.00 | | | |
| $rx^{(10)}$ | 0.66 | 0.92 | 0.98 | 1.00 | | |
| $rx^{(15)}$ | 0.47 | 0.76 | 0.85 | 0.94 | 1.00 | |
| $rx^{(20)}$ | 0.29 | 0.58 | 0.69 | 0.82 | 0.96 | 1.00 |
| Correlation with respective US excess returns | | | | | | |
| | $rx^{(2)}$ | $rx^{(5)}$ | $rx^{(7)}$ | $rx^{(10)}$ | $rx^{(15)}$ | $rx^{(20)}$ |
| | 0.61 | 0.62 | 0.65 | 0.64 | 0.55 | 0.43 |

The differences are partly because of different sample lengths. Interestingly, the correlation between the same maturity premia of the two countries is positive and varies from 0.32 at 20 year to 0.50 at 7 year in the period from July 1977. However, despite a similar pattern across maturities, the correlations increase if the sample starts in June 1998, i.e. they range from 0.43 to 0.65. Furthermore, while shortening the US sample to the length of the UK's one decreases the magnitude of differences between the two countries, the yields' characteristics remain distinguishable.

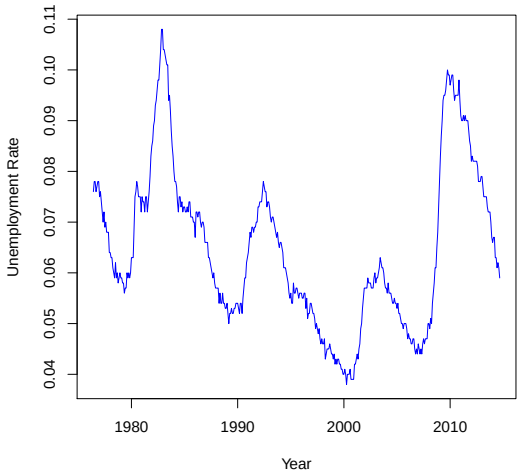



**Figure 2.1:** US unemployment rate.

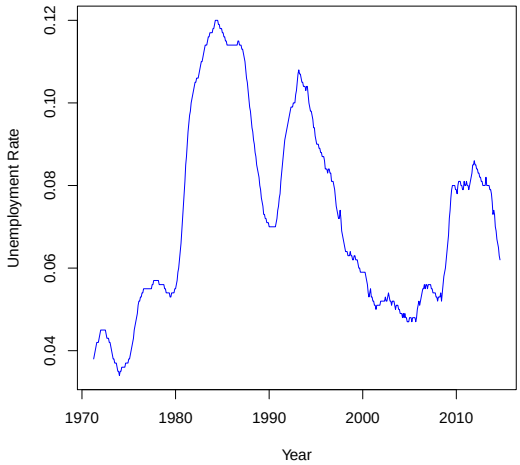



**Figure 2.2:** UK unemployment rate.

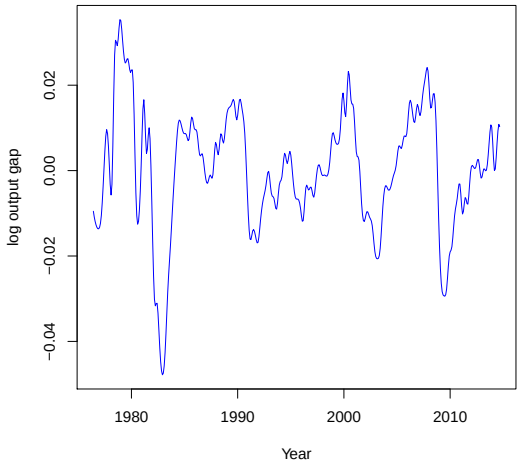



**Figure 2.3:** US output gap.

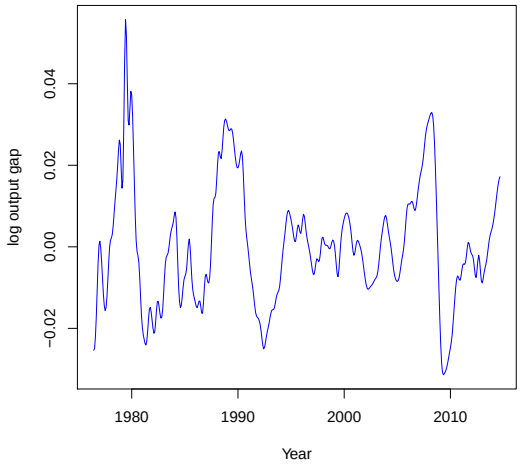



**Figure 2.4:** UK output gap.

A first examination of the data indicates strong cyclical dynamics of the unemployment rate and the output gap. Figures 2.1, 2.2, 2.3 and 2.4 show significant jumps after major shocks, for example the 1979 oil crisis or the 2008 credit crunch. The patterns are similar for both the US and the UK. (Mueller, Vedolin and Zhou 2011) point out that empirically bond excess returns also exhibit spikes around economic crises, notably in the short run. In terms of unemployment, the jumps are followed by slow decreases spanning five to ten years. The output gap exhibits slightly shorter cycles lasting up to

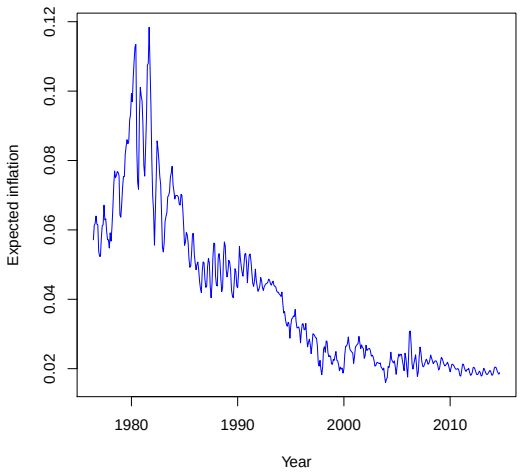



**Figure 2.5:** The US expected inflation estimated through an AR(3) model on a rolling 40 quarters window.

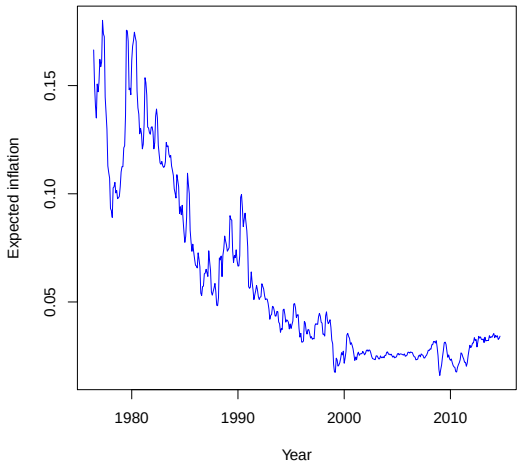



**Figure 2.6:** The UK expected inflation estimated through an AR(3) model on a rolling 40 quarters window.

five years.

It can be seen in Figures 2.5 and 2.6, the estimated expected inflation declines over time in both countries from the aftermath of the oil shock. Additionally, the magnitude of the shocks decreases over time and there is no visible cyclicality pattern in neither of the two series. Two important events are noticeable in the UK expected inflation series: inflation targeting established in 1992 and the independence of the Bank of England in 1998. This sort of behaviour appears pertinent to the predictability of bond excess returns.

The periodograms of the time series of yields, unemployment, HP filtered GDP cycle and expected inflation unveil a similar pattern. All series exhibit downward sloping spectral densities. The densities also indicate that the series are highly persistent. On the other hand, the decomposition of bond excess returns is not monotonically decreasing. The frequencies exhibit a very similar pattern across maturities. This finding may further support the idea of using decomposed series, where one has a control over the frequency shock used.

## 2.3 Methodology

The study commences with an investigation of the monetary policy components on contemporaneous yields. As the return of a bond is equal to the sum of expectations of

short rate $y^{(1)}$ and risk premium $rpy_t^{(n)}$ I get:

$$y_t^{(n)} = \frac{1}{n} E_t \left[ \sum_{i=0}^{n-1} y_{t+i}^{(1)} \right] + rpy_t^{(n)}. \tag{2.3}$$

One can view that the conditional expectation of future short yields is the outcome of the central bank's policy. In addition, monetary policy has a direct impact on the nominal interest rate and inflation expectations through targeting, while the short rate can be further decomposed into the real rate and expected inflation. Based on the previous studies of macroeconomic policy (e.g. (Galí 2011)) the permanent changes in inflation target should have an impact on bond yields and changes in term premia.

A "standard" equation for monetary policy is based on (Taylor 1993) and is in the form of:

$$i_t = a + b(\pi_t - \pi^*) + c(Y_t - Y^*), \tag{2.4}$$

where $Y_t$ is the Gross Domestic Product at time $t$, $Y^*$ is the output target, $\pi_t$ is the realised inflation at time $t$ and $\pi^*$ is the inflation target. The output gap $\hat{Y}_t = Y_t - Y^*$ can be obtained by using the Hodrick-Prescott filter on the log GDP series with $\lambda = 1600$ for the quarterly data. This has been the mainstream of monetary policy modelling. There were only a few exceptions (e.g. (Fair 2001)) where unemployment rate was used as an additional factor. (Ang et al. 2011) and (Chun 2011) also use a variety of Taylor rule specifications to find the link between the central bank's objective function and yields. Moreover, the (Friedman 1968)'s concept of Non-Accelerating Inflation Rate of Unemployment implies that there is a long term unemployment equilibrium which does not impact inflation. Yet it is time varying and shocks to this equilibrium can impact inflation and bond yields in both the short and long run, which can enhance the "standard" monetary policy equation. Thus my monetary policy rule is approximately:

$$i_t = a + b(\pi_t - \pi^*) + c(Y_t - Y^*) + d(unem_t). \tag{2.5}$$

Secondly, I decompose expected inflation, output gap and unemployment series into persistent "scales" - $\pi_t^{(j)}$ by adopting the (Bandi et al. 2019)'s Haar type filter.

Let $\{x_{t-i}\}_{i \epsilon Z}$ be a time series with mean $\pi$. One can rewrite it in the following way $x_t = \sum_{j=1}^{J} x_t^{(j)} + \pi$, where:

$$x_t^{(j)} = \frac{\sum_{i=0}^{2^{(j-1)}-1} x_{t-i}}{2^{j-1}} - \frac{\sum_{i=0}^{2^j-1} x_{t-i}}{2^j} = \pi_t^{(j-1)} - \pi_t^{(j)} \quad \text{and} \quad \pi^{(0)} = x_t. \tag{2.6}$$

The $x_t^{(j)}$ component can be interpreted as the transitory part while the $\pi_t^{(j)}$ as the persistent one. This procedure can be iterated to obtain different frequency scales depending

on the choice of $j$. The scales $i = 1, 2, ..., 8$[1] are extracted from the series, which allows to separate frequencies between 1 and 256 months in $2^{i-1}$ months spans (e.g. scale $i = 1$ explains $1 - 2$ month frequency, $i = 2$ - $2 - 4$ month frequency etc.).

Thirdly, I try to establish the long term equilibrium between bond yields and the each set of scales, where scales play the role of my policy rule (equation 2.5). Such a relationship should exist as monetary policy is a response of central bank to a change in economic conditions. To test this hypothesis, yields are separately regressed on one of contemporaneous scale sets for $n = \{1, 2, 5, 7, 10, 15, 20\}$:

$$y_t^{(n)} = a^{(n)} + b_1'^{(n)}\mathbf{scale}_t + \epsilon_t^{(n)}, \tag{2.7}$$

where $\mathbf{scale}_t$ is a vector of one of the following variables: expected inflation, unemployment or output gap scales at time $t$. This method allows to capture only the frequencies at which each of the series impacts yields. In order to reduce the number of variables, the errors $\epsilon_t^{(n)}$ for $n = \{2, 5, 7, 10, 15, 20\}$ are averaged and denoted $\bar{\epsilon}_t$. Additionally, the one year errors are kept separately in order to maintain the short term dynamics between the variables and yields above what is captured by long term $\bar{\epsilon}_t$

The next step of the analysis is to estimate the predictive regression using the residuals $\epsilon_t^{(n)}$ from each of three sets of equations as well as the errors from regressing the HP trend logGDP obtained in same way as in the case of the other three series:

$$rx_{t+12}^{(n)} = \alpha + \sum_{i=1}^{4} \delta_{1i}\epsilon_t^{(1i)} + \sum_{i=1}^{4} \delta_{2i}\bar{\epsilon}_t^{(i)} + \varepsilon_{t+12}^{(n)}, \tag{2.8}$$

where $i$ corresponds to each of the time series used. The fitted value of the combination of all eight variables regressed on the average term premia $\bar{rx}_{t+12}$ gives the single prediction factor $\mathcal{MP}_t$.

In order to examine the significance of our model, I compare it with two factors from previous studies. I run the equations using $CP$ and $\widehat{cf}_t$. $CP$ is (Cochrane and Piazzesi 2005) linear combination of forward rates. Since this study is focused only on maturities one to five years, $CP$ factors beyond the five year maturity are also generated to maintain comparability. The $\widehat{cf}_t$ is the (Cieslak and Povala 2015) factor obtained from cycles - $c_t^{(i)}$ estimated based on the long run persistent inflation data. It has a very significant predictive ability both in and out of sample. The findings of these previous two studies provide useful proxies for the efficiency of the $\mathcal{MP}_t$ factor.

Before evaluating the single factor performance, two other equations using either

[1] Due to a large number of observations needed to construct the scales, the US expected inflation scales are extracted only up to $i = 7$.

forward rates or cycles are estimated:

$$rx_{t+12}^{(n)} = a_0 + \sum_j a_j f_t^{(j)} + \varepsilon_{t+12}^{(n)}, \tag{2.9}$$

$$rx_{t+12}^{(n)} = b_0 + \sum_j b_j c_t^{(j)} + \varepsilon_{t+12}^{(n)}, \tag{2.10}$$

where $j = \{1, 2, 5, 7, 10, 15, 20\}$[2].

The single factor approach helps to capture different frequency movements in the expectations about the monetary policy and the economy. While three $\epsilon_t^{(1)}$ are more likely to focus on the close future expectations, the components $\bar{\epsilon}_t^{(i)}$ are good indicators of slowly moving business cycles at longer frequencies far beyond one year, with the exact length depending on the variable. Having estimated the single factor we estimate the following restricted predictive model:

$$rx_{t+12}^{(n)} = \alpha_0^{(n)} + \alpha_1^{(n)} \mathcal{MP}_t + \varepsilon_{t+12}^{(n)}, \tag{2.11}$$

$$rx_{t+12}^{(n)} = \delta_0^{(n)} + \delta_1^{(n)} CP_t + \varepsilon_{t+12}^{(n)}, \tag{2.12}$$

$$rx_{t+12}^{(n)} = \beta_0^{(n)} + \beta_1^{(n)} \widehat{cf}_t + \varepsilon_{t+12}^{(n)}. \tag{2.13}$$

In order to test the validity of the model, one can test its "out of sample" performance. It is important to check whether $\mathcal{MP}_t$ can achieve a good level of predictability out of sample and whether it is a better predictor than other factors. These findings are particularly important for investors as well as for policy makers, who can exploit the information about variability of term premia in portfolio management or in policy making. A positive out of sample predictability would imply the empirical usefulness of the model.

In this study the (Campbell and Thompson 2008)'s out of sample $R^2$ measure is used - $R^2_{OOS}$. The idea behind $R^2_{OOS}$ is to compare the difference between fitted values of the model and actual figures against the historical average of the excess returns. The $R^2_{OOS}$ is similar to standard $R^2$ with positive values indicating extra predictive power in comparison to the naive average predictor. The Campbell and Thompson's $R^2$ is computed as follows:

$$R_{OOS}^{2,(n)} = 1 - \frac{\sum_{t=1}^{T-12} (rx_{t+12}^{(n)} - rx_{u,t+12}^{(n)})^2}{\sum_{t=1}^{T-12} (rx_{t+12}^{(n)} - \bar{rx}_{t+12}^{(n)})^2}, \tag{2.14}$$

[2] Cieslak and Povala use a simple average of 19 errors. However, in order to maintain comparability and limit the number of explanatory variables I used only 7 numbers. The results are similar if all 19 values are used.

where $rx_{u,t+12}^{(n)}$ is the fitted value from the predictive model estimated up to time $t$. $\bar{rx}_{t+12}^{(n)}$ is the historical average excess return estimated up to period $t$. If the out of sample $R^2$ is positive then predictive model has lower mean squared prediction error than the historical average return model.

I first obtain initial coefficients using the first 100 observations. Having information until this point I estimate scales and regress them against yields until $t_0$ and run predictive regressions. With estimated coefficients I use errors at $t_0$ in order to predict excess return at time $t_0 + 12$. Then the sample size is incremented by one and follow the same steps until end of the sample i.e. Sep 2014. The same procedure is repeated by incrementing the initial equation sample by 1 until Sep 2013. This procedure allows me to visualise out of sample $R^2$ without a subjective choice of the initial regression window size.

## 2.4 Results

Before evaluating the predictive ability of the single factor, I regress all available scales separately for each of the time series on contemporaneous yields (equation 2.7). I immediately observe that not all scales are statistically significant. This further supports the usefulness of splitting the time series into different frequency scales. Thus, only significant predictors are utilised across all maturities. More specifically, within the US sample used scales are 4 and 7 for inflation, 1 and 8 for output gap and 6, 7, 8 in case of unemployment. Similarly in the UK data the significant scales are 5, 7 and 8 for inflation, 7 and 8 for output gap and 4, 5 and 6 for unemployment. Figures 2.7 to 2.12 display the evolution of the aforementioned scales through time. With the exception of the US output gap, all the variables seem to impact the yields at frequencies spanning more than 8 months. It is possible to use a variety of scales sets. However, the regression results show that too excessive or too small number of scales used lead to worse results in predictive regressions. This is likely the result of the additional noise in case of a too liberal choice and the fact that too much information necessary for monetary policy making is removed in case of models with very few scales.

Table 2.3 presents the predictive regression results. It can be seen that errors from decomposed monetary policy series remain significant in both samples across all maturities. More specifically, I bootstrap the $R^2$ in small samples using 10,000 replications and obtain highly significant predictability of monetary policy errors $\epsilon^{(1i)}$ and $\bar{\epsilon^{i}}$ with the coefficient $R^2$ ranging from 60% to 67% in the US sample and between 64% and 79% within the UK one. The obtained 95% confidence intervals never fall below 42%. There is strong indication that the scales errors have predictive power irrespective of the term premia tenor. Moreover, each of the regressions remain significant at 1% level and, in comparison to forward rates and cycles, the monetary policy errors exhibit superior

predictive power.

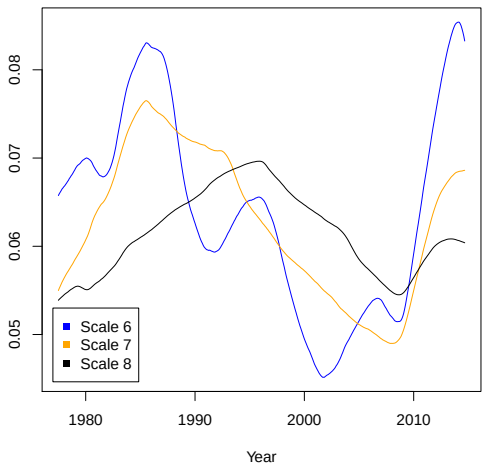



**Figure 2.7:** US unemployment scales

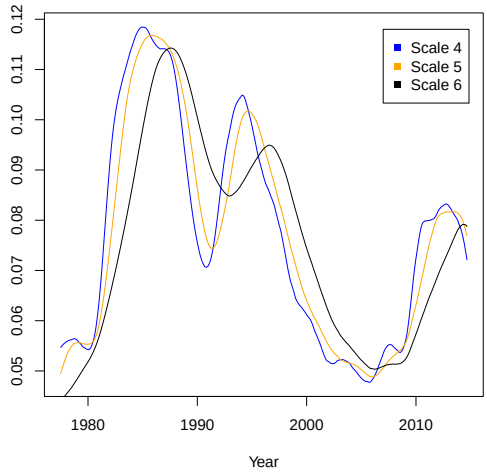



**Figure 2.8:** UK unemployment scales

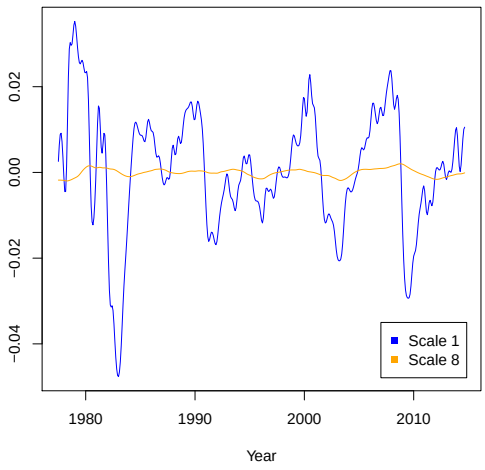



**Figure 2.9:** US output gap scales.

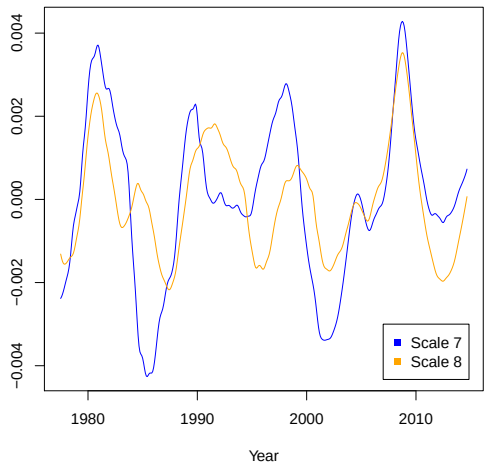



**Figure 2.10:** UK output gap scales.

Tables 2.4 and 2.5 display the single factors predictive regression results. The predictive equations show the high statistical significance of the independent variables. Due to serial correlation, all estimates are computed using Newey-West standard errors with 18 lag adjustments. All regressions are significant at 1% with t-stats ranging from 8.92 to 10.98 and from 3.70 to 13.75 within the US and UK samples, respectively. The dispersion in the range of t-stats is very likely to be affected by different sample lengths.

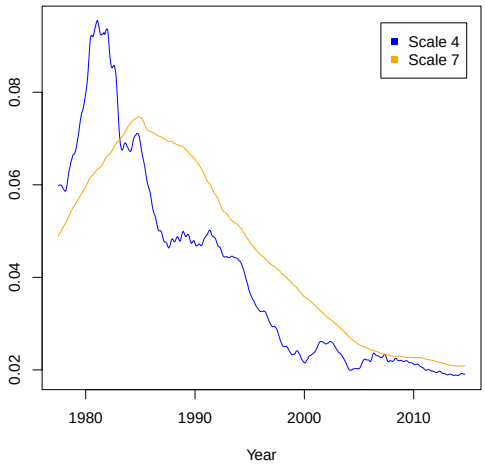



**Figure 2.11:** US expected inflation scales.

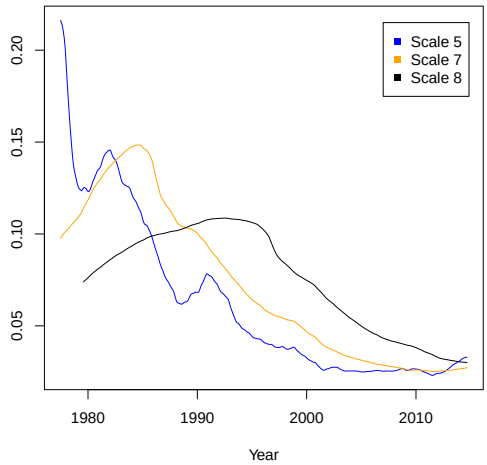



**Figure 2.12:** UK expected inflation scales.

In addition, I applied the (Wei and Wright 2013) reverse regression delta method and obtained robust standard errors, which confirm the hypothesis that there is predictability in bond excess returns. The only exception is $rx^{(2)}$ in the UK sample where the hypothesis of no predictability cannot be rejected at any reasonable level.

**Table 2.3:** Predictive regressions of bond returns.
The table presents the adjusted $R^2$ from predictive regressions using scales and cycles residuals as well as forward rates. The reported p-values are from tests that all coefficients being equal to 0 in full sample NW regressions. NW denotes Newey-West adjusted regressions with 18 lags. Bootstrapped values are from 10,000 replications of small samples (SS) with n=42 using Newey-West errors. Adjusted $R^2$ are expressed in actual values.

| US | $rx^{(2)}$ | $rx^{(5)}$ | $rx^{(7)}$ | $rx^{(10)}$ | $rx^{(15)}$ | $rx^{(20)}$ |
|---|---|---|---|---|---|---|
| Monetary Policy: $rx_{t+12}^{(n)} = \alpha_0 + \alpha' \mathbf{m}_t + \epsilon_{t+12}^{(n)}$ | | | | | | |
| $R^2$ | 0.60 | 0.61 | 0.63 | 0.64 | 0.64 | 0.67 |
| $R^2(SS, 5\%)$ | 0.42 | 0.45 | 0.47 | 0.48 | 0.49 | 0.52 |
| $R^2(SS, 50\%)$ | 0.60 | 0.61 | 0.63 | 0.64 | 0.64 | 0.67 |
| $R^2(SS, 95\%)$ | 0.78 | 0.77 | 0.78 | 0.79 | 0.79 | 0.81 |
| p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Cycle: $rx_{t+12}^{(n)} = \alpha_0 + \alpha' \mathbf{c}_t + \epsilon_{t+12}^{(n)}$ | | | | | | |
| $R^2$ | 0.41 | 0.48 | 0.52 | 0.54 | 0.55 | 0.57 |
| p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Forward rate: $rx_{t+12}^{(n)} = \alpha_0 + \alpha' \mathbf{f}_t + \epsilon_{t+12}^{(n)}$ | | | | | | |
| $R^2$ | 0.16 | 0.16 | 0.17 | 0.17 | 0.16 | 0.22 |
| p-value | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |
| **UK** | $rx^{(2)}$ | $rx^{(5)}$ | $rx^{(7)}$ | $rx^{(10)}$ | $rx^{(15)}$ | $rx^{(20)}$ |
| Monetary Policy: $rx_{t+12}^{(n)} = \alpha_0 + \alpha' \mathbf{m}_t + \epsilon_{t+12}^{(n)}$ | | | | | | |
| $R^2$ | 0.60 | 0.61 | 0.63 | 0.64 | 0.64 | 0.67 |
| $R^2(SS, 5\%)$ | 0.60 | 0.67 | 0.66 | 0.61 | 0.53 | 0.47 |
| $R^2(SS, 50\%)$ | 0.72 | 0.79 | 0.78 | 0.75 | 0.69 | 0.64 |
| $R^2(SS, 95\%)$ | 0.85 | 0.90 | 0.91 | 0.89 | 0.85 | 0.82 |
| p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Cycle: $rx_{t+12}^{(n)} = \alpha_0 + \alpha' \mathbf{c}_t + \epsilon_{t+12}^{(n)}$ | | | | | | |
| $R^2$ | 0.26 | 0.39 | 0.45 | 0.52 | 0.56 | 0.56 |
| p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Forward rate: $rx_{t+12}^{(n)} = \alpha_0 + \alpha' \mathbf{f}_t + \epsilon_{t+12}^{(n)}$ | | | | | | |
| $R^2$ | 0.23 | 0.28 | 0.44 | 0.49 | 0.52 | 0.51 |
| p-value | 0.04 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

**Table 2.4:** Predictive regressions of bond returns using single factors - US.
The table presents results from single factor regressions based on monetary policy, cycles and forward rates factors. The data sample runs from July 1977 to September 2014. T-statistics are estimated with Newey-West (NW) standard errors with 18 lags, while those reported in square brackets are estimated using reverse regression delta method approach (RRDM). Adjusted $R^2$ are expressed in actual values.

| | $rx^{(2)}$ | $rx^{(5)}$ | $rx^{(7)}$ | $rx^{(10)}$ | $rx^{(15)}$ | $rx^{(20)}$ |
|---|---|---|---|---|---|---|
| Monetary policy: $rx_{t+12}^{(n)} = \alpha_0 + \alpha\mathcal{MP} + \epsilon_{t+12}^{(n)}$ | | | | | | |
| $\alpha$ | 0.17 | 0.58 | 0.82 | 1.15 | 1.68 | 2.30 |
| tstat NW | 8.92 | 10.81 | 10.98 | 10.86 | 10.72 | 10.37 |
| tstat RRDM | [2.07] | [2.77] | [3.16] | [3.59] | [4.42] | [5.68] |
| $R^2$ | 0.52 | 0.60 | 0.62 | 0.63 | 0.64 | 0.66 |
| Cycle: $rx_{t+12}^{(n)} = \beta_0 + \beta\widehat{cf}_t + \epsilon_{t+12}^{(n)}$ | | | | | | |
| $\beta$ | 0.16 | 0.57 | 0.82 | 1.16 | 1.70 | 2.30 |
| tstat NW | 5.64 | 8.01 | 8.68 | 9.19 | 8.51 | 9.22 |
| tstat RRDM | [1.65] | [2.31] | [2.62] | [3.07] | [3.88] | [4.83] |
| $R^2$ | 0.38 | 0.46 | 0.49 | 0.51 | 0.51 | 0.53 |
| Forward rates $j = 1, 2, 5, 7, 10, 15, 20$: $rx_{t+12}^{(n)} = \delta_0 + \delta CP_t + \epsilon_{t+12}^{(n)}$ | | | | | | |
| $\delta$ | 0.16 | 0.55 | 0.81 | 1.13 | 1.59 | 2.47 |
| tstat NW | 3.19 | 3.07 | 3.20 | 3.25 | 3.16 | 3.67 |
| tstat RRDM | [1.73] | [1.71] | [1.98] | [2.21] | [2.50] | [3.62] |
| $R^2$ | 0.15 | 0.16 | 0.18 | 0.18 | 0.16 | 0.22 |
| Forward rates $j = 1, 2, 3, 4, 5$: $rx_{t+12}^{(n)} = \delta_0 + \delta CP_t + \epsilon_{t+12}^{(n)}$ | | | | | | |
| $\delta$ | 0.17 | 0.57 | 0.82 | 1.14 | 1.62 | 2.38 |
| tstat NW | 3.76 | 3.78 | 3.88 | 3.96 | 3.85 | 4.24 |
| tstat RRDM | [2.11] | [2.08] | [2.31] | [2.55] | [2.91] | [3.88] |
| $R^2$ | 0.17 | 0.18 | 0.18 | 0.19 | 0.18 | 0.22 |

### 2.4.1 US

Using single factor regressions I find a strong relationship between monetary policy and bond excess returns. The factor shows a strong performance across maturities explaining between 52% and 66% of variation. The $R^2$ are monotonically increasing with the highest being at the tenor of 20 years. It is worth noting that the official long term goals of the FED include maximum employment, stable prices and moderate interest rates[3]. Thus there is a strong indication that the Federal Open Market Committee goals generate higher predictability of future yields close to those goals. Similarly, the $\widehat{cf}$ exhibits

[3] http://www.federalreserve.gov/monetarypolicy/files/FOMC_LongerRunGoals.pdf

**Table 2.5:** Predictive regressions of bond returns using single factors - UK.
The table presents results from single factor regressions based on monetary policy, cycles and forward rates factors. The data sample runs from June 1998 to September 2014. T-statistics are estimated with Newey-West (NW) standard errors with 18 lags while those reported in square brackets are estimated using reverse regression delta method approach (RRDM). Adjusted $R^2$ are expressed in actual values.

| | $rx^{(2)}$ | $rx^{(5)}$ | $rx^{(7)}$ | $rx^{(10)}$ | $rx^{(15)}$ | $rx^{(20)}$ |
|---|---|---|---|---|---|---|
| Monetary policy: $rx_{t+12}^{(n)} = \alpha_0 + \alpha\mathcal{MP} + \epsilon_{t+12}^{(n)}$ | | | | | | |
| $\alpha$ | 0.15 | 0.72 | 1.04 | 1.40 | 1.67 | 1.68 |
| tstat NW | 3.70 | 9.97 | 13.75 | 12.74 | 7.43 | 4.99 |
| tstat RRDM | [1.26] | [2.32] | [2.74] | [3.09] | [3.17] | [2.99] |
| $R^2$ | 0.32 | 0.64 | 0.72 | 0.74 | 0.66 | 0.50 |
| Cycle: $rx_{t+12}^{(n)} = \beta_0 + \beta\widehat{cf}_t + \epsilon_{t+12}^{(n)}$ | | | | | | |
| $\beta$ | 0.13 | 0.65 | 0.93 | 1.27 | 1.72 | 2.00 |
| tstat NW | 3.14 | 4.69 | 3.99 | 3.32 | 3.09 | 3.06 |
| tstat RRDM | [0.60] | [1.41] | [1.71] | [1.99] | [2.33] | [2.52] |
| $R^2$ | 0.12 | 0.29 | 0.32 | 0.34 | 0.38 | 0.39 |
| Forward rates $j = 1, 2, 5, 7, 10, 15, 20$: $rx_{t+12}^{(n)} = \delta_0 + \delta CP_t + \epsilon_{t+12}^{(n)}$ | | | | | | |
| $\delta$ | 0.12 | 0.63 | 0.95 | 1.34 | 1.76 | 1.92 |
| tstat NW | 2.70 | 5.93 | 6.12 | 5.56 | 4.82 | 4.29 |
| tstat RRDM | [0.72] | [1.61] | [2.08] | [2.63] | [3.14] | [3.24] |
| $R^2$ | 0.15 | 0.35 | 0.43 | 0.49 | 0.53 | 0.47 |
| Forward rates $j = 1, 2, 3, 4, 5$: $rx_{t+12}^{(n)} = \delta_0 + \delta CP_t + \epsilon_{t+12}^{(n)}$ | | | | | | |
| $\delta$ | 0.10 | 0.60 | 0.94 | 1.35 | 1.78 | 1.96 |
| tstat NW | 2.67 | 5.28 | 5.60 | 5.42 | 4.77 | 4.24 |
| tstat RRDM | [0.61] | [1.64] | [2.18] | [2.75] | [3.18] | [3.26] |
| $R^2$ | 0.10 | 0.32 | 0.42 | 0.51 | 0.55 | 0.50 |

monotonically increasing $R^2$ along maturities. The factor can explain between 38% and 53% of fluctuation in risk premia. This could be due to the fact that inflation has a direct impact on the asset prices and returns. Our results are also in line with previous studies confirming relatively poor predictive power captured by forward rates. The model based on forward rates has roughly a third of the predictive power with adjusted $R^2$ ranging from 17% to 22% or from 15% to 22% depending on forward rates used.

The $\mathcal{MP}$ factor successfully predicts variation in bond risk premia. It can be noticed that all factors exhibit similar cyclical dynamics. The predictive regressions coefficients are only marginally different as all factors are highly correlated (correlations with $\mathcal{MP}$ span between 0.53 and 0.85). The $\mathcal{MP}$ factor is able to outperform the $\widehat{cf}$ especially in the short term. The findings are important as the $\mathcal{MP}$ is able to account for macroeco-

nomic shocks. For example, a rise in the unemployment rate can reflect an uncertainty shock, which usually spans on the market up to 36 months (Bloom, Floetotto, Jaimovich, Saporta-Eksten and Terry 2012). These shocks in turn are a successful predictor of short run premia due to their direct impact on the prices of assets. This sort of behaviour cannot be predicted by the other two factors. In addition, even if the difference is smaller for longer maturities, the $\mathcal{MP}$ factor is still able to outperform the other widely known predictors of risk premia.

### 2.4.2 UK

The results within the UK sample are generally similar to those in the US. Nonetheless, while the $\mathcal{MP}$ factor still exhibits strong performance in predicting variation in bond risk premia, the highest predictability is achieved at 10 year maturity. This in turn seem to be linked to the Bank of England monetary policy "knockouts"[4]. The Bank focuses on medium term inflation expectations and price stability such as in the case of the US the BoE goals lead to an increase in the predictability of term premia. The factor explains between 32% and 74% of variation.

The $\widehat{cf}$ factor can explain between 12% and 39% while $CP$ from 15% to 55%. All three factors show relatively low performance in predicting the $rx^{(2)}$. This seem to be due to a large drop in short UK yields in the aftermath of the financial crisis of 2008. Similarly to the US case, estimated coefficients across regressions are similar amongst factors. The correlations with $\mathcal{MP}$ are between 0.67 and 0.77. Within this sample the $\mathcal{MP}$ is able to better capture the variation in future premia than the other two factors both in the short and medium term.

It is imperative to see whether all three factors: $\mathcal{MP}$, $\widehat{cf}$ and $CP$ can successfully predict bond excess returns when used together. Table 2.6 presents the regression results with NW t-stats. The regressions yield at best only marginal extra predictive power. In both samples, such regression is not able to outperform the $\mathcal{MP}$ factor in maturities up to five years. In addition, even at the longer part of yield curve the extra $R^2$ rises at best by 5% in the UK sample and by 1% in the US. These results confirm the previous findings and the fact that the factor is able to capture most of the information presented by the other two variables. The $\mathcal{MP}$ is the only significant variable within the US sample. In the UK sample, $CP$ becomes significant in regressions from medium term on, while $\widehat{cf}$ is only statistically significant at $rx^{(10)}$.

In order to further corroborate my findings I will perform a variety of tests for robustness and economic significance of the estimated regressions.

[4] http://www.bankofengland.co.uk/publications/Documents/inflationreport/2013/ir13augforwardguidance.pdf

**Table 2.6:** Predictive regressions of bond returns using all factors.
The table presents results from three factor regression: $rx_{t+12}^{(n)} = \alpha + \beta \mathcal{MP}_t + \delta \hat{cf}_t + \gamma CP_t + \epsilon_{t+12}^{(n)}$. The CP factor here is computed on the basis of six forward rates. The results are marginally more significant when compared to the CP constructed using only five rates. All t statistics in brackets are based on Newey-West with 18 lags errors. The estimates for constant are omitted from the table. $\Delta R^2$ shows the additional adjusted $R^2$ compared to single factor monetary policy regression. Adjusted $R^2$ are expressed in actual values. $*, **$ denotes significance at 5% and 1% respectively.

| US | $rx^{(2)}$ | $rx^{(5)}$ | $rx^{(7)}$ | $rx^{(10)}$ | $rx^{(15)}$ | $rx^{(20)}$ |
|---|---|---|---|---|---|---|
| $\beta$ | 0.18 | 0.57 | 0.79 | 1.05 | 1.56 | 2.14 |
| | (3.71)** | (3.39)** | (3.44)** | (3.38)** | (3.62)** | (3.69)** |
| $\delta$ | −0.01 | 0.05 | 0.08 | 0.18 | 0.30 | 0.18 |
| | (−0.21) | (0.26) | (0.28) | (0.50) | (0.58) | (0.26) |
| $\gamma$ | −0.01 | −0.09 | −0.09 | −0.15 | −0.35 | 0.04 |
| | (−0.25) | (−0.65) | (−0.44) | (−0.51) | (−0.85) | (0.07) |
| $R^2$ | 0.52 | 0.60 | 0.62 | 0.64 | 0.64 | 0.66 |
| $\Delta R^2$ | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 |
| **UK** | $rx^{(2)}$ | $rx^{(5)}$ | $rx^{(7)}$ | $rx^{(10)}$ | $rx^{(15)}$ | $rx^{(20)}$ |
| $\beta$ | 0.17 | 0.72 | 1.01 | 1.28 | 1.28 | 1.02 |
| | (3.13)** | (5.47)** | (6.99)** | (7.78)** | (4.47)** | (2.32)* |
| $\delta$ | −0.03 | −0.13 | −0.31 | −0.55 | −0.41 | 0.12 |
| | (−0.27) | (−0.43) | (−1.12) | (−2.27)* | (−1.12) | (0.21) |
| $\gamma$ | 0.00 | 0.11 | 0.31 | 0.64 | 0.96 | 0.95 |
| | (0.01) | (0.45) | (1.18) | (2.38)* | (3.19)** | (2.32)* |
| $R^2$ | 0.32 | 0.63 | 0.73 | 0.77 | 0.70 | 0.56 |
| $\Delta R^2$ | 0.00 | −0.01 | 0.01 | 0.03 | 0.04 | 0.06 |

## 2.5 Robustness

To satisfy curiosity, let me examine, whether the results are not dependent on the samples or are the effect of regressing persistent monetary policy scales on persistent yields. Apart from using Newey-West Standard errors, I additionally use the reverse regression delta method errors and perform the same analysis on non overlapping 12 month periods for both of the two countries. We find that the results hold even in such small non overlapping samples. This is further supported by bootstrapping ten thousand times small samples of size $n = 42$, which is equal to $2\sqrt{T}$ of the US sample. We decide to keep it the same for both samples for comparability reasons. The obtained results reassert the large sample findings in both samples. The significance of $\epsilon_t$ is confirmed by Wald test at 1%. Moreover, bootstrapped 5% bounds of $R^2$ are higher than $R^2$ from forward rates regressions except in $rx_t^{(20)}$ within the UK sample. The small sample

results yield also strong predictability of future premia. Based on these estimates the regressions yield $R^2$ between 53% and 79%. Although the Wald test statistic supports the significance of the small sample regressions at 1%, one should be cautious as the $R^2$ may be upward biased due to the sample size.

I also consider generating the $\mathcal{MP}$ using all available scales, as predicted the predictive power of the new factor is lower but still statistically significant. This test provides evidence that all three economic times series provide important information about the future state of the economy. In addition, the lower predictability can stem from polluted data as the insignificant scales impact the errors I use in the construction of the single factor.

**Table 2.7:** Predictive regressions of bond returns using single factors - Japan and Switzerland. The table presents results from single factor regressions based on monetary policy factor $rx_{t+12}^{(n)} = \alpha_0 + \alpha\mathcal{MP} + \epsilon_{t+12}^{(n)}$. The data sample runs from April 1998 to September 2014 for Japan and from January 2000 to September 2014 in case of Switzerland. T-statistics are estimated with Newey-West standard errors with 18 lags. Adjusted $R^2$ are expressed in actual values.

| | $rx^{(2)}$ | $rx^{(5)}$ | $rx^{(7)}$ | $rx^{(10)}$ | $rx^{(15)}$ | $rx^{(20)}$ |
|---|---|---|---|---|---|---|
| Japan | | | | | | |
| $\alpha$ | 0.03 | 0.32 | 0.65 | 1.05 | 1.72 | 2.30 |
| tstat NW | 2.11 | 4.90 | 8.38 | 13.17 | 12.25 | 8.78 |
| $R^2$ | 0.10 | 0.43 | 0.64 | 0.74 | 0.77 | 0.69 |
| Switzerland | | | | | | |
| $\alpha$ | 0.11 | 0.50 | 0.75 | 1.09 | 1.56 | 1.99 |
| tstat NW | 4.91 | 8.21 | 12.05 | 16.10 | 13.42 | 10.94 |
| $R^2$ | 0.35 | 0.59 | 0.69 | 0.74 | 0.73 | 0.69 |

Furthermore, I collect data for additional two countries, namely, Japan and Switzerland with 198 and 177 observations, respectively. Again, the sample sizes were chosen such they cover fully independent monetary policies; Japanese sample starts in April 1998, while the Swiss in January 2000. I perform the same steps as in the case of the UK and the US. The results broadly confirm what I have found in the US and UK samples. Table 2.7 displays the single factor predictive regressions results. The predictability in Japan ranges from 10% to 77%. The lowest value seem to be the result of deflation, lower bound on the short interest rates and inefficient monetary policy (Ito and Mishkin 2006). In Switzerland, obtained $R^2$ vary between 35% and 74%. Most importantly, in both cases the highest predictability is achieved around tenors tied to respective monetary policy goals.

### 2.5.1 Out of Sample Predictability

In order to test the economic significance of the $\mathcal{MP}$ regressor, equation 2.14 is used. The Campbell and Thompson statistics yield positive results only in the very recent period but for most of the remaining part of the two samples the model performs significantly worse than the naive average. The results mean that $\mathcal{MP}$ could have been successfully adapted by investors or policy makers to infer the information about the future bond excess returns only in the post crisis period. The lack of predictability could be the effect of both the construction of the regressors which involves the use of many past observations and a fairly short period of fully independent monetary policy.

Another justification for the lack of out of sample predictability lies in the time varying relationship. Such time changing behaviour is difficult to be captured out of sample. Nevertheless, the results are not very surprising as monetary policy is meant to stimulate or cool down the economy depending on the macroeconomic conditions. The fact that the factor can predict risk premia in sample is the result of the observed state of the economy and monetary policy, which tries to address such macro shocks, but is not meant to predict such events.

(Jurado, Ludvigson and Ng 2015) argue that due to time variation, macro uncertainty negatively impacts predictability. They find that despite being fairly infrequent, the effects of high uncertainty periods are persistent. (Piazzesi and Schneider 2011) show that adaptive learning models provide better explanation for subjective expectations and tend give results closer to the expectation hypothesis.

In order to test this hypothesis, I fix the regression window size in the $R^2_{OOS}$ statistic to 100 and rerun the test on a rolling basis values over sample periods. It can be immediately seen in Figures 2.13 and 2.14 that the model still performs poorly in the first half of the US sample but it can consistently beat the naive average for the longer maturity premia for approximately 12 years in the US and medium term premia for around 4 years in the UK.

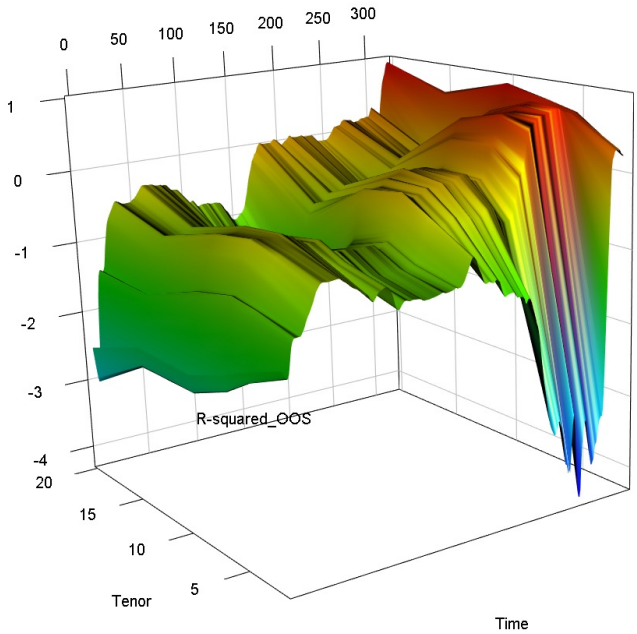



**Figure 2.13:** Evolution of $R^2_{OOS}$ estimated on a rolling window of 100 observations - US.

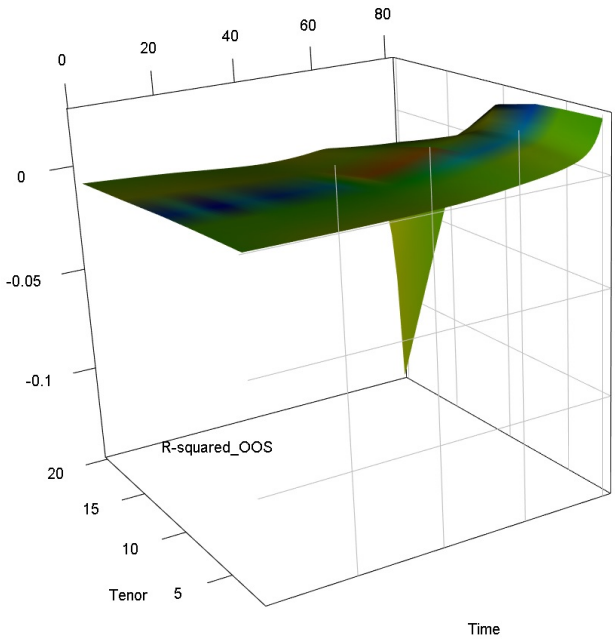



**Figure 2.14:** Evolution of $R^2_{OOS}$ estimated on a rolling window of 100 observations - UK.

The findings seem to be the result of effective and committed inflation targeting introduced in both countries and furthered by fully independent monetary policy. I

believe that the lack of out of sample predictability in the short maturities in the late sample periods is due to the crisis and ultra low short rates caused by the quantitative easing.

## 2.6 Conclusion

In conclusion, this study has provided a new insight into the bond risk premia literature by utilising an extended monetary policy rule to predict bonds excess returns. The approach allowed to account for different frequency economic forces driving the premia. Firstly, the decomposition of output gap, expected inflation and unemployment rate into scales allowed us to efficiently capture different frequency shocks impacting the yields. Secondly, I was able to accommodate two effects in the single $\mathcal{MP}$ factor: slow persistent equilibrium and short exogenous shocks. These two effects have produced a significant predictive power of bond excess returns. Thirdly, it has been shown that the high predictability is very likely to come from the commitment of the central bank to its goals. The results are consistent among four countries known to have independent monetary policy. The model has been checked with various tests and still yielded a convincing performance and statistical significance. Lastly, the out of sample tests suggested the time varying relation between the variables in question. This was further proved in the moving window out of sample tests, where the $\mathcal{MP}$ achieved a good level of predictability above the naive historical average. The test also indicated that the more committed is the central bank to its goals, the better are our factor forecasts.

# Chapter 3

# Corporate Bond Dealers' Inventory Risk and FOMC

THE impact of monetary policy announcements has been a focus of many recent studies in financial economics e.g. (Lucca and Moench 2015) and (Hausman and Wongswan 2011). In general, it has been shown that the policy has a significant impact on asset prices and their returns. As one of the key tools of policy makers is the setting of the short term interest rate, also known as the *funds rate*, monetary policy decisions have a direct influence on various financial instruments. Furthermore, the funds rate is often directly used to compute prices of several interest rate derivatives. It is, therefore, pertinent to understand whether markets participants incorporate the policy announcements into the prices effectively.

If a fraction of market participants possesses superior knowledge about a future value of an asset, trades should reveal this information to the market. Even when information at disposal of traders is the same, different interpretations of the same piece of news can trigger the exact effect as asymmetric information would, as in (Fleming and Remolona 1997). In equilibrium, the price sensitivity to an order flow depends on the prevailing level of information asymmetry. (Kim and Verrecchia 1997) argue that it can be interpreted as the ability to infer a signal from the news. In this study we focus on transaction prices and test whether both buyers and sellers interpret the news in a similar fashion.

This paper examines the behaviour of bid and ask prices on the corporate bond market in the US around the Federal Open Market Committee (FOMC) meetings. The corporate bond market is a dealership market, which operates mainly via request for quotes. In this market, dealers have to face the bargaining power of a counterparty when providing liquidity. In addition, the bilateral nature of transactions decreases the diffusion and incorporation of an information flow. Given these characteristics, dealers are exposed to a consistent inventory risk around announcements of macroeconomic

data.

(Gürkaynak, Sack and Swanson 2007a) find that 30 day Federal funds futures provide superior information about future monetary policy. Building on this result we use the futures prices to study the corporate bond quotes behaviour during the FOMC meetings weeks.

The 30 day Federal funds futures were introduced in 1988 at the CBOT. They are interest rate contracts which cash settle at the average Federal funds rate over the contract month.

This paper contributes to the existing literature in two ways. Firstly, it is presented that bid and ask prices do not react symmetrically to the uncertainty about monetary policy expectations. Due to large inventory risk aversion, the dealers tend to decrease the bid prices before announcements. Moreover, the dealers also provide a discount at the ask in order to reduce their exposure to the unexpected monetary policy change. This effect is even more pronounced for counter-cyclical sectors, which can further translate to similar premiums as in the stock market. Secondly, our results support the hypothesis that there is a flow of information from the 30 day Fed funds futures market ahead of the monetary committee meetings. In particular, the dealers use prices and adjust bond spreads such that it is impossible to trade on this information in the corporate bond market. Our GMM model confirms that the market makers do not face large adverse selection costs around the FOMC meetings, but decrease their order processing costs in order to adjust their inventories accordingly. Our study is most closely related to (Friewald and Nagler 2016)'s paper and our results in part confirm their findings. Nevertheless, in contrast to their arguments, we find that there is no premium at the FOMC if prices are accounted for trading costs. Furthermore, due to higher frequency data we demonstrate that the inventory effect is apparent only on the announcement days.

This chapter is structured as follows. The next section reviews the literature in related fields of monetary policy and market microstructure. We describe our methodology and computation of most important explanatory variables in Section 3.2. Summary statistics and the key results are presented in Parts 3.3 and 3.4. Robustness checks are outlined in Section 3.5, followed by conclusion in Part 3.6.

## 3.1 Literature review

*Information quality*

This paper primarily focuses on the effect of an information flow between different financial markets. (Ross 1989) analyses the effects of information flow changes on asset prices and volatility in an arbitrage free economy. He documents a direct relation between an information flow and volatility. Moreover, the timing of uncertainty resolution is irrele-

vant for asset prices if the terminal pay-off is not affected. (Kim and Verrecchia 1994) identify different components that drive price and volume around public announcements: the price reaction depends on the unexpected portion of information contained in the announcement, while volume depends on the magnitude of price reaction. Hence, it is also indirectly impacted by the surprise component. In addition, the authors argue that volume is subject to the heterogeneity of private signals variance, public signal variance and to the amount of pre-announcement information.

(Admati 1985) develops a multi asset model, where he shows that one can asses the quality of information by looking at the performance of market participants. The author argues that either not fully informative prices and agents with superior information, or perfect news dissemination and informative prices can be observed. In addition, (Vega 2006) argues that public announcements can be split into two categories. One that can create under-reaction and the other that increases market efficiency, the types are closely related to the arrival of uninformed or informed traders, respectively. In line with this argument, (Chan 2003) discovers a momentum after news releases in stock prices and reversal if there are no significant news. These studies lay good fundamentals to empirically test whether dealers prefer to maintain uninformative prices or face the risk of trading with better informed market participants.

However, although the FED releases its announcements on a scheduled basis and future policy measures are easy to infer, traders are likely to have different beliefs on the effects of such policies and their trading is influenced by such views (Fleming and Remolona 1997). As remarked in (Green 2004), information asymmetries in the debt market do not arise from the lack of public information but from differences in the ability to process such releases. The adverse selection is a major determinant of trading costs in the Treasury bond market. Numerous other studies looked at price patterns around public announcements for different asset classes (e.g. (Fleming and Remolona 1999), (Andersen, Bollerslev, Diebold and Vega 2003) or (Flannery and Protopapadakis 2002)), yet to the best of our knowledge there is no study of the corporate bond market.

The corporate bond market is also affected by adverse selection (Kedia and Zhou 2014). Nevertheless, mandatory reporting of corporate bond transactions mitigates these information asymmetries (Bessembinder and Maxwell 2008). As informed traders have become more active in the more opaque credit default swap market the percolation of information is lower.

*Order flow and information asymmetry*

In the (Cao, Lyons and Evans 2003) model the inventory risk compensation leads to a link between an order flow and prices even if the order flow is uninformed. On the other hand, (Green 2004) argues that the hedging pressure initiated by more precise announcements lead to a greater information asymmetry. He adds that more influen-

tial releases should increase the informational role of trading, and it is related to both the announcement itself and the surprise component. Moreover, he documents that important information releases create short periods of uncertainty, which is in contrast to the general consensus that prices are less sensitive during periods of high liquidity (e.g. (Brandt and Kavajecz 2004)). (Green 2004) also highlights that, in the liquid Treasury market, 30 minutes before an announcement volume and volatility drop while the spread widens. Yet after the release the opposite happens.

(Chae 2005) points out that theoretical models do not provide consistent predictions about volume around significant information releases. For example, in (Kyle 1985) the volume should rise in line with the information asymmetry. However, if the liquidity traders are able to postpone their trading until uncertainty is resolved, the volume could decrease before an announcement and the price sensitivity to order flows could rise (Foster and Viswanathan 1990). Thus, it is possible to observe increased trading activity after announcements. (Lee, Mucklow and Ready 1993) detect a similar pattern. They find that the spreads widen and order book depth falls before the announcements. Albeit they point out that spreads can be wider after significant news releases, the effect disappears if controlled for volume. This could further support the claim that dealers engage more in risk management practices before the FOMC meetings than after. (Chae 2005) shows via a simple test, using abnormal turnover, that there is a drop in trading before scheduled earnings (and other corporate) announcements. The author also discovers asymmetric price sensitivity before and after a news release.

*Monetary policy announcements*

The discussion about FOMC meetings and, in particular, their importance for asset pricing has been initiated by the (Bernanke and Kuttner 2005)'s seminal paper. The authors document a significant stock market reaction to unanticipated changes in the Fed funds rate. The announcements impact financial assets not only by setting the level of the short term rate, but also by signalling future policy. In particular, the policy statements affect long term rates (Gurkaynak, Sack and Swanson 2005a). The transmission channel of the target rate change on the term premia is represented by yield oriented investors. Some financial institutions can "window dress" their balance sheets by purchasing high yield securities, hence when the short term rate is low they purchase longer term bonds and decrease the long end of the curve (Hanson and Stein 2015). Compared to other central banks, the Federal Reserve decisions have a consistent impact on bond prices volatility (Andersson et al. 2010). Furthermore, the announcements have a positive effect on the stock market: prior to FOMC meetings we observe a positive drift in the level of S&P500 index. There is no similar reaction in either other macro announcements or other asset classes. This effect is fully compatible with neither political nor liquidity risk (Lucca and Moench 2015).

Monetary policy alone is unlikely to affect credit risk, which is another principal risk factor in the fixed income markets. The Federal Reserve intervenes on this variable by its credit policy, such as the Term Auction Facility in 2007 (Price 2012). A possible effect of monetary policy on credit risk can manifest through banks' increasing risk taking in presence of easier credit (Jiménez, Ongena, Peydró and Saurina 2014). On the other hand, (Ehrmann and Fratzscher 2009) find that the cyclical and capital intensive sectors respond more significantly to policy shocks. In addition, the monetary policy affects the low debt firms in the most significant fashion. The authors use Tobin's q as a proxy for different industry characteristics and find that the effect could be the result of financial constraints. Firms with low level of debt cannot borrow more. Overall, the message is that both financial constraints and investment opportunities drive the monetary policy impact.

## 3.2 Methodology

### 3.2.1 Data sources

This analysis focuses on the determinants of the corporate bonds liquidity. To assess the trading costs, we rely on the audit trail of corporate bond transactions disseminated through TRACE. We use an enhanced version[1] of the dataset containing more information such as the side of the initiator, and uncensored trade volume. To avoid the diffusion of information about dealers' inventory, this version of the dataset is made available with a 18 month lag. Therefore, our sample contains all FOMC announcements from November 2004 (since when all corporate bonds transactions had to be reported) to December 2014. We apply the cleaning procedure outlined by (Dick-Nielsen 2009) and (Dick-Nielsen 2014) thus we remove double reported inter-dealer transactions by matching buy and sell sides by cusip, date, time and volume.

We obtain general information about corporate bonds such as date of issuance, maturity, industry sector and embedded options from Thomson Reuters. We also add the credit rating history from Mergent Fixed Income Securities Database. We assign integer numbers to these bond ratings (i.e., AAA=1, AA+=2, . . . , D=22). To gauge the expectations about the future monetary policy, we use 30 day Fed funds futures transaction data, which is acquired from CME DataMine. Finally, the dates of the FOMC meetings and the new target rate are publicly disclosed through the website of the Federal Reserve Board.

[1] The enhanced version is distributed through WRDS. It is different from the academic version of TRACE - distributed directly by the FINRA.

### 3.2.2 Empirical analysis

The empirical analysis aims to identify the effect of different FOMC announcement-related variables on the corporate bond market liquidity The first step is to compare different conditions offered by the market makers around the FOMC announcement. To do so, we construct a measure of price deviation: we take the difference between an executed price and a daily average price for each bond that has at least 5 trades on a given day with at least one buy and one sell. For each trade $j$ in day $t$ of bond $i$ we define the deviation to be equal to:

$$\delta_{i,j,t} = 1/\bar{P}_{i,t}\left(P_{i,j,t} - \bar{P}_{i,t}\right) = 1/\bar{P}_{i,t}\left(P_{i,j,t} - \frac{1}{N_{i,t}}\Sigma_j P_{i,j,t}\right), \tag{3.1}$$

where $P$ is the price of the security and $N$ is the number of trades. Using this measure, we compute effective spreads under a regular assumption that mid price is the same for both quoted (which we do not observe) and executed prices. Our measure is very similar to round-trip costs as proposed by (Chakravarty and Sarkar 2003) or (Hong and Warga 2000). Therefore, for brevity, whenever we refer to bid or ask it means either an executed buy or sell price.

One of the determinants of the price offered by the dealers is return uncertainty (Ho and Stoll 1981). Obviously, such ambiguity is high around interest rate moving events such as the FOMC announcements. To measure future monetary policy actions expectations and their uncertainty, we compute implied probabilities of the interest rate changes from the Federal funds futures. To do so, we follow the methodology outlined in the white papers of (CME Group 2017) and in (Geraty 2000).

The Fed funds future price at time $t$ for the contract month ($T_0$ to $T_1$) is defined as:

$$FF(t, T_0, T_1) := 100 - 100 \times \mathbb{E}_t^{\mathbb{Q}}\left[\int_{T_0}^{T_1} r_s ds\right], \tag{3.2}$$

where $\mathbb{E}_t^{\mathbb{Q}}$ denotes the risk neutral expectation and $T_0 < T_1$. The buyer of the futures contract locks in the $FF(t, T_0, T_1)$ rate. At the end of the period the buyer receives the futures rate minus the realised average Fed funds rate $r_{T_0,T_1}$. Trivially, it follows that for $T_0 < t < T_1$ and $t \to T_1$ the $FF$ price becomes less dependent on the expectation part and more on the realised one - $\int_{T_0}^{t} r_s ds$.

Using the above definition we can obtain market expectations of the average rate over a contract month. This also means that each two $FF$ reflect independent information about the Fed policy during a two month period. Under the assumption that a shift in the funds rate can happen only on the FOMC announcement day we can obtain future implied probabilities of such a change. To do so, one needs to consider two cases:

- No meeting in the following month: in this case, we can derive a measure of the

expectation of the interest rate under the new policy from the future contract of the following month.

$$\begin{aligned} FFER(end) &= 100 - FF(t,\ \text{following month}), \\ ImpliedRate &= 100 - FF(t,\ \text{meeting month}), \\ FFER(start) &= \frac{N}{M}\left(ImpliedRate - \frac{N-M}{N}FFER(end)\right). \end{aligned} \tag{3.3}$$

- No meeting in the preceding month: in such situation, we can derive the interest rate expectation at the beginning of the period.

$$\begin{aligned} FFER(start) &= 100 - FF(t, \text{previous month}), \\ ImpliedRate &= 100 - FF(t, \text{meeting month}), \\ FFER(end) &= \frac{N}{N-M}\left(ImpliedRate - \frac{M}{N}FFER(start)\right), \end{aligned} \tag{3.4}$$

where $FF$ is the futures contract price, $FFER(start)$ and $FFER(end)$ are the expected fed rates at the beginning and the end of the meeting month, respectively. $N = \#$ of days in the meeting month and $M =$ FOMC meeting day $- 1$. It follows that risk neutral Expected Change $= FFER(end) - FFER(start)$ in both cases.

Since the Fed changes the overnight rate by multiples of a quarter percentage point, we compute the probabilities of policy change by assuming a binomial tree model. The two possible outcomes in this lattice are hike (ease) of at least 25 bps if the expected change is positive (negative), and no action. The probability of a monetary policy action is:

$$\mathbb{P}(\text{action}) := \min\{4 \times |\text{Expected change}|, 1\}. \tag{3.5}$$

It can be seen that $\mathbb{P}(\text{action}) \in [0, 1]$ for any Expected Change value. With these implied probabilities we can compute a measure of future monetary policy uncertainty, which is simply the Bernoulli distribution's variance:

$$\text{Entropy} := \mathbb{P}(\text{action}) \times (1 - \mathbb{P}(\text{action})). \tag{3.6}$$

In the next step of our study, we employ the (Glosten and Milgrom 1985)'s model. According to the model, ask ($a_t$) and bid ($b_t$) quotes at time $t$ can be represented as follows:

$$a_t = \mu_{t-1} + \frac{\Pi\theta_{t-1}(1-\theta_{t-1})}{\Pi\theta_{t-1} + \frac{1}{2}(1-\Pi)}(V^H - V^L), \tag{3.7}$$

$$b_t = \mu_{t-1} - \frac{\Pi\theta_{t-1}(1-\theta_{t-1})}{\Pi(1-\theta_{t-1}) + \frac{1}{2}(1-\Pi)}(V^H - V^L), \tag{3.8}$$

where $\mu_{t-1}$ is the fundamental value of the asset, $\Pi$ is the fraction of informed traders on the market. $V^L$ and $V^H$ correspond to possible final values of an asset - *low* and *high*, respectively. Lastly, $\theta_{t-1}$ is the probability of the future value being equal to $V^H$. In the case of the FOMC announcements we compute $\theta_{t-1}$ using the futures prices using the procedure described above. In terms of the last part of the equations 3.7 and 3.8, we compute the bond price difference given a jump in the short rate - $r$ at the announcement:

$$V^H - V^L = \mathbb{E}_t^{\mathbb{Q}}\left[\exp\left(-\int_t^T (r_s + c_s)ds\right)\right] - \mathbb{E}_t^{\mathbb{Q}}\left[\exp\left(-\int_t^T (R_s + c_s)ds\right)\right], \tag{3.9}$$

where $c_s$ is the credit spread at time $s$, $R_s = r_s + 0.0025m$ for $m \in \mathbb{Z}$ and $\mathbb{E}_t^{\mathbb{Q}}$ is the expectation under risk neutral measure at time $t$. $m$ can be obtained from the futures prices and we define it as $m := \left\lceil |\text{Expected Change}/0.25| \right\rceil$. The equation holds also for $m < 0$. However, superscripts $H$ and $L$ change their position. We remove this problem by using the absolute value. The difference thus is equal to:

$$V^H - V^L = \mathbb{E}_t^{\mathbb{Q}}\left[\exp\left(-\int_t^T (r_s + c_s)ds\right)(1 - \exp(-0.0025m(T-t))\right], \tag{3.10}$$

while if we use $m < 0$ the last part becomes $(\exp(-0.0025m(T-t)) - 1)$. As expected the difference is always positive. The theoretical values for constant yields are plotted in Figure 3.1. This result suggests that, in addition to the bond's sensitivity to interest rate changes, we have to take into account the maturity and the level of interest rates.

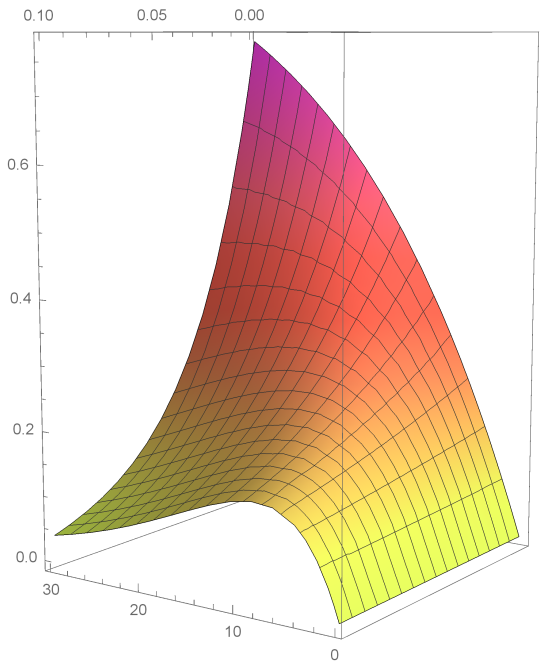
We create $V^H - V^L$ variable by daily interpolating the risk free yield curve obtained from the H.15 release published by the Federal Reserve. Next, we match the bond maturity with an appropriate yield and add the Moody's Aaa credit spread value. Then we take the difference between the price of such a zero coupon bond and a theoretical value in case of $m = 1 \Rightarrow 25$ basis points jump in the risk free rate.

To link the variables related to the FOMC announcement with the conditions offered by dealers, we run separate regressions of the price deviation measure for buy and sell trades occurring in the two days before the meeting and the meeting day before the announcement time[2]:

$$\begin{aligned} deviation_{it} = \alpha &+ \beta_1 Entropy_t + \beta_2 ExpectedChange_t + \beta_3 logVolume_{it} + \beta_4 (V^H - V^L)_{it} \\ &+ \beta_5 logDealerVolume_{it} + \beta_6 logStaleness_{it} + \beta_7 SellFraction_{it} \\ &+ \beta_8 Maturity_{it} + \beta_9 Yield_{it} + \beta_{10} CreditSpread_{it} + \beta_{11} BondRating_{it} + \epsilon_{it}, \end{aligned} \tag{3.11}$$

[2] We define this time frame as the period before the meeting.

**Figure 3.1:** Difference between $V^H$ and $V^L$ of a corporate bond for maturities 0 to 30 years and a constant yield between 0 and 10%.




and for trades occurring after the announcement time and in the following two days[3]:

$$\begin{aligned} deviation_{it} = \alpha &+ \beta_1 logVolume_{it} + \beta_2 (V^H - V^L)_{it} + \beta_3 logDealerVolume_{it} \\ &+ \beta_4 logStaleness_{it} + \beta_5 SellFraction_{it} + \beta_6 Maturity_{it} + \beta_7 Yield_{it} \\ &+ \beta_8 CreditSpread_{it} + \beta_9 BondRating_{it} + \beta_{10} AbsoluteSurprise_{it} + \epsilon_{it}. \end{aligned} \tag{3.12}$$

During the pre announcement period, the explanatory variables are: monetary policy expectation and uncertainty, the interest rate sensitivity of the security price, the time to maturity, the risk free rate, the credit spread and the bond rating. We control for the bargaining power of the initiator and market liquidity by including the volume of the transaction and the amount of each security traded in the inter-dealer market, respectively. We also include measures of order imbalance and price staleness. For trades after the event, the expectation and uncertainty variables are replaced with a measure of the unexpected movement of interest rates. A detailed description of these variables is reported in Table 3.1. To control for the heterogeneity across securities we include bond fixed effects. In addition, since the bond market order flow is correlated, and each

[3] We refer to this as the period after the meeting.

**Table 3.1:** Description of Regression Variables and Data Sources.
This table presents the variable names, definition and data source of the explanatory variables used in equations 3.11 and 3.12.

| | Variable | Description | Data Source |
|---|---|---|---|
| 1 | Expected Change | Change in fed funds rate obtained from 30-day Fed Funds futures prices | CME DataMine |
| 2 | Entropy | Uncertainty about expected change | Own calculation |
| 3 | Credit Spread | Moody's Seasoned Baa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity | FRED Economic Data |
| 4 | Maturity | Maturity of the bond | Thomson Reuters |
| 5 | Value difference | Theoretical bond price difference in case of a 25bps jump in the level of interest rates. Expressed in % | Own calculation |
| 6 | Yield | Risk free rate adjusted by the maturity of a bond. | Fed H.15 series |
| 7 | Absolute Surprise | Absolute value of a difference between last expected change and actual FOMC decision | Own calculation |
| 8 | Max Surprise | Maximum of the differences between the expected change and the two possible outcomes of the binomial tree. | Own calculation |
| 9 | Staleness | Opposite of the weighted sum of the volume of the 5 previous trading days. For each bond $i$, $Staleness_{i,t} = -\sum_{j=0}^{5} Volume_{i,t-j} * 2^{-j}$ | TRACE |
| 10 | Deviation | Distance from the theoretical mid price on a given day. Expressed in bps. | TRACE |
| 11 | Spread | Difference between Buy and Sell prices computed using either a full day or morning/afternoon transactions. Expressed in bps. | TRACE |
| 12 | Sell fraction | Sell trades volume divided by all trades volume in a given day. | TRACE |
| 13 | Bond Rating | Last observed bond's credit rating. If there are more ratings available the lowest is used. | Mergent |

announcement characteristics affect the whole cross section of securities, we cluster by the week around each FOMC meeting in all regressions.

Building on the literature and to break down the effect of the FOMC announcements on bond liquidity, we further analyse bonds with embedded options, as well as bonds issued by companies in different sectors separately.

In the last part of our analysis, we estimate an extended microstructure GMM model based on (Madhavan, Richardson and Roomans 1997). We follow an approach similar to (Green 2004). The model decomposes bid-ask spreads into compensation for liquidity provision (order processing costs) and adverse selection components. The latter measures price of information revealed by the order flow. The model also allows to quantify the premium related to the news announcement as well as to identify the cause of the change in trading costs around the FOMC statement releases.

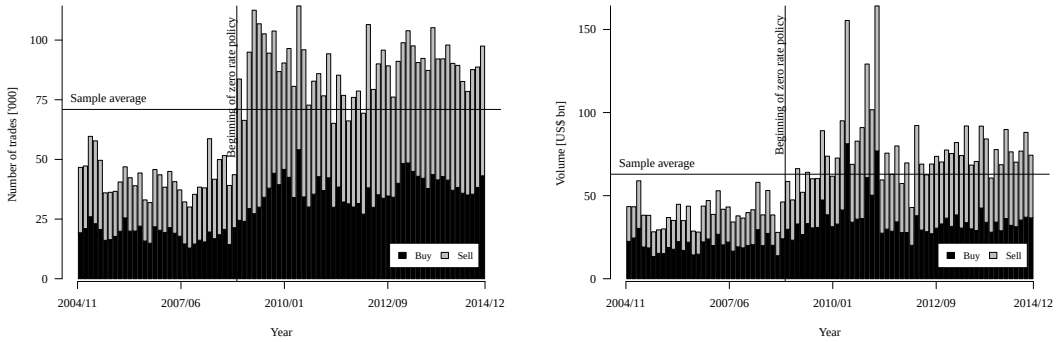
## 3.3 Summary Statistics

The data used in this study is downloaded from the TRACE database and covers the US market corporate bond trades. We keep only bonds with both buy (from the dealer's perspective) and sell dealer-customer transactions on a particular day. Furthermore, we match those trades by CUSIP codes with single bond characteristics and delete all the entries which indicated maturity less than zero as well as all of those without a match in the bond characteristics file. The final sample thus totals 5,817,147 corporate bond trades with 2,453,991 buy (bid) and 3,363,156 sell (ask) transactions. The dataset consists of 71,250 different bonds, with an average number of about 82 trades per bond, with minimum and maximum equal to 2 and 19,247, respectively. The average bond maturity in our sample is about 8.5 years.

Since the study focuses on behaviour during the FOMC meeting weeks, the trades span weeks around all FOMC meetings from 8 Nov 2004 to 19 Dec 2014 (announcements between 10 Nov 2004 and 17 Dec 2014) which equals to 82 event weeks[4]. There are few occasions when a public holiday occurs during such a week. For these cases we use the data from preceding Friday or up to following Monday so that we work on a consistent five working day window. The average number of transactions during a meeting week is around 65,000 while minimum and maximum are approximately 28,500 and 105,000, respectively. However, before the end of 2008 the number of trades was below the average, yet after the Fed rate reached 0-0.25% it increased significantly (see Figure 3.2a). On the other hand, while volume increased over time, there is no such a jump in the quantity of trades during the low interest rates regime (Figure 3.2b). Both trends suggest that an average deal size shrank during the period.

[4] There was a single change of -75bps outside scheduled meetings on 21 January 2008.

**Figure 3.2:** Trade quantity and volume of corporate bonds during FOMC meeting weeks 8 Nov 2004 - 19 Dec 2014.



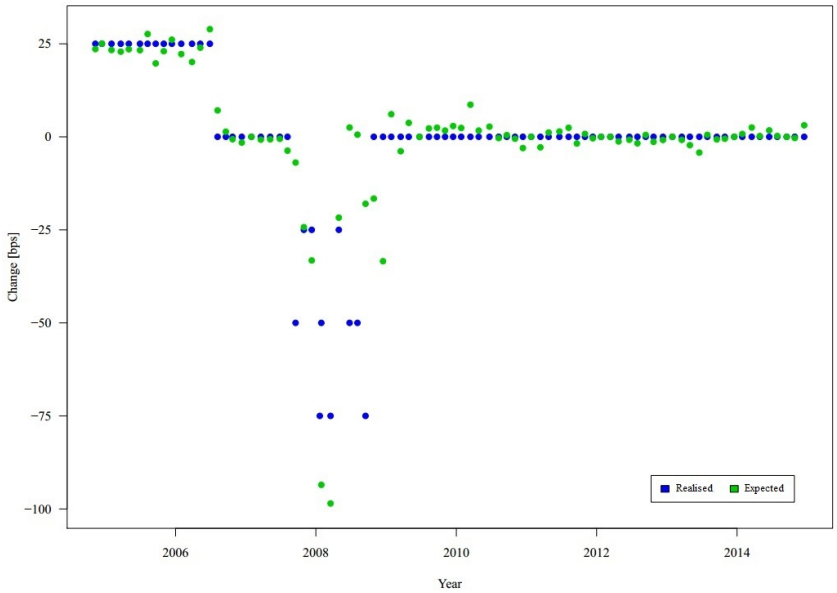

**(a)** Trade quantity **(b)** Trade volume

In order to compute the expected change in the federal funds rate, we download the daily 30 day Federal funds futures data from CME and compute the expected changes. The daily federal funds rate is a transaction-weighted rate and it is an important reference rate in the US. It is used in forming monetary policy decision as well as pricing interest rate products such as OIS. The federal funds market is an interbank OTC market for reserves held by Federal Reserve banks. The Federal funds futures are traded at the CBOT. They are interest rate contracts which cash settle at the average federal funds rate over the contract month. Neither there are up front costs of buying a contract nor the notional ($5 million) changes hands. The price is quoted as 100 minus the average overnight Federal funds rate for the delivery month.

During the period there were 15 up, 10 down and 59 no change movements in the federal funds rate. The policy shocks varied from $-75$bps to 25bps. As it can be seen in Figure 3.3, all up movements happened at the beginning of the period, while the drops around years 2007 and 2008. Expected changes on a day before each meeting obtained from the futures prices are also plotted in the figure. Simple summary statistics unveil that there is a rise in the number of trades around the FOMC meetings with the peak on the day preceding the meeting (22.7% of all trades). On the other hand, the daily volume peaks on the day after the meeting (23.54%). Both metrics show a significant decline in market activity on -2 and +2 days from the meeting. Further analysis shows that the market dealers are buying more after the meeting, while other participants are more likely to buy before the monetary policy action announcement.

We compute spreads based on all trades available on a single day and, where possible, we also split each day into morning and afternoon sessions with the cut-off point set up at 2:15pm. The split is dictated by the timing of the Federal Reserve announcements.

**Figure 3.3:** Realised and Expected changes in Fed Funds Rate as of each FOMC announcement between 10 Nov 2004 - 17 Dec 2014.




Additionally, both types of spreads are computed as volume-weighted and simple mean quantities. All four series were truncated at 0.5% and 99.5%. The summary statistics unveil similar pattern across the different measures of the spread. The most noticeable feature is that the value weighted spreads are in general lower than the standard ones, which is in line with the previous studies. Average spreads are equal to 103bps and 137bps in cases of the value weighted and standard full day measures, respectively.

Table 3.2 presents correlations between the variables used in our study. Most of them are lowly correlated. However, as expected there is high positive correlation between maturity, the risk free yield and $V^H - V^L$ (correlations between 0.3 and 0.5). While the credit spread is negatively correlated with the risk free rate and $V^H - V^L$ with correlations $-0.47$ and $-0.23$, respectively.

**Table 3.2:** Correlations.
The table reports correlations between variables. The sample is based on the US transaction data of corporate bonds from TRACE, provided by WRDS for the period during FOMC weeks from 8 Nov 2004 until 19 Dec 2014 - 5,817,147 observations. The correlations between bid/ask deviation are computed on the respective part of the dataset separately.

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Entropy | 1 | | | | | | | | | | | | | |
| 2. $V^H - V^L$ | -0.06 | 1 | | | | | | | | | | | | |
| 3. Bid/Ask deviation | -.06/.02 | -.10/.05 | 1 | | | | | | | | | | | |
| 4. log Volume | -0.02 | 0.02 | .22/-.21 | 1 | | | | | | | | | | |
| 5. log Dealer Volume | 0.03 | -0.03 | -.07/.02 | -0.18 | 1 | | | | | | | | | |
| 6. Maturity | -0.02 | 0.30 | -.14/.10 | 0.02 | -0.09 | 1 | | | | | | | | |
| 7. Expected Change | 0.06 | -0.01 | .03/.00 | 0.00 | -0.02 | -0.00 | 1 | | | | | | | |
| 8. Surprise Level | 0.02 | 0.02 | .02/-.02 | -0.00 | 0.01 | 0.00 | -0.00 | 1 | | | | | | |
| 9. Spread VW | 0.07 | 0.10 | -.53/.39 | -0.26 | 0.05 | 0.20 | -0.04 | -0.03 | 1 | | | | | |
| 10. Risk free rate | 0.03 | 0.35 | -.13/.11 | 0.01 | -0.07 | 0.49 | 0.09 | -0.06 | 0.16 | 1 | | | | |
| 11. Credit Spread | 0.18 | -0.23 | -.09/.01 | -0.06 | 0.08 | -0.03 | -0.07 | 0.05 | 0.12 | -0.47 | 1 | | | |
| 12. Sell Fraction | -0.01 | -0.02 | -.10/.12 | 0.02 | 0.00 | -0.02 | 0.01 | -0.01 | -0.01 | -0.00 | -0.02 | 1 | | |
| 13. log Staleness | -0.01 | 0.03 | -.02/-.01 | -0.01 | -0.60 | 0.07 | 0.01 | -0.00 | 0.07 | 0.01 | -0.00 | -0.08 | 1 | |
| 14. PIN | -0.07 | -0.09 | -.03/-.01 | -0.03 | 0.03 | -0.01 | -0.00 | 0.04 | 0.04 | -0.38 | 0.54 | -0.02 | 0.01 | 1 |

## 3.4 Results

In this section, we examine trading costs determinants for the whole sample of bonds. A higher volume of traded bonds around the FOMC meeting days can be linked to the flow of informed trading triggered by the expectations about future monetary policy, as predicted by (Kim and Verrecchia 1994). We see instead that announcement related variables have little influence on the trading volume and on the order imbalance: Figures 3.2a and 3.2b show that these variables follow a path not influenced by Fed announcements. Moreover, the paltry R-squared of the regressions reported in Tables 3.3 and 3.4 confirm the visual impression of the aforementioned figures.

In the first step, we analyse the behaviour of spreads before and after the announcement. Corporate bond dealers do not face a "toxic" order flow deriving from informed trading but rather confront traders with heterogeneous beliefs. Hence the FOMC announcement *per se* should not create a shock in the order flow that the dealers have to manage. At odds with these predictions, the dealers increase the price for liquidity provision before the announcement, in particular when the uncertainty about future monetary policy is high (see Table 3.5). In line with (Glosten and Milgrom 1985), a shift from a situation where there is no uncertainty (Entropy $= 0 \Leftrightarrow \theta_{t-1} \in \{0, 1\}$) to a case where future monetary policy is perceived like a coin flip (Entropy $= 0.25 \Leftrightarrow \theta_{t-1} = 0.5$) causes the bid ask spread to widen by approximately 35 bps. The value difference ($V^H - V^L$) indicates that the dealers account for a potential loss due to a jump in interest rates at any time. Moreover, there is some evidence of the usefulness of the 30 day Fed funds futures as predictor of monetary policy as the coefficient of unexpected monetary policy (difference between futures implied rate and the actual rate) shocks is large and significant. After an announcement, the dealers respond to the surprise component by widening the bid-ask spread. This happens irrespectively of the unexpected shock direction. (Comerton-Forde, Hendershott, Jones, Moulton and Seasholes 2010) unveil a similar pattern in equity markets. They point out that when dealers experience a revenue shock, they try to recover it by increasing the price for liquidity provision.

Consequently, we turn to deviation regressions where we can observe a more detailed dealers' response. We split the sample into four subcategories in order to study the behaviour of bids and asks during two periods separately. The findings are presented in Table 3.6. The regressions suggest that the uncertainty about interest rate changes and the future bond value affects bids more than asks. *Entropy* is both statistically and economically significant for both bid and ask prices. The effect of monetary uncertainty is approximately twice as large at bid (-60.94) than at ask (32.22). Additionally, the dealers do not change their sensitivity to $V^H - V^L$ on the buy side while they do not price it before the meetings on the sell side. This indicates that they are more likely to sell before the meeting in order to avoid holding the inventory over the announcement

**Table 3.3:** Volume regressions.
The table presents fixed effects panel data regressions results, where *Volume* is the dependent variable measured in billions of dollars. All t-statistics in brackets are based on robust clustered by the FOMC meeting weeks standard errors. The sample is based on the US corporate bonds transaction data from TRACE, provided by WRDS for the period during FOMC weeks from 8 Nov 2004 until 19 Dec 2014 - 838,882 observations averaged daily for each cusip. All reported regressions are estimated with bond fixed effects. $*, **, ***$ denote significance at 10%, 5% and 1%, respectively.

| | Volume [bn] | | | | |
|---|---|---|---|---|---|
| Horizon = −2 | 14.2 | 14.0 | 15.0 | 13.4 | 14.5 |
| | (1.54) | (1.51) | (1.44) | (1.43) | (1.37) |
| Horizon = −1 | 38.4 | 38.2 | 39.4 | 37.6 | 38.8 |
| | (4.51)*** | (4.48)*** | (4.03)*** | (4.32)*** | (3.92)*** |
| Horizon = 0 | 30.2 | 30.1 | 30.8 | 29.7 | 30.5 |
| | (4.12)*** | (4.10)*** | (4.02)*** | (4.02)*** | (3.95)*** |
| Horizon = 1 | 37.8 | 37.8 | 37.8 | 37.8 | 37.8 |
| | (3.83)*** | (3.82)*** | (3.82)*** | (3.83)*** | (3.83)*** |
| ExpectedChange | 1.18 | 2.26 | 2.88 | 0.54 | 1.18 |
| | (0.12) | (0.23) | (0.28) | (0.05) | (0.11) |
| max_surprise | 3.36 | 3.53 | 4.04 | 3.34 | 3.87 |
| | (0.21) | (0.22) | (0.26) | (0.21) | (0.25) |
| SurpriseLevel | | 21.4 | 21.4 | | |
| | | (1.04) | (1.04) | | |
| Entropy | | | -21.6 | | -22.7 |
| | | | (0.35) | | (0.37) |
| Absolute Surprise | | | | -16.7 | -17.1 |
| | | | | (0.70) | (0.72) |
| Constant | 78.4 | 78.6 | 78.6 | 79.2 | 79.2 |
| | (12.86)*** | (12.88)*** | (12.89)*** | (12.62)*** | (12.64)*** |
| F statistic | 4.9 | 4.5 | 3.9 | 4.3 | 3.8 |
| Adjusted R-squared | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

**Table 3.4:** Imbalance regressions.
The table presents fixed effects panel data regressions results, where *Imbalance* is the dependent variable measured as the normal quantile of the fraction of sell volume. All t-statistics in brackets are based on robust clustered by the FOMC meeting weeks standard errors. The sample is based on the US corporate bonds transaction data of from TRACE, provided by WRDS for the period during FOMC weeks from 8 Nov 2004 until 19 Dec 2014 - 838,882 observations averaged daily for each cusip. All reported regressions are estimated with bond fixed effects. $*, **, ***$ denote significance at 10%, 5% and 1%, respectively.

| | Imbalance | | | | |
|---|---|---|---|---|---|
| Horizon = −2 | -0.02 | -0.02 | -0.04 | -0.02 | -0.03 |
| | (1.86)* | (1.82)* | (2.58)** | (1.20) | (2.04)** |
| Horizon = −1 | -0.04 | -0.04 | -0.05 | -0.03 | -0.05 |
| | (3.13)*** | (3.09)*** | (3.85)*** | (2.38)** | (3.25)*** |
| Horizon = 0 | -0.03 | -0.03 | -0.04 | -0.03 | -0.04 |
| | (3.10)*** | (3.07)*** | (3.83)*** | (2.58)** | (3.39)*** |
| Horizon = 1 | -0.03 | -0.03 | -0.03 | -0.03 | -0.03 |
| | (2.67)*** | (2.66)*** | (2.65)*** | (2.67)*** | (2.67)*** |
| ExpectedChange | -0.00 | -0.00 | -0.01 | 0.01 | -0.00 |
| | (0.06) | (0.14) | (0.39) | (0.17) | (0.10) |
| max_surprise | -0.04 | -0.04 | -0.05 | -0.04 | -0.05 |
| | (1.42) | (1.43) | (1.64) | (1.40) | (1.61) |
| SurpriseLevel | | -0.05 | -0.05 | | |
| | | (1.38) | (1.35) | | |
| Entropy | | | 0.28 | | 0.29 |
| | | | (2.77)*** | | (2.85)*** |
| Absolute Surprise | | | | 0.18 | 0.18 |
| | | | | (6.61)*** | (6.71)*** |
| Constant | -4.41 | -4.42 | -4.42 | -4.42 | -4.42 |
| | (544.92)*** | (543.13)*** | (542.03)*** | (529.20)*** | (528.29)*** |
| F statistic | 2.9 | 2.9 | 3.3 | 9.6 | 8.9 |
| Adjusted R-squared | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

**Table 3.5:** Spread regressions.
Regressions before and after the announcement of value weighted spread based on RHS variables from Equations3.11 and 3.12. All t-statistics in brackets are based on robust clustered by the FOMC meeting weeks standard errors. The sample is based on the US transaction data of corporate bonds from TRACE, provided by WRDS for the period during FOMC weeks from 8 Nov 2004 until 19 Dec 2014. All reported regressions are estimated with bond fixed effects and control variables. $*, **, ***$ denote significance at 10%, 5% and 1%, respectively.

| | Before | After |
|---|---|---|
| | Spread [bps] | |
| Entropy | 139.07 | |
| | (2.98)*** | |
| ExpectedChange | -67.54 | |
| | (4.29)*** | |
| $V^H - V^L$ [%] | 18.43 | 25.16 |
| | (4.45)*** | (5.90)*** |
| Maturity | 7.95 | 7.06 |
| | (5.34)*** | (4.93)*** |
| Yield [%] | 5.30 | 2.12 |
| | (2.37)** | (0.86) |
| Credit Spread [%] | 17.02 | 16.84 |
| | (10.20)*** | (8.82)*** |
| Bond Rating | 4.00 | 4.24 |
| | (5.12)*** | (6.98)*** |
| Absolute Surprise | | 135.34 |
| | | (2.63)** |
| Constant | 12.67 | 15.09 |
| | (0.99) | (0.95) |
| F statistic | 252.7 | 129.6 |
| Adjusted R-squared | 0.11 | 0.10 |
| $N$ | 2,991,049 | 2,782,502 |

period. Surprisingly, the expectation of an interest rate hike decreases the trading costs on the bid side. To explain this counter-intuitive behaviour, we look at the average price movements before the announcement: we can see in Table 3.7 that the average price is significantly lower when traders expect a rise in interest rates. Moreover, an unreported regression of the average relative price on the expected change suggests that price decrease of 10 bps per percentage point of expected positive jump. The increased liquidity on the bid side is likely to be caused by dealers competing to purchase securities

**Table 3.6:** Deviation regressions.
Regressions before and after the announcement of deviation and split between sides as per Equations 3.11 and 3.12. All t-statistics in brackets are based on robust clustered by the FOMC meeting weeks standard errors. The sample is based on the US transaction data of corporate bonds from TRACE, provided by WRDS for the period during FOMC weeks from 8 Nov 2004 until 19 Dec 2014. All reported regressions are estimated with bond fixed effects and control variables. $*, **, ***$ denote significance at 10%, 5% and 1%, respectively.

| | Before | | After | |
|---|---|---|---|---|
| | Bid | Ask | Bid | Ask |
| Entropy | -60.94 | 32.22 | | |
| | (2.30)** | (2.05)** | | |
| ExpectedChange | 45.09 | -6.87 | | |
| | (6.58)*** | (1.57) | | |
| $V^H - V^L$ [%] | -11.09 | 3.66 | -11.69 | 7.99 |
| | (4.73)*** | (1.52) | (5.38)*** | (3.79)*** |
| Maturity | -8.56 | 0.01 | -7.40 | 0.59 |
| | (10.89)*** | (0.02) | (7.95)*** | (1.46) |
| Yield [%] | -2.18 | 4.18 | -1.55 | 2.13 |
| | (1.68)* | (5.45)*** | (0.97) | (2.66)*** |
| Credit Spread [%] | -11.84 | 2.99 | -11.14 | 3.15 |
| | (10.02)*** | (5.22)*** | (8.95)*** | (5.25)*** |
| Bond Rating | 2.05 | 4.30 | 1.75 | 4.21 |
| | (5.50)*** | (16.60)*** | (4.36)*** | (16.41)*** |
| Absolute Surprise | | | -59.68 | 42.65 |
| | | | (3.59)*** | (2.20)** |
| Constant | -4.49 | 57.57 | -14.25 | 51.52 |
| | (0.47) | (10.42)*** | (1.46) | (8.36)*** |
| F statistic | 106.0 | 242.6 | 86.5 | 296.0 |
| Adjusted R-squared | 0.11 | 0.05 | 0.09 | 0.05 |
| $N$ | 1,252,620 | 1,738,429 | 1,189,452 | 1,593,050 |

at a distressed price. Moreover, it further supports our claim that market participants closely observe the monetary policy news and incorporate them into prices even before the FOMC announcement.

When considering the difference between high and low security value state, we observe that the more interest rate sensitive a security is, the lower the bid price posted by the dealers. The ask price is not affected by this variable: dealers are prone to reduce

their inventory before the FOMC announcement and offer better conditions to players on the ask side. After the uncertainty is resolved, we can see that the bid price continues to be affected in the same way and that ask quotes are adjusted accordingly: without an imminent threat of a value shock to their inventory, dealers respond to interest rate sensitivity with a symmetric adjustment of both bid and ask prices. Unsurprisingly, the

**Table 3.7:** Average price and policy expectations.
Comparison of the average relative price in presence of expectation of interest rate hike or ease. The standard errors of the mean are reported in parenthesis. The t-test is based on the alternative hypothesis that the average price in presence of hike expectations is lower than in presence of ease expectations. $*, **, ***$ denote significance at 10%, 5% and 1%, respectively.

| Horizon | -2 | -1 | 0 |
|---|---|---|---|
| Hike | 1 | 1.000 | 1.001 |
| | | (0.013) | (0.015) |
| Ease | 1 | 1.001 | 1.002 |
| | | (0.075) | (0.022) |
| t-stat | | -1.401* | -5.353*** |

interest rate sensitivity is reflected by credit ratings. As the yield of a AAA bond is predominantly determined by the risk free curve, a change in policy rates has a greater impact on such a bond compared to one with a larger credit spread. As a result, the dealers require higher compensation the better rating bond has. Conversely, when clients want to buy speculative securities, the dealers can infer positive idiosyncratic information. In fact, despite the higher risk of such securities, dealers charge relatively more to sell them. In addition, the adjustment for credit rating does not change on the sell side after the announcement; therefore, it is likely to be related to issuer-specific information that can be released at any moment.

### 3.4.1 Embedded options

The prices of bonds with and without embedded options should react differently to changes in interest rates. As a substantial part of the bonds traded contain one or more embedded option, we test whether our results are not driven by the option components. In order to perform the tests, we obtain embedded options data from Thomson Reuters and we run the regressions separately for callable, convertible, putable, and no option bonds.

The liquidity of callable bonds behaves in a different way as compared to the general results (see Table 3.8). Despite having a similar reaction to the monetary policy un-

certainty, it moves in the opposite direction to the expected change and to the interest rates sensitivity. The bid price increases as observed in the whole sample, while the ask decreases in the anticipated adjustment. Overall, dealers' compensation is decreasing in the expected shift in policy rates. An explanation might lie in the option component of such bonds: a higher interest rate pushes the embedded call option out of the money, this translates into lower volatility of the optionality component of the price (Duffee 1998). In general, the lower the security volatility, the higher its liquidity.

In terms of the interest rates sensitivity, we observe that bid prices do not respond to larger price sensitivity (unlike in our general results), but ask prices do. This might be an exacerbation of the dealers behaviour, who set ask prices to dispose the most sensitive assets. Lastly, the trading costs of callable bonds after the announcement are not affected by the securities' responsiveness.

Next we turn to bonds without options. Thanks to this separate analysis, we can identify which of the general results are driven by plain vanilla bonds, and those caused by callable bonds. These two categories represent most of the trades in our sample, therefore they are likely to be the main drivers of our general results.

First, we notice that the *Entropy* affects only the bid price of simple bonds. Hence, the general worsening of the trading cost presented in Table 3.6 is partly caused by callable bonds. It appears that the dealers require a compensation to sell callable bonds before the FOMC announcement. Before the meeting, prices of callable bonds might be distressed because higher entropy means an increase in the value of the embedded call option. Therefore, the dealers prefer to wait for an announcement when the uncertainty about future monetary policy is high.

Second, the expectations of higher interest rates increase the bid price for straight bonds, possibly because of the presence of depressed prices. However, we do not observe any liquidity improvements on the ask side. As in the case of callable bonds dealers do not want to sell at a distressed price in presence of uncertainty. Nevertheless, this case is (somewhat) different because the price is unlikely to revert after a hike in the interest rates. In summary, dealers prefer to wait until the last moment to realize losses.

Lastly, it can be noticed that the interest rates sensitivity affects bid and ask prices both before and after the announcement. We conclude that the non-significant coefficient for the ask price before the meeting is caused by dealers offering favourable ask price to eliminate the risk of holding callable bonds.

In terms of credit rating, the adjustment for callable bonds is lower in magnitude than in the case of straight bonds. A smaller shift translates into worse trading conditions on the buy side, and in favourable on the sell side for low-rated callable bonds. Such change suggests a larger inventory risk aversion for callable bonds. In fact, interest rate movements can affect the value of the embedded option of low rated firms, which issue these instruments to be exposed to favorable interest rate movements. In summary, the

dealers fear changes in the value of callable bonds embedded options and idiosyncratic changes of the issuer credit quality for straight bonds.

We now turn to the analysis of convertible and putable bonds (Table 3.9). These securities represent a smaller fraction of trades compared to callables and plain vanilla bonds. The sensitivity of convertibles to the future monetary policy uncertainty moves in the same way as in the case of callable bonds. This result comes from the fact that around 40% of convertibles (accounting for about half of trades) are also callable: in fact, the measure of sensitivity to the entropy is smaller and noisier that the one for callables. The expectations of a rise in the interest rate increases the liquidity of convertibles. This behaviour is related to the raised moneyness of the conversion option, due to both a lower bond value and higher policy rates which is related to booming stock markets (Rigobon and Sack 2003). The bond price will then become close to the price of the company equity which is traded on a more liquid market. Another surprising result is the low response of the ask price to interest rate sensitivity: unlike other securities, convertibles react neither before, nor after the news release. However, the dealers require higher compensation for buying this type of bonds before the announcement the lower bonds credit quality.

We observe that the entropy does not affect putable bonds liquidity. The presence of an embedded long put option insures the dealers' inventory against adverse interest rates movements. Given this insurance, dealers can perform their market making activity with lower risk and, therefore demand a lower compensation. Like other bonds with embedded options, the outlook of higher interest rates boosts their liquidity. In this case, an increased moneyness of the put option is the key driver and the bond price gets closer to the exercise trigger point. In addition, thanks to the put protection, the individual bond rating does not play a role when the dealers acquire such bonds.

**Table 3.8:** No embedded option and callable bonds regressions.
The table presents fixed effects panel data regressions results, where *deviation* is the dependent variable measured in basis points. Some explanatory variables are not reported the table. All t-statistics in brackets are based on robust clustered by the FOMC meeting weeks standard errors. The sample is based on the US transaction data of corporate bonds from TRACE, provided by WRDS for the period during FOMC weeks from 8 Nov 2004 until 19 Dec 2014. All reported regressions are estimated with bond fixed effects and control variables. $*, **, ***$ denote significance at 10%, 5% and 1%, respectively.

| | Before | | | | After | | | |
|---|---|---|---|---|---|---|---|---|
| | Bid Callable | Bid No Option | Ask Callable | Ask No Option | Bid Callable | Bid No Option | Ask Callable | Ask No Option |
| Entropy | -33.94 | -51.09 | 58.24 | 22.07 | | | | |
| | (1.55) | (2.08)** | (3.30)*** | (1.36) | | | | |
| Expected Change | 19.35 | 52.94 | -16.86 | -5.29 | | | | |
| | (3.06)*** | (8.46)*** | (4.53)*** | (1.08) | | | | |
| $V^H - V^L$ [%] | 0.55 | -13.25 | -14.14 | 10.98 | -0.10 | -12.75 | -4.83 | 16.44 |
| | (0.12) | (6.01)*** | (3.56)*** | (4.03)*** | (0.04) | (6.09)*** | (1.19) | (6.14)*** |
| Maturity [years] | -11.67 | -6.18 | 2.21 | -1.18 | -10.48 | -6.05 | 2.35 | -0.30 |
| | (11.40)*** | (8.50)*** | (3.41)*** | (2.35)** | (11.57)*** | (5.91)*** | (3.08)*** | (0.65) |
| Yield [%] | 3.47 | -4.43 | 4.45 | 4.52 | 4.61 | -3.53 | 3.26 | 2.13 |
| | (2.68)*** | (3.41)*** | (4.14)*** | (5.37)*** | (3.21)*** | (1.94)* | (3.34)*** | (2.41)** |
| Credit Spread [%] | -8.03 | -14.29 | 2.68 | 3.56 | -6.86 | -13.11 | 3.52 | 3.33 |
| | (7.46)*** | (12.22)*** | (2.53)** | (6.12)*** | (7.72)*** | (9.63)*** | (2.98)*** | (5.36)*** |
| Bond Rating | 1.53 | 2.04 | 3.31 | 4.73 | 1.96 | 1.53 | 3.10 | 4.67 |
| | (3.53)*** | (4.18)*** | (6.88)*** | (16.62)*** | (5.31)*** | (2.93)*** | (7.16)*** | (15.28)*** |
| Absolute Surprise | | | | | -20.70 | -69.05 | 38.89 | 44.64 |
| | | | | | (2.52)** | (3.20)*** | (5.08)*** | (1.93)* |
| Constant | -204.09 | -351.22 | 326.75 | 97.64 | -86.71 | -206.24 | 175.10 | -6.46 |
| | (4.33)*** | (6.27)*** | (6.42)*** | (2.86)*** | (1.50) | (3.19)*** | (4.39)*** | (0.16) |
| F statistic | 76.3 | 85.4 | 150.9 | 272.2 | 86.1 | 69.9 | 237.8 | 255.8 |
| Adjusted R-squared | 0.08 | 0.14 | 0.05 | 0.05 | 0.07 | 0.11 | 0.05 | 0.05 |
| $N$ | 296,309 | 914,563 | 403,882 | 1,288,760 | 279,195 | 867,629 | 375,911 | 1,171,971 |

**Table 3.9:** Convertible and putable bonds regressions.
The table presents fixed effects panel data regressions results, where *deviation* is the dependent variable measured in basis points. Some explanatory variables are not reported the table. All t-statistics in brackets are based on robust clustered by the FOMC meeting weeks standard errors. The sample is based on the US transaction data of corporate bonds from TRACE, provided by WRDS for the period during FOMC weeks from 8 Nov 2004 until 19 Dec 2014. All reported regressions are estimated with bond fixed effects and control variables. $*, **, ***$ denote significance at 10%, 5% and 1%, respectively.

| | Before | | | | After | | | |
|---|---|---|---|---|---|---|---|---|
| | Bid Convertible | Bid Putable | Ask Convertible | Ask Putable | Bid Convertible | Bid Putable | Ask Convertible | Ask Putable |
| Entropy | 14.03 | 8.03 | 28.60 | 8.22 | | | | |
| | (0.65) | (0.41) | (1.43) | (0.37) | | | | |
| Expected Change | 12.99 | 12.76 | -16.87 | -12.58 | | | | |
| | (3.05)*** | (3.28)*** | (3.77)*** | (3.47)*** | | | | |
| $V^H - V^L$ [%] | -3.53 | -4.88 | -1.09 | -2.37 | -2.82 | -3.75 | 0.69 | 0.22 |
| | (5.48)*** | (7.16)*** | (1.28) | (2.77)*** | (4.59)*** | (4.51)*** | (0.79) | (0.22) |
| Maturity [years] | -3.53 | -4.88 | -1.09 | -2.37 | -2.82 | -3.75 | 0.69 | 0.22 |
| | (5.48)*** | (7.16)*** | (1.28) | (2.77)*** | (4.59)*** | (4.51)*** | (0.79) | (0.22) |
| Yield [%] | -0.40 | -6.37 | 5.11 | 12.72 | -1.64 | -2.54 | 1.92 | 6.91 |
| | (0.31) | (2.66)*** | (3.84)*** | (5.33)*** | (1.37) | (1.04) | (1.36) | (2.28)** |
| Credit Spread [%] | -6.57 | -11.57 | 7.04 | 12.06 | -6.80 | -6.81 | 5.98 | 9.73 |
| | (8.00)*** | (7.57)*** | (8.07)*** | (7.19)*** | (8.95)*** | (4.58)*** | (5.46)*** | (6.40)*** |
| Bond Rating | -1.43 | 0.12 | 2.93 | 4.41 | -0.90 | 0.47 | 3.09 | 5.18 |
| | (2.91)*** | (0.14) | (5.24)*** | (5.62)*** | (1.46) | (0.47) | (4.49)*** | (4.04)*** |
| Absolute Surprise | | | | | -6.06 | -9.49 | 30.93 | 28.05 |
| | | | | | (0.59) | (1.03) | (3.02)*** | (3.22)*** |
| Constant | -373.60 | -196.82 | 231.61 | 276.65 | -290.62 | -141.95 | 109.75 | -7.77 |
| | (6.72)*** | (2.76)*** | (3.34)*** | (3.29)*** | (4.55)*** | (2.20)** | (2.19)** | (0.09) |
| F statistic | 68.4 | 71.1 | 56.8 | 42.9 | 66.4 | 57.0 | 75.1 | 52.4 |
| Adjusted R-squared | 0.17 | 0.18 | 0.06 | 0.06 | 0.15 | 0.15 | 0.06 | 0.05 |
| $N$ | 74,847 | 35,478 | 71,598 | 32,667 | 78,288 | 37,288 | 72,424 | 33,741 |

### 3.4.2 Industry

Building on vast literature (e.g. (Ehrmann and Fratzscher 2004) or (Dedola and Lippi 2005)), we proceed to examine the difference in sensitivity of various industries to the FOMC policy. In order to do so, we split the sample into seven groups based on SIC codes and grouping described by Kenneth French five portfolios[5] adjusted by separating finance and utilities sectors from "other" due to their well documented sensitivity to interest rate movements (e.g. (Sweeney and Warga 1986)).

Following the same procedure as before, we estimate the regressions on separate industry sub-samples ahead and after the announcement for buy and sell transactions. All results are displayed in tables 3.10, 3.11, 3.12 and 3.13. It can be seen that there is some dispersion in the price of uncertainty. The dealers are particularly averse to acquire Manufacturing, Utilities and Healthcare bonds before the meeting. Even more interestingly, the market makers perceive a possible change in bond value differently across sectors.

On the other hand, the examination of ask quotes reveals a substantially different behaviour. The dealers do not incorporate the interest rate uncertainty into their quoted prices. These results suggest that market makers prefer to sell the bonds irrespectively of the predicted outcome. Furthermore, the value difference variable is only significant for Financial, Consumer and Health industries. This phenomenon could indicate that the dealers prefer to sell bonds before instead of holding them through the news release period. They are not interested in potential distribution of the value, the inventory risk reduction plays a more important role at that point.

Next, we turn our analysis to the post-meeting period. The value difference variable is still significant across industries except Consumer products. Moreover, absolute surprise impacts all but Other sectors at the bid, while it is the most significant for this sector on the ask side. The total effect is the largest for Finance industry which is likely to be linked to the sector's sensitivity to the interest rate level.

[5] Further information about the codes allocation can be found on http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_5_ind_port.html

**Table 3.10:** Bid transactions before FOMC split by industry.
The table presents fixed effects panel data regressions results for the bid trades that occurred before the monetary policy announcement. *Deviation* is the dependent variable measured in basis points. All bonds with embedded options are removed from this analysis. Some explanatory variables are not reported in the table. All t-statistics in brackets are based on robust clustered by the FOMC meeting weeks standard errors. The sample is based on the US transaction data of corporate bonds from TRACE, provided by WRDS for the period during FOMC weeks from 8 Nov 2004 until 19 Dec 2014. All reported regressions are estimated with bond fixed effects and control variables. $*, **, ***$ denote significance at 10%, 5% and 1%, respectively.

| | Bid before announcement | | | | | | |
|---|---|---|---|---|---|---|---|
| Sector | Finance | Consumer | Manufacturing | Utilities | HiTec | Health | Other |
| Entropy | -58.02 | -69.67 | -101.30 | -71.89 | -57.55 | -93.60 | -66.54 |
| | (2.07)** | (2.05)** | (2.12)** | (1.93)* | (2.00)** | (2.43)** | (2.03)** |
| ExpectedChange | 58.83 | 57.16 | 48.52 | 52.18 | 58.87 | 40.11 | 32.96 |
| | (9.90)*** | (6.06)*** | (4.99)*** | (3.48)*** | (5.04)*** | (4.36)*** | (3.40)*** |
| $V^H - V^L$ [%] | -18.82 | 6.96 | -18.62 | -16.33 | -19.28 | -3.97 | -33.86 |
| | (5.68)*** | (1.45) | (5.06)*** | (3.46)*** | (4.49)*** | (1.03) | (4.78)*** |
| Maturity | -5.78 | -10.58 | -7.27 | -6.04 | -6.34 | -5.22 | -3.01 |
| | (6.29)*** | (11.98)*** | (5.88)*** | (5.55)*** | (5.85)*** | (4.91)*** | (3.02)*** |
| Yield [%] | -6.56 | -3.65 | -2.60 | -1.95 | -2.06 | -5.31 | -4.27 |
| | (3.88)*** | (2.14)** | (1.11) | (1.13) | (1.39) | (3.05)*** | (2.56)** |
| Credit Spread [%] | -14.55 | -13.15 | -15.11 | -11.51 | -8.90 | -8.33 | -14.72 |
| | (10.31)*** | (11.48)*** | (8.06)*** | (7.73)*** | (6.39)*** | (7.22)*** | (13.37)*** |
| Bond Rating | 1.26 | 3.39 | 4.30 | 4.83 | 2.95 | -0.47 | 2.75 |
| | (2.75)*** | (2.97)*** | (3.62)*** | (3.10)*** | (4.55)*** | (0.70) | (1.71)* |
| Constant | 16.50 | -21.16 | 32.34 | -53.04 | -0.31 | 4.50 | -42.40 |
| | (1.67)* | (1.34) | (1.78)* | (3.07)*** | (0.03) | (0.46) | (2.35)** |
| F statistic | 67.1 | 79.5 | 74.5 | 45.0 | 54.7 | 33.7 | 47.9 |
| Adjusted R-squared | 0.14 | 0.14 | 0.17 | 0.14 | 0.11 | 0.16 | 0.09 |
| $N$ | 521,887 | 102,557 | 109,777 | 23,464 | 95,931 | 26,024 | 34,923 |

**Table 3.11:** Ask transactions before FOMC split by industry.
The table presents fixed effects panel data regressions results for the ask trades that occurred before the monetary policy announcement. *Deviation* is the dependent variable measured in basis points. All bonds with embedded options are removed from this analysis. Some explanatory variables are not reported in the table. All t-statistics in brackets are based on robust clustered by the FOMC meeting weeks standard errors. The sample is based on the US transaction data of corporate bonds from TRACE, provided by WRDS for the period during FOMC weeks from 8 Nov 2004 until 19 Dec 2014. All reported regressions are estimated with bond fixed effects and control variables. $*, **, ***$ denote significance at 10%, 5% and 1%, respectively.

| | Ask before announcement | | | | | | |
|---|---|---|---|---|---|---|---|
| Sector | Finance | Consumer | Manufacturing | Utilities | HiTec | Health | Other |
| Entropy | 31.25 | 11.23 | -9.87 | 42.39 | 24.64 | -8.33 | 64.36 |
| | (1.54) | (0.65) | (0.52) | (1.77)* | (2.64)*** | (0.50) | (1.81)* |
| ExpectedChange | -7.27 | 6.29 | 12.67 | -19.42 | -12.58 | 2.13 | -23.94 |
| | (1.04) | (1.09) | (2.26)** | (2.94)*** | (3.03)*** | (0.43) | (3.67)*** |
| $V^H - V^L$ [%] | 17.99 | 6.02 | -1.32 | 3.12 | 1.64 | 10.21 | 8.25 |
| | (5.40)*** | (1.49) | (0.30) | (0.84) | (0.46) | (2.28)** | (1.39) |
| Maturity [years] | -1.86 | 1.54 | -0.31 | -2.06 | -1.37 | 0.44 | -1.24 |
| | (2.81)*** | (1.83)* | (0.37) | (2.70)*** | (2.52)** | (0.47) | (0.99) |
| Yield [%] | 4.58 | 1.53 | 4.60 | 5.32 | 6.64 | 3.20 | 6.22 |
| | (4.60)*** | (1.21) | (3.64)*** | (3.55)*** | (8.26)*** | (2.16)** | (3.49)*** |
| Credit Spread [%] | 4.32 | 0.84 | 1.50 | 1.80 | 3.60 | 3.58 | 5.37 |
| | (6.72)*** | (1.16) | (1.82)* | (2.17)** | (6.55)*** | (4.63)*** | (4.05)*** |
| Bond Rating | 4.02 | 7.15 | 3.55 | 7.86 | 3.97 | 2.70 | 7.18 |
| | (9.71)*** | (12.04)*** | (4.77)*** | (4.32)*** | (5.91)*** | (5.55)*** | (7.50)*** |
| Constant | 46.04 | 63.78 | 91.25 | 29.95 | 65.26 | 36.91 | 5.03 |
| | (7.80)*** | (5.91)*** | (5.82)*** | (1.46) | (6.16)*** | (4.08)*** | (0.39) |
| F statistic | 223.9 | 68.5 | 94.9 | 51.8 | 128.9 | 38.9 | 63.1 |
| Adjusted R-squared | 0.05 | 0.06 | 0.04 | 0.05 | 0.05 | 0.06 | 0.06 |
| $N$ | 743,263 | 133,327 | 163,313 | 30,382 | 135,242 | 33,125 | 50,108 |

**Table 3.12:** Bid transactions after FOMC split by industry.
The table presents fixed effects panel data regressions results for the bid trades that occurred after the monetary policy announcement. *Deviation* is the dependent variable measured in basis points. All bonds with embedded options are removed from this analysis. Some explanatory variables are not reported in the table. All t-statistics in brackets are based on robust clustered by the FOMC meeting weeks standard errors. The sample is based on the US transaction data of corporate bonds from TRACE, provided by WRDS for the period during FOMC weeks from 8 Nov 2004 until 19 Dec 2014. All reported regressions are estimated with bond fixed effects and control variables. $*, **, ***$ denote significance at 10%, 5% and 1%, respectively.

| | Bid after announcement | | | | | | |
|---|---|---|---|---|---|---|---|
| Sector | Finance | Consumer | Manufacturing | Utilities | HiTec | Health | Other |
| $V^H - V^L$ [%] | -18.99 | 2.57 | -12.19 | -19.78 | -13.07 | -5.90 | -40.35 |
| | (5.64)*** | (0.53) | (3.07)*** | (4.96)*** | (2.87)*** | (1.63) | (6.26)*** |
| Maturity [years] | -5.33 | -8.58 | -6.49 | -4.59 | -4.74 | -3.86 | -2.70 |
| | (4.55)*** | (8.16)*** | (4.43)*** | (3.99)*** | (3.89)*** | (3.35)*** | (2.36)** |
| Yield [%] | -4.25 | -4.14 | -4.49 | -4.55 | -4.35 | -6.79 | -3.60 |
| | (1.88)* | (2.00)** | (1.67)* | (2.56)** | (2.69)*** | (2.83)*** | (1.78)* |
| Credit Spread [%] | -13.27 | -12.18 | -14.96 | -12.44 | -8.88 | -7.71 | -14.74 |
| | (8.78)*** | (7.64)*** | (7.54)*** | (8.51)*** | (5.54)*** | (4.57)*** | (8.90)*** |
| Bond Rating | 0.88 | 2.48 | 2.95 | 5.27 | 2.69 | -1.74 | 1.71 |
| | (1.68)* | (2.12)** | (2.32)** | (3.13)*** | (4.68)*** | (2.35)** | (1.21) |
| Absolute Surprise | -81.64 | -70.24 | -66.24 | -55.19 | -65.73 | -39.39 | -14.76 |
| | (3.43)*** | (6.44)*** | (2.26)** | (3.88)*** | (4.35)*** | (3.06)*** | (1.16) |
| Constant | 11.10 | -29.21 | 32.07 | -54.09 | -30.69 | -6.33 | -39.80 |
| | (1.08) | (1.60) | (1.74)* | (2.71)*** | (2.45)** | (0.52) | (2.18)** |
| F statistic | 59.5 | 72.1 | 68.5 | 50.4 | 55.9 | 33.4 | 85.4 |
| Adjusted R-squared | 0.11 | 0.12 | 0.15 | 0.13 | 0.10 | 0.12 | 0.09 |
| $N$ | 498,139 | 100,013 | 101,087 | 21,408 | 89,370 | 23,834 | 33,778 |

**Table 3.13:** Ask transactions after FOMC split by industry.
The table presents fixed effects panel data regressions results for the ask trades that occurred after the monetary policy announcement. *Deviation* is the dependent variable measured in basis points. All bonds with embedded options are removed from this analysis. Some explanatory variables are not reported in the table. All t-statistics in brackets are based on robust clustered by the FOMC meeting weeks standard errors. The sample is based on the US transaction data of corporate bonds from TRACE, provided by WRDS for the period during FOMC weeks from 8 Nov 2004 until 19 Dec 2014. All reported regressions are estimated with bond fixed effects and control variables. $*, **, ***$ denote significance at 10%, 5% and 1%, respectively.

| | Ask after announcement | | | | | | |
|---|---|---|---|---|---|---|---|
| Sector | Finance | Consumer | Manufacturing | Utilities | HiTec | Health | Other |
| $V^H - V^L$ [%] | 20.45 | 9.69 | 5.41 | 12.18 | 10.20 | 14.74 | 14.30 |
| | (6.08)*** | (2.32)** | (1.27) | (3.77)*** | (2.82)*** | (3.57)*** | (2.57)** |
| Maturity [years] | -0.92 | 2.36 | 1.38 | -1.10 | -0.73 | 2.47 | -1.33 |
| | (1.48) | (3.27)*** | (1.83)* | (1.38) | (1.18) | (2.89)*** | (1.37) |
| Yield [%] | 1.96 | 0.03 | -0.49 | 3.29 | 3.83 | -0.77 | 4.23 |
| | (1.69)* | (0.03) | (0.37) | (2.56)** | (3.73)*** | (0.58) | (2.21)** |
| Credit Spread [%] | 3.96 | 1.44 | 1.41 | 4.29 | 3.48 | 3.96 | 4.90 |
| | (5.56)*** | (1.76)* | (2.13)** | (6.55)*** | (4.79)*** | (6.65)*** | (4.97)*** |
| Bond Rating | 3.36 | 8.61 | 3.55 | 10.22 | 4.67 | 3.55 | 6.55 |
| | (8.68)*** | (15.02)*** | (3.66)*** | (5.46)*** | (9.65)*** | (5.13)*** | (6.43)*** |
| Absolute Surprise | 50.27 | 10.63 | 26.47 | 13.36 | 31.77 | 13.43 | 99.61 |
| | (1.83)* | (0.85) | (1.47) | (1.89)* | (2.40)** | (1.25) | (2.33)** |
| Constant | 47.69 | 35.87 | 69.02 | -3.84 | 49.09 | 20.98 | 13.59 |
| | (6.97)*** | (3.00)*** | (6.10)*** | (0.22) | (5.62)*** | (2.29)** | (1.07) |
| F statistic | 161.8 | 93.0 | 70.6 | 39.1 | 86.7 | 78.6 | 55.6 |
| Adjusted R-squared | 0.05 | 0.07 | 0.04 | 0.05 | 0.05 | 0.06 | 0.06 |
| $N$ | 681,849 | 124,429 | 144,419 | 27,749 | 118,300 | 29,627 | 45,598 |

### 3.4.3 Risk aversion

In the previous sections, we have documented an asymmetric response to the information from the futures markets. The results point towards abnormally large risk aversion of dealers ahead of the FOMC meetings. In order to measure what fraction of the spread is related to information asymmetry, we estimate a generalised version of a microstructure model which allows for autocorrelation in the order flow[6]. We include indicator functions in order to disentangle effects in time series: days with no news releases, the announcement day before and after 2:15pm, as well as in cross section: bid and ask transactions.

The GMM results confirm our previous hypothesis and are presented in the panel A of table 3.14. It can be seen that the information about monetary policy is disseminated efficiently as the adverse selection coefficients are negative and the premium coefficient - $\gamma$ is not statistically different from 0. Dealers only fear some information asymmetry from the buy orders just before the announcements when $\theta_{BA} = 0.16$. Moreover, despite higher adverse selection costs, the dealers reduce the liquidity provision costs significantly. This is in line with the previous results, we can see that the market makers do so in order to adjust their inventories before the news release and are also willing to forego a part of their profits. We conclude that the inventory risk aversion causes an asymmetric response to *Entropy*. In addition, it is likely to be the key factor influencing its lack of statistical significance at the ask.

Linear tests of estimated coefficients further corroborate panel data regressions. The cost fractions vary among periods and sides. All linear tests are significant at 1% (Panel B, table 3.14). However, the total costs ($\theta + \phi$) are not statistically different for *Before* and *No Announcement* at the bid, and *Before* and *After* at the ask. This is why we do not observe a large difference in spreads ahead and after the releases within our sample.

We have also shown that ask is typically not affected by value difference before the announcement, we believe that the results from 3.6 can be linked to the shift of dealers' focus from bond price fluctuations to the possibility of trading with an informed trader. The liquidity providers sharply decrease their order processing costs at both bid and ask but more so at the ask price (20 vs 8 cents). Interestingly, the costs surge immediately after the announcement by 13 and 1 cent above the *No Announcement* period levels for the ask and the bid side, respectively. Since the order processing costs fall significantly while adverse selection costs rise during the morning of the monetary policy news release it is likely that the variation translates to poor performance of $V^H - V^L$.

[6] See A.1 for the details of the model and its estimation.

**Table 3.14:** GMM model estimates.
The table presents GMM results from the model fit to transaction price changes between 11:00 and 17:00 during the period of FOMC weeks from 8 Nov 2004 until 19 Dec 2014 based on the US transaction data of corporate bonds from TRACE, provided by WRDS - 5,414,855 observations. The model is estimated using Equation A.1. Indicator variables are fitted to account for *no announcement* - $N$, *before* - $B$ and *after* - $A$, and for bid and ask sides - $B$ and $A$ (from the dealer's perspective), respectively. All t statistics in brackets are based on robust weight matrix and clustered by the FOMC meeting weeks. $*, **, ***$ denote significance at 10%, 5% and 1%, respectively.

| A: GMM | | | | | |
|---|---|---|---|---|---|
| No Announcement | | Before | | After | |
| Autocorrelation of trades | | | | | |
| $\rho_{NA}$ | 0.68 | $\rho_{BA}$ | 0.79 | $\rho_{AA}$ | 0.38 |
| | (68.91)*** | | (101.60)*** | | (23.86)*** |
| $\rho_{NB}$ | 0.26 | $\rho_{BB}$ | 0.49 | $\rho_{AB}$ | 0.01 |
| | (28.26)*** | | (60.92)*** | | (0.77) |
| Order processing cost | | | | | |
| $\phi_{NA}$ | 0.47 | $\phi_{BA}$ | 0.27 | $\phi_{AA}$ | 0.60 |
| | (38.81)*** | | (9.03)*** | | (25.24)*** |
| $\phi_{NB}$ | 0.71 | $\phi_{BB}$ | 0.63 | $\phi_{AB}$ | 0.72 |
| | (16.23)*** | | (21.36)*** | | (22.47)*** |
| Adverse selection | | | | | |
| $\theta_{NA}$ | -0.02 | $\theta_{BA}$ | 0.16 | $\theta_{AA}$ | -0.11 |
| | (1.57) | | (6.45)*** | | (8.21)*** |
| $\theta_{NB}$ | -0.11 | $\theta_{BB}$ | -0.06 | $\theta_{AB}$ | -0.12 |
| | (6.75)*** | | (4.02)*** | | (17.12)*** |
| $\gamma$ | 0.04 | | | | |
| | (0.54) | | | | |

| B: Tests | | | |
|---|---|---|---|
| Time periods | | | |
| $\rho_{NB} = \rho_{BB} = \rho_{AB}$ | | $\chi^2_2 = 5699.04^{***}$ | |
| $\rho_{NA} = \rho_{BA} = \rho_{AA}$ | | $\chi^2_2 = 1760.11^{***}$ | |
| $\phi_{NB} = \phi_{BB} = \phi_{AB}$ | | $\chi^2_2 = 111.87^{***}$ | |
| $\phi_{NA} = \phi_{BA} = \phi_{AA}$ | | $\chi^2_2 = 217.75^{***}$ | |
| $\theta_{NB} = \theta_{BB} = \theta_{AB}$ | | $\chi^2_2 = 226.34^{***}$ | |
| $\theta_{NA} = \theta_{BA} = \theta_{AA}$ | | $\chi^2_2 = 317.86^{***}$ | |
| Transaction side | | | |
| $\rho_{NB} = \rho_{NA}$ | $\chi^2_1 = 1005.58^{***}$ | $\rho_{BB} = \rho_{BA}$ | $\chi^2_1 = 659.70^{***}$ |
| $\rho_{AB} = \rho_{AA}$ | $\chi^2_1 = 410.36^{***}$ | | |
| $\phi_{NB} = \phi_{NA}$ | $\chi^2_1 = 28.66^{***}$ | $\phi_{BB} = \phi_{BA}$ | $\chi^2_1 = 60.04^{***}$ |
| $\phi_{AB} = \phi_{AA}$ | $\chi^2_1 = 15.09^{***}$ | | |
| $\theta_{NB} = \theta_{NA}$ | $\chi^2_1 = 26.29^{***}$ | $\theta_{BB} = \theta_{BA}$ | $\chi^2_1 = 47.31^{***}$ |
| $\theta_{AB} = \theta_{AA}$ | $\chi^2_1 = 0.34$ | | |

It can be also seen that the adverse selection coefficient is negative at the bid during all time periods. This means that the quoted prices are already adjusted for the possible information asymmetry and that the order flow should not carry any additional information.

In conclusion, these results attribute the cause of lower liquidity around the FOMC announcements to the inventory risk rather than adverse selection. However, it remains unclear why dealers display such risk aversion in presence of a non "toxic" order flow.

## 3.5 Robustness

To further corroborate our results, we perform an analysis using different measures of computed spreads. We find that our results do not change substantially and key findings stand for spreads calculated using transaction value or equal weights. The findings are also robust to spreads computed based on full day transactions versus those utilising morning and afternoon trades separately. In addition, following previous studies (Goldstein, Hotchkiss and Sirri 2006) we test whether our results change if we remove bonds with less than a year to maturity or those with less than $10 million at the issue and we find that our results are not affected by these assets.

Moreover, we created two other possible empirical counterparts of the value difference variable - Equation 3.9. The conclusions remain broadly the same even if we change the credit spread to Moody's Baa or employ the (Gürkaynak, Sack and Wright 2007b)'s yields.

Next we tested our findings of a popular measure of adverse selection: the PIN metric proposed by (Easley, Hvidkjaer and O'Hara 2002)[7]. Our goal is to see whether the variables which are determined by the announcement affect the amount of information contained in the order flow.

The results of these regressions[8] suggest that none of the variables has a significant effect of the probability of informed trading. The only exceptions are the entropy and the Baa-Treasury credit spread. The remainder of this section provides some comments about the coherency of these results with those presented previously.

The negative relation between the PIN and the monetary policy uncertainty confirms the information spillover between the Fed fund futures and the corporate bond markets. We can see that when the futures market does not convey information, the corporate bonds traders are more likely to transact for liquidity reasons. This result is in line with dealers widening their spread in presence of uncertainty: since the information about

[7] The procedure of how we compute the variable is outlined in Section A.2.

[8] For the sake of brevity we do not report the output of this robustness check. The authors are available to provide it upon request.

future monetary policy is available to almost all market participants, dealers are less exposed to heterogeneous beliefs when the orientation of the Fed is clear. Therefore, they can quote a tight bid-ask spread around the asset value under the new policy regime. This result is very close to the (Glosten and Milgrom 1985) prediction when all traders are informed.

The low explanatory power of the other announcement-related variables confirms the results of the GMM model discussed in the previous section. We notice that the fluctuations in the bid-ask spread are caused by the variation in order processing costs charged by the dealers, rather than by adverse selection. Neither the expected change of interest rates nor the surprise component affects the probability of informed trading. It can be confirmed that dealers set their quotes according to their inventory aversion and not as a response to the order flow toxicity.

Finally, the positive sign of the credit spread coefficient is likely to be a consequence of flights to quality: when the market price for default risk is high, traders are selling low quality bonds in favour of safer securities, the PIN metric is likely to capture such effects.

### 3.5.1 The financial crisis

We also test whether the 2007-2009 financial crisis drives our results. We investigate on the effect of the turmoil by creating expansion and recession periods dummy variables, as defined by the NBER. As a result we have one contraction period from December 2007 to June 2009. In addition, we split the remaining two expansion periods into two - one before and one after the recession. We run the regressions described by Equations 3.11 and 3.12 augmented with two dummy variables $XII07 - VI09$ and $XI04 - XI07$ which take value 1 during corresponding dates and 0 otherwise.

Table 3.15 reports regressions results. We observe that during the turmoil despite dealers offering worse conditions at buy both before and after the meetings - *Deviation* is 34bps and 33bps further down for the respective periods, *Entropy* is still both economically and statistically significant. While during the financial crisis interest rates were falling, there were several other documented issues during that time. Participants in this market faced trading frictions and limited access to funding (Dick-Nielsen, Feldhütter and Lando 2012). In addition, the default of a major corporate bond dealer caused illiquidity spillovers (Di Maggio, Kermani and Song 2016). This further supports the inventory management strategies story. Moreover, the dummy variable $XI04 - XI07$ is significant at the sell before the announcement. This was a period of monetary tightening thus unsurprisingly dealers preferred to sell bonds before the news release in order to avoid potential losses due to an unexpected increase in the interest rates.

**Table 3.15:** Deviation regressions with recession and expansion dummies.
Regressions before and after the announcement of deviation and split between sides as per Equations 3.11 and 3.12. The recession period is defined by NBER: *XII07-VI09* corresponds to all meetings between December 2007 and June 2009 - contraction. The variable takes value 1 during that period and 0 otherwise. *XI04-XI07* takes value 1 from November 2004 until November 2007 and 0 otherwise. All t-statistics in brackets are based on robust clustered by the FOMC meeting weeks standard errors. The sample is based on the US transaction data of corporate bonds from TRACE, provided by WRDS for the period during FOMC weeks from 8 Nov 2004 until 19 Dec 2014. All reported regressions are estimated with bond fixed effects and control variables. $*, **, ***$ denote significance at 10%, 5% and 1%, respectively.

| | Before | | After | |
|---|---|---|---|---|
| | Buy | Sell | Buy | Sell |
| Entropy | -51.94 | 28.05 | | |
| | (2.78)*** | (1.50) | | |
| ExpectedChange | 28.54 | 0.37 | | |
| | (4.10)*** | (0.05) | | |
| $V^H - V^L$ [%] | -10.21 | 12.89 | -9.21 | 16.94 |
| | (5.43)*** | (5.67)*** | (4.39)*** | (6.90)*** |
| Maturity | -5.20 | 0.15 | -5.31 | 0.31 |
| | (6.23)*** | (0.22) | (5.17)*** | (0.49) |
| Yield [%] | -2.74 | 5.28 | -3.26 | 2.54 |
| | (1.95)* | (5.66)*** | (1.81)* | (2.68)*** |
| Credit Spread [%] | -11.05 | 2.00 | -9.21 | 2.69 |
| | (8.23)*** | (1.28) | (6.71)*** | (2.50)** |
| Bond Rating | 1.95 | 4.58 | 1.50 | 4.60 |
| | (3.91)*** | (16.69)*** | (2.74)*** | (14.67)*** |
| Absolute Surprise | | | -24.36 | 40.23 |
| | | | (1.12) | (1.79)* |
| XII07-VI09 | -34.46 | -4.31 | -32.92 | -1.56 |
| | (6.90)*** | (1.06) | (6.46)*** | (0.48) |
| XI04-XI07 | -15.13 | -20.09 | -2.08 | -9.87 |
| | (1.59) | (2.50)** | (0.21) | (1.42) |
| Constant | -17.61 | 51.17 | -24.11 | 44.91 |
| | (1.86)* | (7.93)*** | (2.87)*** | (7.28)*** |
| F statistic | 107.5 | 216.2 | 98.7 | 242.5 |
| Adjusted R-squared | 0.14 | 0.05 | 0.12 | 0.05 |
| $N$ | 914,563 | 1,288,760 | 867,629 | 1,171,971 |

## 3.6 Conclusion

This paper has studied the effects of the FOMC announcements on the US corporate bond market liquidity. Since the decisions of the Fed affect bond prices, and market participants may have heterogeneous views about future monetary policy, corporate bond dealers have to set their bid and ask prices such that they compensate for this asymmetric information.

Despite the fact that FOMC decisions themselves do not trigger any toxic order flow, the dealers decrease liquidity provision in the presence of future monetary policy uncertainty. They display an inventory aversion and are willing to avoid carrying sensitive securities over the announcement period by selling them at a relative discount. In addition, the market makers try to recover losses caused by unexpected rate movements through an increase in the liquidity provision costs.

These general results are determined by the behaviour of different bond types. In particular, the embedded option moneyness of some bonds affects the price volatility and, in turn, its liquidity. While the underlying mechanism is different, we observe a direct relation between expected policy rates and the liquidity of bonds with embedded options. The industry of the issuer also influences the movements in the bond liquidity. The sensitivity of some sectors to the interest rate was well documented before. Further analysis is needed to fully understand the reason for such a variation in liquidity across industries.

In conclusion, the decomposition of the bid-ask spread into order processing cost and adverse selection reveals that the dealers set prices as an implementation of inventory management policies, rather than as a response to informed trading. The monetary policy announcements affect the behaviour of corporate bond liquidity providers. However, this reaction is not justified neither by adverse selection nor by imbalanced order flows. Moreover, corporate bond prices appear to incorporate the future monetary policy expectations as measured by the 30-day Fed rate futures. This result supports the claim that the dissemination of information is efficient in the case of monetary policy actions and the Fed fund futures play an important role in bid-ask formation. However, the dealership structure of the US corporate bond market proves to be inadequate to accommodate heterogeneous beliefs, even if the adverse selection is low.

# Appendix A

# Appendix to Corporate Bond Dealers' Inventory Risk and FOMC

## A.1 GMM Model

Our estimation method follows (Green 2004). However, we have adjusted the time indicator functions to incorporate the characteristics of the OTC market. We have allowed for longer time periods before and after the announcements as search time is significantly longer due to lower liquidity of corporate bonds as compared to the Treasury market depicted by Greene. Additionally, we were able to split the sample in separate conditions for both buy (bid) and sell (ask) transactions:

$$\begin{aligned} p_t - p_{t-1} = {} & (\phi_{NB} + \theta_{NB}) I_{NB,t} x_t + (\phi_{BB} + \theta_{BB}) I_{BB,t} x_t + (\phi_{AB} + \theta_{AB}) I_{AB,t} x_t \\ & + (\phi_{NA} + \theta_{NA}) I_{NA,t} x_t + (\phi_{BA} + \theta_{BA}) I_{BA,t} x_t + (\phi_{AA} + \theta_{AA}) I_{AA,t} x_t \\ & - (\phi_{NB} + \rho_{NB}\theta_{NB}) I_{NB,t-1} x_{t-1} - (\phi_{BB} + \rho_{BB}\theta_{BB}) I_{BB,t-1} x_{t-1} \\ & - (\phi_{AB} + \rho_{AB}\theta_{AB}) I_{AB,t-1} x_{t-1} - (\phi_{NA} + \rho_{NA}\theta_{NA}) I_{NA,t-1} x_{t-1} \\ & - (\phi_{BA} + \rho_{BA}\theta_{BA}) I_{BA,t-1} x_{t-1} - (\phi_{AA} + \rho_{AA}\theta_{AA}) I_{AA,t-1} x_{t-1} + \gamma S_t + \varepsilon_t, \end{aligned} \tag{A.1}$$

where $p_t$ is a bond price at time $t$, $x_t = 1$ if a trade is a buy and $x_t = -1$ for a sell. Moreover, $I_{Ni,t} = 1$ if the transactions take place during days $\{-2, -1, 1, 2\}$ for $i$ side - $B$ or $A$ and 0 otherwise. The indicators $I_{Bi,t}$ and $I_{Ai,t}$ are equal to 1 for the period before and after the announcement on the day 0, respectively. Using the following equations

$$\begin{aligned} v_t = x_t & - \rho_{NB} I_{NB,t-1} x_{t-1} - \rho_{BB} I_{BB,t-1} x_{t-1} \rho_{AB} I_{AB,t-1} x_{t-1} \\ & - \rho_{NA} I_{NA,t-1} x_{t-1} - \rho_{BA} I_{BA,t-1} x_{t-1} - \rho_{AA} I_{AA,t-1} x_{t-1} \end{aligned} \tag{A.2}$$

and

$$\begin{aligned} u_t = p_t - p_{t-1} &- (\phi_{NB} + \theta_{NB}) I_{NB,t} x_t - (\phi_{BB} + \theta_{BB}) I_{BB,t} x_t - (\phi_{AB} + \theta_{AB}) I_{AB,t} x_t \\ &- (\phi_{NA} + \theta_{NA}) I_{NA,t} x_t - (\phi_{BA} + \theta_{BA}) I_{BA,t} x_t - (\phi_{AA} + \theta_{AA}) I_{AA,t} x_t \\ &+ (\phi_{NB} + \rho_{NB}\theta_{NB}) I_{NB,t-1} x_{t-1} + (\phi_{BB} + \rho_{BB}\theta_{BB}) I_{BB,t-1} x_{t-1} \\ &+ (\phi_{AB} + \rho_{AB}\theta_{AB}) I_{AB,t-1} x_{t-1} + (\phi_{NA} + \rho_{NA}\theta_{NA}) I_{NA,t-1} x_{t-1} \\ &+ (\phi_{BA} + \rho_{BA}\theta_{BA}) I_{BA,t-1} x_{t-1} + (\phi_{AA} + \rho_{AA}\theta_{AA}) I_{AA,t-1} x_{t-1} - \gamma S_t \end{aligned} \tag{A.3}$$

we can obtain an exactly identified parameter vector. Equation A.1 implies the following moment conditions:

$$\mathbb{E} = \begin{bmatrix} v_t I_{ij,t-1} x_{t-1} \\ u_t \\ u_t I_{ij,t} x_t \\ u_t I_{ij,t-1} x_{t-1} \\ u_t S_t \end{bmatrix} = 0, \tag{A.4}$$

for $i \in \{N, B, A\}$ and $j \in \{B, A\}$.

## A.2 PIN

The PIN variable is based on the (Easley and O'hara 1992)'s model and it was proposed by (Easley et al. 2002). There are three types of market participants: uniformed traders, informed traders and market makers. We have that orders arrive according to a Poisson distribution with a rate of $\lambda$. Next, it is assumed that a signal can be bad with probability $\delta > 0$ and good with $1 - \delta > 0$. The private information is captured by $0 < \alpha < 1$, which can be interpreted as an arrival rate of informed traders. Lastly, it is assumed that informed traders profit at the cost of the dealers and that the market makers expect a fraction of informed transactions to be equal $0 < \mu < 1$.

In order to compute PIN we begin with a daily likelihood:

$$L(\Theta|B_t, S_t) = \alpha(1-\delta)e^{-(2\lambda+\mu)} \frac{(\lambda+\mu)^{B_t}\lambda^{S_t}}{B_t!S_t!} + \alpha\delta e^{-(2\lambda+\mu)} \frac{\lambda^{B_t}(\lambda+\mu)^{S_t}}{B_t!S_t!} + (1-\alpha)\delta e^{-2\lambda} \frac{\lambda^{B_t+S_t}}{B_t!S_t!}, \tag{A.5}$$

where $B_t$ and $S_t$ are the numbers of buy and sell orders on a day $t$. Next we estimate the set of parameters $\Theta = \{\lambda, \delta, \alpha, \mu\}$ by maximizing the log likelihood function under the assumption of independent evolution of trades across days and the history of order flow $\mathcal{F} = \{B_t, S_t\}_{t=1}^{T}$:

$$l(\Theta|\mathcal{F}) = \sum_{t=1}^{T} \log\left(L(\Theta|B_t, S_t)\right). \tag{A.6}$$

In the empirical analysis we set $T = 25$ in order to avoid estimating the parameter values over two adjacent FOMC meeting periods. Therefore it is necessary to use a full TRACE sample spanning over the study period. We obtain the parameter set $\Theta$ for each bond separately and define

$$PIN := \frac{\hat{\alpha}\hat{\mu}}{\hat{\alpha}\hat{\mu} + 2\hat{\lambda}}. \tag{A.7}$$

Lastly, we take a simple average of all $PIN$ values on a day $t$ to use it as a market wide probability of informed trading.

# Chapter 4

# Costs of Monetary Policy Uncertainty

POLICY uncertainty, measured as the 30 day Fed funds futures microstructure noise, variation throughout a Federal Open Market Committee cycle (time period between two consecutive and scheduled meetings) is the focus of this chapter. I present an explanation to how changes in uncertainty lead to patterns in returns and liquidity of the US corporate bond market. I show that the FOMC communication generates two distinct corporate bond return regimes. They correspond to odd and even FOMC cycle weeks[1] with significantly different loads on risk factors and my measure of uncertainty. Moreover, I advocate that the cycle pattern in bond returns can be partially explained by a significant difference in transaction costs between the two periods. The effective half spreads are from 3 to 25 bps smaller in odd weeks due to increased levels of risk and a drop in financial intermediaries' inventory capacity.

My study unveils that the excess returns patterns coincide with liquidity regimes. I show that they are related to uncertainty about future monetary policy and describe a mechanism which can explain the empirical facts. This is consistent with previous research on liquidity risk[2]. For instance, (Bao, Pan and Wang 2011) show that such risk leads to substantial excess returns and changes in bond yields. They examine the pricing impact of illiquidity in corporate bond spreads and find that, in aggregate, their measure is most important for high credit grade bonds.

[1] I refer to weeks 0 (working days 0-4), 2 (10-14), 4 (20-24) and 6 (30-34) in relation to FOMC meetings as even weeks during FOMC cycles.

[2] Throughout this study, as well as in related literature, the liquidity risk is not limited to significant changes in volume. In fact, most of the conclusions relate to effective spreads and transaction costs often being named as *liquidity* in the OTC markets.

Recent publications report that there are strong patterns in returns on the FOMC announcement days see (Hausman and Wongswan 2011) or(Lucca and Moench 2015). The authors argue that policy decisions releases have a significant positive effect on stock prices. In bond markets, (Faust and Wright 2009) and (Savor and Wilson 2013) document positive risk premia in macroeconomic announcements. Moreover, (Cieslak, Morse and Vissing-Jorgensen 2018) highlight that during periods from one Fed meeting to another, monetary policy details leaks lead to a bi-weekly pattern in realised stock returns. They show that most of the equity premium is only earned during the even cycle weeks. They also point out that the most of previously documented announcement day drift effects are part of the large FOMC cycle effect, where important information is published in a regular fashion leading to the observed phenomena. I show that a similar bi-weekly pattern exists in the corporate bond market and it is both statistically and economically significant.

One of the most important channels of Fed policy transmission is through the Fed funds rate. As markets participants closely follow the policy makers guidance, the response to the surprise component of Fed Reserve actions is greater than the reaction to the target rate changes (Kuttner 2001). Although expectations of Fed policy decisions are not easily observable, 30 day Fed funds [FF] futures prices provide the most efficient, market-based proxy for those expectations (Gürkaynak et al. 2007a). Shocks specific to information arrival and liquidity supply in the futures market can propagate to other asset classes. I test whether such variation leads to transaction costs changes in the US corporate bond market. My results demonstrate that the liquidity providers both infer information from the futures market ahead of even weeks and decrease the transaction costs due to policy uncertainty. The relative difference between odd and even weeks can vary from 15% to 70% depending on transaction size.

Major macroeconomic news releases can lead to liquidity evaporation. It is because market makers in one asset obtain fundamental information from other instruments' prices. Assuming that dealers in some market $A$ have limited capability to follow all news related to market $B$, they use asset $B$ prices as signals in order to obtain additional information about $B$ crucial for pricing asset $A$. This channel can lead to a chain effect on various markets and it matters for asset pricing and market stability. (Cespa and Foucault 2014) point out that such interconnected instruments lead to amplified variation in liquidity across seemingly diverse markets.

Is it possible that liquidity shocks in the futures market can spread to other asset classes and lead to changes in market makers' adverse selection or shift the demand to post fundamental information announcement periods? If the latter is true, to what extent are the dealers in other markets impacted by less accurate monetary policy signals? If the former, is there a gain to investors to trade after the news releases?

There are two complementary channels through which a surge in liquidity provision

costs can happen. First, a rise in demand for liquidity from the public or a drop in market makers' liquidity supply in response to elevated levels of risk. Second, aggravated adverse selection problems can increase information sensitivity of assets. Such issues typically arise in periods ahead of public announcements. The 30 day FF futures prices' signal to market microstructure noise ratio (price informativeness) is used in this study to understand whether corporate bond market participants employ information from the derivative market to price the macroeconomic uncertainty and whether it can be linked to liquidity provision. I estimate a hidden Markov regime switching model to assess this hypothesis. In line with the theoretical model prediction, the estimated signal to noise ratio provides information to corporate bond market participants only in certain periods. I find that investment grade corporate bond prices react very differently to the futures price informativeness during a FOMC cycle. In addition, this exercise sheds new evidence on the impact of liquidity on corporate bond returns during periods before and after monetary policy related news releases. I highlight in this paper how economic announcements, despite revealing more fundamental information, lead to higher market making costs due to an increased inventory risk ahead of information releases during FOMC cycles.

(Bollerslev, Li and Xue 2018) study the S&P 500 index ETF and show an increase volume and volatility at announcement times. They argue that difference between periods is driven by high levels of disagreement. My results also point towards greater dissent occurring on the corporate bond market ahead of monetary policy announcements.

Stock and bond market volatility shocks are informative in predicting shifts in liquidity as positive volatility innovations predict an increase in quoted spreads and a reduction of depth in those markets. (Brunnermeier and Pedersen 2009) show that such a relation exists due to variation in funding liquidity in times of distress. Furthermore, (Hameed, Kang and Viswanathan 2010) document spillover effects in liquidity after negative stock returns. The dry ups arise from capital constraints in the market making sector. A related argument is provided by (Nagel 2012), who examines reversal strategies and finds the inventory-related component that drives the return from liquidity provision. The author argues that such returns can be predicted using VIX. According to this view, the conditions during crises raise the expected return from liquidity provision as price impact of trades is higher when the volatility risk premium component in VIX is high. Other publications show that volatility is negatively related to liquidity. (Chordia, Sarkar and Subrahmanyam 2004) indicate that stock and bond market liquidity, and volatility are significantly correlated, implying that common factors drive liquidity and volatility in these markets. My findings confirm that the VIX index drives transaction costs, yet the signal to noise ratio provides additional monetary policy related information which can explain bi-weekly patterns in both excess returns and liquidity regimes.

Lastly, I analyse the behaviour of bond transaction prices using periods predicted by

the regime switching model. Set against this background, instead of focusing on returns I estimate transaction costs in these regimes separately. (Harris and Piwowar 2006) and (Edwards, Harris and Piwowar 2007) develop a regression approach to examine the secondary transaction costs of corporate bonds. I employ their econometric model as it is relevant for a market with the lack of firm bid and ask quotes, and infrequent trading. I estimate effective spreads on all TRACE transactions split into two groups: odd and even FOMC cycle weeks. The split permits to assess the average costs in two liquidity/return regimes. Odd weeks correspond to days preceding FOMC news releases with high levels of disagreement while even weeks are those which typically experience abnormally large excess returns as reported by (Cieslak et al. 2018) in a study of the stock market. Although variation in liquidity regimes across cycles is statistically significant only for investment grade bonds, the greatest change in effective trading costs is experienced by low quality bonds despite the fact that this group should be least sensitive to interest rate news due to a large credit component. The results confirm large disparity in the two periods transaction costs. Obtained effective spreads are significantly smaller ahead of policy announcements with the difference ranging between 3 and 25 basis points.

### 4.0.1 Literature

The academic literature on both liquidity and macroeconomic effects on asset prices is vast. Several authors show that monetary policy has a significant effect on various financial assets returns. These studies document a substantial stock market reaction to unexpected changes in the Fed funds rate see, e.g.(Cochrane and Piazzesi 2002), (Rigobon and Sack 2004),(Bernanke and Kuttner 2005) or (Gurkaynak et al. 2005a). The announcements impact financial assets not only by setting the level of the short term rate, but also by signaling future policy. As a result, the policy statements affect the whole yield curve. Previous studies also highlight that risk-free interest rates and credit risk are not the only factors that drive corporate bond prices and provide support for liquidity effects in the corporate bond market. This result is established including information from, among others, CDS and equity markets see, for example (Collin-Dufresne and Goldstein 2001), (Longstaff, Mithal and Neis 2005), (Duffie, Saita and Wang 2007a), (Huang and Huang 2012) or (Bao and Pan 2013).

Furthermore, assorted papers examine the impact of liquidity, based on corporate bond yields or spreads over a risk-free rate. This literature employs indirect proxies based on various bond characteristics such as the coupon, maturity, amount issued, credit rating, or embedded options. Some authors additionally use market-related proxies based on trading activity such as transaction or daily volume, number of trades, number of dealers, and the round trip costs. In essence, all these studies argue that liquidity is priced in bond yields. Yet, the magnitude and importance of liquidity proxies varies across samples (Eom, Helwege and Huang 2004), (Harris and Piwowar 2006), (Chen,

Lesmond and Wei 2007), (Edwards et al. 2007), (Comerton-Forde et al. 2010), (Dick-Nielsen et al. 2012), (Acharya, Amihud and Bharath 2013). In contrast, I control for market-wide credit, duration and liquidity risks, and measure the impact of macro news uncertainty. I report that there are two liquidity regimes in which the bonds experience significantly different sensitivity to common risk factors.

Another strand of literature focuses on alternative liquidity measures at an individual bond level. The research employs variables such as transaction costs, market impact, or turnover in order to analyze liquidity in the corporate bond market. (Chen et al. 2007), using illiquidity proxies, find that more illiquid bonds have higher yield spreads. (Bao et al. 2011) concentrate on price reversals captured by the auto-covariance of price changes. They demonstrate that the reversals are asymmetric and their the magnitude is much greater what can be explained by bid-ask bounce. (Amihud 2002) measures the price impact of a trade with the transaction volume and frequency of trades. (Duffie, Gârleanu and Pedersen 2007b) show that transaction costs in OTC markets are driven by search frictions, inventory holding costs, and bargaining power in this particular market structure. (Jankowitsch, Nashikkar and Subrahmanyam 2011) develop the price dispersion measure, which is based on the dispersion of market transaction prices of an asset around its consensus valuation by market participants and reach a similar conclusion. (Friewald, Jankowitsch and Subrahmanyam 2012) point out that the economic impact of the liquidity measures is not negligible and significantly larger in periods of high uncertainty levels in the economy. Other evidence suggests that changes in illiquidity affect the variation in high credit quality bonds' spreads and that the spread over treasury bonds is not driven by credit risk (Huang and Huang 2012).

My empirical findings contribute to this literature in several ways. I am able to successfully measure average trading costs in a representative sample, add to the risk aversion literature and highlight an important interaction between bond portfolio returns and inventory risk. I also show that individual bond characteristics, such as credit rating, play a key role during FOMC cycles.

(Green 2004) reports that following macroeconomic news announcements there is a significant increase in the impact of changes in order flow on bond prices in the U.S. Treasury bond market. He suggests that this price impact of trades may be attributed to greater information asymmetry at the time of the macro announcements. In line with this argument, (Pasquariello and Vega 2007) find that the impact of unanticipated daily order flow in the U.S. Treasury bond market is larger when the dispersion in beliefs among market participants is high and when the public news announcement is more noisy. Moreover, (Ruzza and Zurowski 2017) document an increase in corporate bond dealers' risk aversion and a more aggressive inventory adjustments ahead of more uncertain FOMC meetings. My paper focuses not only on monetary policy announcements

but also on a broader set of macro news as reflected by 30 day FF futures[3]. With intra day data, I gain additional information on market consensus expectations and compute microstructure noise of the futures prices efficiently on all days. This data provides a proxy for a noisy policy signal as used by market participants in the corporate bond market. I show a channel of information and illiquidity spillover, and compute an important additional measure relevant to transaction costs.

This chapter is organised as follows. I describe the data in Section 4.1 and estimate a statistical model to determine liquidity regimes across FOMC cycles in Section 4.2. Part 4.3 introduces the transaction cost model and demonstrates the difference in spreads between the two regimes. Section 4.4 provides concluding remarks, while all tables are displayed at the end.

## 4.1 Macroeconomic Signals

### 4.1.1 Data and summary statistics

I obtain corporate bond prices, volumes and transaction times from Trade Reporting and Compliance Engine (TRACE) enhanced spanning from 01 October 2004 to 31 December 2014. This period covers 83 FOMC meetings. I apply the cleaning procedure outlined by (Dick-Nielsen 2009) and (Dick-Nielsen 2014), and remove double reported inter-dealer transactions by matching buy and sell sides by CUSIP, date, time and volume. I then merge the transaction data with bond-specific information (amount issued, coupon rate, offering date, maturity, embedded options, SIC code and credit rating history), which I obtain from the Mergent Fixed Income Securities Database and remove all CUSIPs which are not covered by the latter dataset. I assign credit rating values in the following way: $AAA = 1$, $AA+ = 2$, ..., $D = 22$. Following the common literature on corporate bonds, I exclude bonds that are either convertible or with variable coupons. Additionally, I compute the maturity of the bonds and remove all transactions with negative values and all CUSIPs with fewer than 9 trades - a constraint imposed by the trading costs regression model. This leaves about 60.7 million intra-day transactions from 32,304 bonds, which are used to calculate daily returns and transaction costs in a later part of the study. Most of the bonds in the sample are investment grade (approximately 78%). The data is dominated by small (47.2%) and medium size (34.9%) issues. Nonetheless, the biggest issues (above $ 500 million) are the most frequently traded (63.6% of transactions) with 76.4% of total volume. Bonds issued by the financial sector consist 64.3% of CUSIPs with about half (50.2%) of total volume traded. Bonds between 2 and 10 years to maturity

[3] The futures prices react significantly not only to FOMC statements but other macro news such as: GDP growth, change in non-farm payrolls, inflation or ISM manufacturing index. Appendix B.1 provides a simple analysis and some evidence for this argument.

are most actively traded with 67.7% of transactions and 65.1% of volume being traded in this category. Table 4.1 displays the cross-sectional distributions of various bond features in this sample TRACE data. The CME's DataMine provides the 30-day FF

**Table 4.1:** Cross-sectional distribution of TRACE transactions.
This table characterises the cross sectional features of TRACE transactions used in the study. Credit quality and age are based on the lowest available rating and exact age at transaction time. The number of bonds is higher for certain categories as a CUSIP can be assigned to multiple features. The data covers the period between 1 Oct 2004 and 31 Dec 2014.

| | Bonds in Sample | | Trades in Sample | | Total Value Traded | |
|---|---|---|---|---|---|---|
| Feature | Number | Percent | Thousands | Percent | $ Billions | Percent |
| ALL | 32,304 | 100 | 60,732 | 100 | 33,926 | 100 |
| **Trade Size** | | | | | | |
| Small Retail (<$10 thousand) | 28,434 | 20.9 | 11,416 | 18.8 | 51 | 0.2 |
| Medium Retail ($10-$50 thousand) | 31,201 | 22.9 | 26,664 | 43.9 | 526 | 1.6 |
| Large Retail ($50-$100 thousand) | 28,241 | 20.7 | 9,751 | 16.1 | 356 | 1.0 |
| Small ($100-$1,000 thousand) | 27,728 | 20.4 | 6,029 | 9.9 | 2,705 | 8.0 |
| Large (>$1 million) | 20,599 | 15.1 | 6,872 | 11.3 | 30,287 | 89.2 |
| **Credit quality** | | | | | | |
| AA- and up | 8,731 | 20.6 | 8,907 | 14.7 | 4,929 | 14.5 |
| BBB- to A+ | 24,433 | 57.8 | 36,994 | 60.9 | 19,966 | 58.9 |
| Below BBB- | 8,420 | 19.9 | 14,439 | 23.8 | 8,669 | 25.6 |
| Defaulted | 711 | 1.7 | 391 | 0.6 | 360 | 1.1 |
| **Issue size** | | | | | | |
| Small (<$100 million) | 15,272 | 47.2 | 4,309 | 7.1 | 264 | 0.8 |
| Medium ($100 to $500 million) | 11,262 | 34.9 | 17,767 | 29.3 | 7,742 | 22.8 |
| Large (>$500 million) | 5,770 | 17.9 | 38,655 | 63.6 | 25,920 | 76.4 |
| **Age** | | | | | | |
| 0-12 months | 10,401 | 16.3 | 3,714 | 6.1 | 1,836 | 5.4 |
| 1-2 years | 11,506 | 18.0 | 5,033 | 8.3 | 2,138 | 6.3 |
| 2-5 years | 16,404 | 25.7 | 18,902 | 31.1 | 8,605 | 25.4 |
| 5-10 years | 14,982 | 23.5 | 22,233 | 36.6 | 13,466 | 39.7 |
| Over 10 years | 10,544 | 16.5 | 10,848 | 17.9 | 7,880 | 23.2 |
| **Industry** | | | | | | |
| Finance | 20,782 | 64.3 | 32,907 | 54.2 | 17,029 | 50.2 |
| Utilities | 1,819 | 5.6 | 1,528 | 2.5 | 994 | 2.9 |
| Manufacturing | 3,341 | 10.3 | 8,432 | 13.9 | 4,341 | 12.8 |
| Other | 6,362 | 19.7 | 17,865 | 29.4 | 12,555 | 37.0 |

futures transaction level data: trade price, volume and contract maturity. The VIX end of day data is also obtained from this provider. Both datasets match the TRACE's

sample period.

### 4.1.2 Daily variables calculation

I calculate a midprice $M_t^i$ in bond $i$ at time $t$, as the average of volume-weighted buy and sell prices, respectively. As a result, I require at least one buy and sell trade at time $t$ and $t+1$. The return is equal to:

$$r_{t+1}^i = \frac{(M_{t+1}^i + AI_{t+1}^i) - (M_t^i + AI_t^i) + C_{t+1}^i}{M_t^i + AI_t^i}, \tag{4.1}$$

where $AI_t^i$ is the accrued interest and $C_{t+1}^i$ is the coupon payment, if any, at time $t+1$. In order to obtain excess returns the 1-month Treasury bill rate (downloaded from the H.15 constant maturities Fed data release)[4] is subtracted from the returns computed in Equation 4.1. The resulting sample contains just under 3.7 million bond-day return observations. Next, I calculate volume weighted market wide excess daily returns and sort them by the distance from a FOMC meeting expressed in working days. In case of 2-day FOMC meetings, the second day is marked as "0".

In addition, I define several control variables used in both returns and transaction costs regressions. Borrowing from (Gebhardt, Hvidkjaer and Swaminathan 2005) and (Acharya et al. 2013), I compute a $TERM$ factor as the difference in daily 30-year government bond return and one-month T-bill returns (both from H.15), and a credit risk factor, $DEF$, as the difference between daily return on an equally weighted market portfolio of all corporate bonds and the average return on equally weighted one-year and 30-year government bonds. Additionally, I follow (Amihud 2002) and create a liquidity risk factor, $ILLIQ$, calculated as errors from an AR(2) model run on the equally weighted average of the daily ratio of absolute all TRACE bonds returns to their respective daily dollar volume.

Panel A in Table 4.2 presents summary statistics of daily variables. The returns range between -49 and 81 basis points with an average equal to 10 bps. $TERM$ and $DEF$ factors are also on average positive with means of 2 and 10 bps, respectively. Panel B shows daily aggregated correlations between the variables. Most of them are very lowly correlated except the pairs: VIX-Round-trip costs, $DEF$-Return and $SNR$-Round-trip costs with correlations of 0.8, 0.58 and -0.41, respectively, being a result of returns aggregation and the way $DEF$ is computed. The correlations shrink to 0.22, 0.13 and $-0.13$ if returns and trading costs are kept at the CUSIP level (not reported in the table).

[4] The Fed data can be downloaded from https://www.federalreserve.gov/datadownload/Choose.aspx?rel=H15

**Table 4.2:** Summary statistics and correlations.
Panel A presents summary statistics of the variables at a daily level. The units are shown in square brackets. Panel B show correlations between daily aggregated pairs. The data runs from from 1 Oct 2004 to 31 Dec 2014 and covers all TRACE transactions. $TERM$ is a difference in return between long and short maturity bonds, while $DEF$ is a difference between corporate and Treasury (1 and 30 years) equally weighted bond portfolios. $SNR$ is computed using first six maturities of 30 day Fed funds rate on available on each day.

Panel A: Summary Statistics

| Statistic | N | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|---|
| Return [%] | 2,581 | 0.1 | 0.4 | −4.9 | 8.1 |
| TERM [%] | 2,554 | 0.04 | 1.8 | −8.3 | 10.5 |
| DEF [%] | 2,554 | 0.1 | 0.3 | −3.3 | 3.8 |
| ILLIQ | 2,550 | −0.02 | 2.04 | −0.46 | 9.9 |
| SNR | 2,581 | 0.94 | 0.07 | 0.47 | 1 |
| Round-trip costs [%] | 2,581 | 1.2 | 0.5 | 0 | 4.9 |
| VIX/100 | 2,572 | 0.2 | 0.1 | 0.1 | 0.8 |

Panel B: Correlations

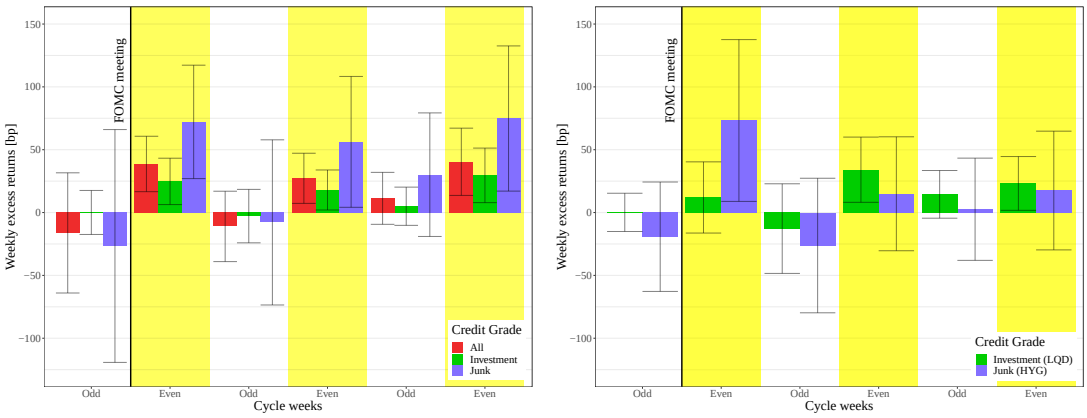
| | Return | TERM | DEF | ILLIQ | SNR | Costs | VIX |
|---|---|---|---|---|---|---|---|
| Return | 1 | | | | | | |
| TERM | −0.01 | 1 | | | | | |
| DEF | 0.58 | −0.25 | 1 | | | | |
| ILLIQ | −0.01 | 0.04 | 0.03 | 1 | | | |
| SNR | 0.07 | −0.01 | −0.07 | −0.06 | 1 | | |
| Costs | −0.04 | 0.03 | 0.11 | 0.19 | −0.41 | 1 | |
| VIX | −0.02 | 0.07 | 0.08 | 0.18 | −0.31 | 0.80 | 1 |

### 4.1.3 FOMC cycle returns

(Cieslak et al. 2018) report a bi-weekly pattern in stock returns across FOMC cycles. The authors argue that the variation is mostly due to significant policy information leaks and the policy being more accommodating than market consensus, with the latter effect being more pronounced. US corporate bond market excess returns exhibit a similar trend at both daily and weekly frequencies. Figure 4.1a displays weekly excess returns over the 1 month Treasury bill together with 95% confidence intervals for all, investment and non-investment grades bond trades reported in TRACE between 1 Oct 2004 and 31 Dec 2014. Since the main driver of price fluctuations is the interest rate related news, there is some difference between investment grade bonds and junk grade bonds excess returns behaviour. Data from Blackrock iShares investment corporate grade bonds ETF for the respective credit groups is also obtained for the same sample period. The effect seems

to be smaller and much less volatile for this asset type, almost all weeks and categories are not statstically different from zero. There are two exceptions: week 0 for junk and weeks 4 and 6 for investment grade contract (Figure 4.1b). In sum, the corporate bond market is more likely to be affected by policy shocks during FOMC cycles than the ETF market despite that both markets are related to the same underlying transactions. It suggests that the structure of the market itself can play a role. A simple regression of

**Figure 4.1:** Weekly excess returns across FOMC cycles.
The graphs display simple average patterns in daily value weighted excess returns around FOMC cycles from 1 Oct 2004 to 31 Dec 2014 - 83 cycles for (a) All bond transactions in TRACE split into three credit risk categories, (b) Blackrock's iShares iBoxx $ Corporate Bond ETF (seprately for LQD and HYG tickers). Convertible bonds are removed from computations. Highlighted areas correspond to even cycle weeks.




**(a)** TRACE transactions **(b)** iShares Corporate Bond ETF

dummy variables being equal to 1 in each of the FOMC weeks separately (from week -1 to week 6) and 0 otherwise[5] on daily excess returns shows that only for junk bonds there is a statistically significant difference between odd and even weeks returns. Other categories despite positive coefficients in even weeks and negative in odd weeks, are not statistically significant (except week -1 and 4 for all TRACE transactions). Correspondingly, the regressions on weekly excess returns unveil a strong bi-weekly pattern in all groups. Weeks 0, 2 and 4 excess returns are statistically positive ranging from about 18 to 75 bps. All other weeks' coefficients are not statistically different from 0 at any reasonable level of significance. Investment grade bond excess returns exhibit less variation (in absolute terms) between odd and even weeks than junk bonds. The difference in sta-

[5] There are only a few FOMC cycles with more than 7 weeks between the meetings. Hence due to a decreasing number of observations for weeks 5 and 6 (days 25 to 34 after the last FOMC meeting) the estimates for these dummies are affected and shown in the table only for completeness.

tistical significance between daily and weekly frequencies comes from the fact that many bonds do not trade everyday. Therefore, daily observations are impacted by single name variation caused by, for example, credit risk. In addition, due to the OTC structure the information dissemination can take much longer time for less frequently traded issues.

**Table 4.3:** Daily and weekly excess returns during FOMC cycle weeks.
The table presents daily and weekly volume weighted excess return regressions results on dummy variables equal 1 in respective FOMC cycle weeks and 0 otherwise. The dependent variable is measured in basis points. All t-statistics reported in brackets are based on heteroscedasticity robust standard errors. The daily (weekly) samples are based on the US investment and non-investment grade corporate bonds transaction data from TRACE, provided by WRDS for the period during FOMC weeks from 1 Oct 2004 until 31 Dec 2014 - 2,544 (474 non-overlapping) observations averaged daily (weekly) from all available CUSIPs in each group and day (week). ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. *IG* and *NIG* stand for investment and non-investment credit grade groups.

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | Daily excess return | | | Weekly excess return | | |
| | ALL | IG | NIG | ALL | IG | NIG |
| Week -1 | -8.00* | -3.99 | -5.38 | -16.20 | 0.08 | -26.60 |
| | (-1.82) | (1.40) | (-0.67) | (-1.13) | (0.01) | (-0.88) |
| Week 0 | 5.72 | 1.52 | 17.70** | 38.66*** | 24.79*** | 72.14** |
| | (1.29) | (0.53) | (2.20) | (2.64) | (2.74) | (2.33) |
| Week 1 | -1.00 | -4.32 | 9.03 | -11.03 | -2.83 | -7.83 |
| | (-0.22) | (1.47) | (1.10) | (-0.74) | (-0.31) | (-0.25) |
| Week 2 | 6.05 | 1.95 | 18.52** | 27.25* | 17.96* | 56.24* |
| | (1.32) | (0.65) | (2.21) | (1.77) | (1.88) | (1.72) |
| Week 3 | -1.13 | -3.83 | 8.05 | 11.31 | 5.02 | 30.14 |
| | (-0.25) | (1.30) | (0.98) | (0.74) | (0.53) | (0.94) |
| Week 4 | 8.41* | 2.80 | 23.80*** | 40.39** | 29.59*** | 74.83** |
| | (1.82) | (0.93) | (2.83) | (2.53) | (2.98) | (2.21) |
| Week 5 | -1.47 | -6.56 | 9.53 | -1.47 | -19.46 | 39.41 |
| | (-0.23) | (1.57) | (0.81) | (-0.06) | (-1.26) | (0.74) |
| Week 6 | -6.20 | -7.44 | -5.63 | 15.74 | -5.20 | 66.88 |
| | (-0.45) | (0.83) | (-0.22) | (0.32) | (-0.17) | (0.64) |
| Adjusted $R^2$ | 0.00 | 0.00 | 0.01 | 0.02 | 0.03 | 0.02 |
| F Statistic | 1.30 | 1.31 | 2.63*** | 2.37** | 2.74*** | 2.00** |

The weekly frequency alleviates both problems thus the bi-weekly pattern is more pronounced. I find that on average high yield bonds earn much higher excess returns in my sample. However, this is due to the fact that default information is not fully reflected in the transaction prices. Table 4.3 reports the above regression results.

The presented empirical facts imply that the corporate bond prices are also impacted by the Fed's policy announcements in an important way. In the following section I will present how monetary policy can be incorporated into the bond pricing and how it can affect both their returns and transaction costs.

### 4.1.4 Signal-to-noise ratio

Building on the empirical facts from the previous section, the focus of this study is directed at the market expectations of future monetary policy decisions. As (Gürkaynak et al. 2007a) point out, the 30 day FF futures[6] provide the most efficient proxy of these expectations. Under a mild assumption that market participants in the futures are more informed about the monetary policy while corporate bond dealers have limited attention to follow most macroeconomic news, the derivatives prices should provide additional information about fundamental value for corporate bond market traders. Yet, poor signal quality adds extra volatility component to pricing equation and therefore leads to drop in the bond liquidity as intermediaries have to widen their spreads to avoid losses. Appendix B.2 presents further details of this theoretical model.

**Figure 4.2:** Liquidity spillover mechanism.

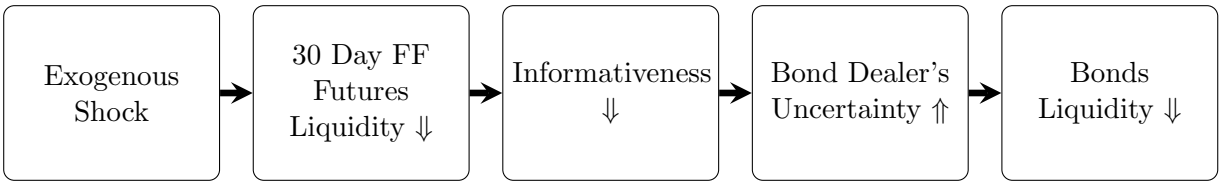



Chart 4.2 illustrates a simple model's mechanism, where liquidity of one asset propagates into another market. The futures informativeness falls after an exogenous shock to their liquidity. Next, noisier fundamental signals from the derivatives prices lead to higher uncertainty and costs of liquidity provision for corporate bond market makers so

[6] The daily Fed funds rate is a transaction-weighted rate. The Fed rate is a reference rate in the US and is used in forming monetary policy decisions. The FF market is an interbank OTC market for reserves held by Federal Reserve banks. 30 day FF futures are interest rate contracts which cash settle at the average FF rate over the contract month. The futures price is quoted as 100 minus the average overnight FF rate for the delivery month. Currently, thirty-six monthly contracts are quoted at any time but only a few leading ones are actively traded and, in practice, the volume (open interest) of contracts with maturity beyond one year is virtually zero (very low).

the bonds illiqudity increases.

If the above prediction is true, higher futures price informativeness should predict lower transaction costs only if these asset prices supply additional fundamental information to bond market participants.

Next, I compute daily micro-structure noise and fundamental volatility from the intraday 30 day FF futures transaction prices across six maturities - current to five months ahead as these contracts are significantly more frequently traded than those with maturities further out in the future. This is an important feature in order to estimate the noise efficiently.

In order to measure the futures price informativeness, defined as a signal to noise ratio, and its persistence, I apply (Aït-Sahalia, Mykland and Zhang 2005)'s parametric maximum likelihood method. The choice of multiple contracts allows for more precise estimation.

Let $p_t = \ln P_t$, denote the observed transaction log price at time $t$, and be equal to the sum of an unobservable efficient (or fundamental) price, $v_t$, and a transitory noise component, $\epsilon_t$, which can be interpreted as the level of illiquidity in the market arising due to the imperfections of trading:

$$p_t = v_t + \epsilon_t. \tag{4.2}$$

Investors are often interested in estimating the volatility of the efficient log-price process $dv_t = \mu_t dt + \sigma_t dW_t$, where $W_t$ is a Brownian motion and $\sigma_t$ can be viewed as a risk factor. In case there was no noise ($\epsilon = 0$), the log returns, $ret_i$, would be distributed as $\mathcal{N}(0, \Delta\sigma^2)$ and the maximum likelihood estimator for $\sigma^2$ would coincide with the realized volatility of the process, $\hat{\sigma}^2 = \frac{1}{T}\sum_{i=1}^{n} ret_i^2$.

Under an assumption that the observed (at discrete intervals) prices are noisy with $\epsilon \sim \mathcal{N}(0, \mathbb{E}[\epsilon^2])$ the log returns follow a MA(1) process as each $ret_t = \sigma(W_t - W_{t-1}) + \epsilon_t - \epsilon_{t-1} \equiv u_t + \kappa u_{t-1}$, where $u$'s are mean zero and variance $\iota^2$ and $\iota^2(1+\kappa^2) = \mathbb{V}[ret_t] = \Delta\sigma^2 + 2\mathbb{E}[\epsilon^2]$ and $\mathbb{C}\text{ov}[ret_t, ret_{t-1}] = -\mathbb{E}[\epsilon^2]$. It can be shown that the estimator of $(\hat{\sigma}^2, \widehat{\mathbb{E}[\epsilon^2]})$ is consistent[7].

Next, I calculate the signal to noise ratio, defined as:

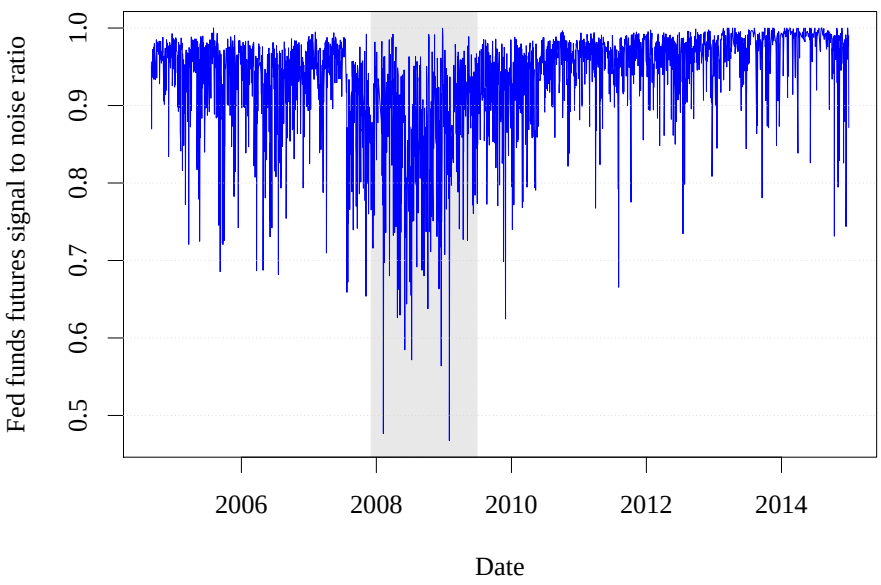
$$SNR := \frac{\text{fundamental volatility}}{\text{total volatility}} = \frac{\Delta\sigma^2}{\Delta\sigma^2 + 2\mathbb{E}[\epsilon^2]}. \tag{4.3}$$

The value is averaged each day across maturities. Figure 4.3 below presents the daily SNR computed from the futures prices. It can be seen that the overall quality of signals

[7] In fact, the estimator is also robust to deviations such as jumps or stochastic volatility. More details and properties of the estimator can be found in (Ait-Sahalia and Yu 2008)

is relatively high with most of the observations being above 90% and the minimum being equal to 47%. It only deteriorates during the financial crisis and towards the sample end where the probability of the Fed funds rate jump increases.

**Figure 4.3:** Daily 30 day FF futures signal to noise ratio.
The chart shows average daily signal to noise ratio computed using Equation 4.3. The values are obtained from intraday prices of six maturities. The data covers the period from 1 Oct 2004 to 31 Dec 2014. The shaded area corresponds to a contraction period from Dec 2007 to Jun 2009 as defined by NBER.




The noise estimates are not affected by the level of interest rates albeit a substantial part of the sample falls in a period of time with interest rates close to zero lower bound (ZLB). While a drop in trading activity or stale prices may be a concern, during the ZLB period the FF futures transaction frequency is not reduced. Moreover, the prices, while less volatile, experience a substantial amount of microstructure noise, this is particularly pronounced in the prices of contracts further out in future. This corresponds to non-negligible amount of disagreement about policy prospects on the market.

I test whether the computed price informativeness predicts lower US corporate bond market transaction costs, as predicted by the theoretical model, by regressing *SNR* on market aggregated daily round trip costs:

$$\text{round-trip costs}_t = \alpha + \beta_1 SNR_t + controls_t + \epsilon_t \tag{4.4}$$

I define the costs as a difference between buying and selling prices of a bond on a particular day computed using volume weighted bids and asks available for each CUSIP. $controls_t$ include $TERM$, $DEF$, $ILLIQ$ and VIX variables at a daily frequency. 4.4 displays the regression results. As predicted, the $\beta_1$ has a negative statistically significant coefficient for both investment grade and junk bonds in all specifications. In addition, the effect is virtually identical if the VIX index is excluded. The $SNR$ variable is able to explain between 11% and 13% of the variation in the corporate bonds round trip costs. High yield bond trading costs are on average higher and more sensitive to the other market factors. In line with previous studies (Nagel 2012) the VIX index is closely related to the market makers returns from liquidity provision and provides the most information about transaction costs, yet it does not exhibit a significant behaviour across the FOMC cycles. Rather, as the index is more persistent than $SNR$, it is more suitable to explain the variation in transaction costs between the cycles. While it does not necessarily mean that the VIX index itself is the state variable driving changes in liquidity levels, it is very probable that the VIX is correlated with underlying state variables that drive the liquidity providers' capacity or demand for liquidity from investors at a lower frequency. Nonetheless, both $SNR$ and VIX coefficients are statistically and economically significant. It is apparent that they complement each other in explaining the variation in round trip costs because they proxy different types of risks.

The above results confirm that transaction prices reflect the costs of monetary policy uncertainty, as measured by the 30 day FF futures prices informativeness, on top of what the general market conditions can already explain. More importantly, the illiquidity spillover applies to all corporate bonds in the same direction, as predicted by the theoretical model. In the next section, I examine whether bonds returns reflect monetary policy uncertainty during the FOMC cycles.

## 4.2 Statistical Regimes

Building on the bi-weekly pattern in excess bond returns, I seek to identify whether macroeconomic news impact corporate bond market liquidity during a FOMC cycle. In order to study potentially different effects of news spillovers on bond returns during high and low return weeks, I estimate a hidden Markov regime switching model. I average cusip-day level data across days in relation to FOMC meetings for days -3 to 28. This is required due to a sharp drop in trading volume for later days, as cycles vary in length with majority being up to 6 weeks long (30 working days). I do not impose any assumptions on the timing of the states. In the model I allow for coefficients to vary between two regimes and two groups: investment and non-investment grade. I run the

**Table 4.4:** Round-trip costs and 30 day Fed futures.
The table presents daily round-trip costs regressions results on signal-to-noise variable, $SNR$, computed from 30 day Fed funds futures. All heteroscedasticity robust standard errors are reported in brackets. The sample is based on the US corporate bonds transaction data from TRACE, provided by WRDS for the period during FOMC weeks from 1 Oct 2004 until 31 Dec 2014 - averaged daily from all available CUSIPs numbers on each day. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

| | Investment Grade | | | Junk Grade | | |
|---|---|---|---|---|---|---|
| | *Dependent variable:* | | | | | |
| | Round Trip Costs | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| SNR | −0.029*** | −0.029*** | −0.010*** | −0.031*** | −0.028*** | −0.016*** |
| | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) | (0.001) |
| TERM | | 0.011** | −0.008*** | | 0.023*** | 0.011** |
| | | (0.005) | (0.003) | | (0.006) | (0.005) |
| DEF | | 0.152*** | 0.032* | | 0.256*** | 0.193*** |
| | | (0.035) | (0.019) | | (0.037) | (0.033) |
| ILLIQ | | 0.002*** | 0.004*** | | 0.015*** | 0.014*** |
| | | (0.000) | (0.000) | | (0.001) | (0.001) |
| VIX | | | 0.041*** | | | 0.028*** |
| | | | (0.000) | | | (0.000) |
| (Intercept) | 0.038*** | 0.037*** | 0.012*** | 0.045*** | 0.041*** | 0.023*** |
| | (0.001) | (0.001) | (0.001) | (0.002) | (0.001) | (0.001) |
| Observations | 2,572 | 2,550 | 2,541 | 2,572 | 2,549 | 2,539 |
| Adjusted $R^2$ | 0.132 | 0.178 | 0.758 | 0.108 | 0.331 | 0.491 |
| F Statistic | 394 | 139 | 1589 | 313 | 315 | 490 |

following regression:

$$\bar{r}_{it} = a^j + b_1^j \times TERM_{it} + b_2^j \times DEF_{it} + b_3^j \times ILLIQ_{it} + b_4^j \times SNR_{it} + \epsilon_{it}^j, \tag{4.5}$$

where $\bar{r}_{it}$ is the averaged volume weighted return from equation 4.1, $i \in \{IG, Junk\}$ and $j \in \{1, 2\}$. The state variable $s_t$ determines whether it is regime 1 or 2, and the Markov transition probability is equal to:

$$P(s_t = 1 | s_{t-1} = 1) = p, \tag{4.6a}$$

$$P(s_t = 2 | s_{t-1} = 2) = q. \tag{4.6b}$$

Table 4.5 reports the model's results. Both groups show variability in the estimated coefficients between two regimes. For IG bonds in regime 1 all variables are statistically significant at 1% confidence level (expect $TERM$, which is significant at 5%), while in regime 2 only $DEF$ is significant at 5% level. The $ILLIQ$ coefficient switches from negative to insignificant. It indicates that returns are only sensitive to liquidity risk in regime 1 (-0.013 vs insignificant 0.013 in regime 2). Similarly, $SNR$ and $TERM$ move from positive to insignificant, demonstrating that returns are sensitive to monetary policy news and duration risks only in regime 1.

Junk bonds results unveil a similar pattern. All but $ILLIQ$ variables are highly significant in regime 1, while only $DEF$ and $ILLIQ$ are priced in regime 2. The sensitivity to default risk is the largest for this group. Surprisingly, there is an opposite effect of the Fed funds futures price informativeness as the $SNR$ coefficient is negative. This means that a higher signal to noise ratio is associated with lower junk bonds returns. One possible explanation is that investors observing more accurate signals move capital to other markets, for instance investment grade bonds. This result is likely to further push non-investment grade prices down ahead of announcements so liquidity providers are likely to be even more aggressive in inventory management for this category. The $ILLIQ$ coefficient is only significant in regime 2, which implies that the importance of liquidity risk changes between the regimes in this credit group as well.

Figure 4.4a plots the model-implied smoothed probabilities of being in one of the two states for investment grade bonds. The two estimated regimes are relatively persistent with $p = 0.77$ and $q = 0.80$. Figure 4.4b displays the probabilities for high yield bonds. There is a clear weekly pattern for investment grades with regimes switching almost exactly every 5 days after FOMC announcement. It can be seen that regime 1 with high sensitivity to $SNR$ and $ILLIQ$ happens just before announcement dates and even weeks during the FOMC cycle. This pattern coincides with (Cieslak et al. 2018) findings on monetary policy leaks during periods between monetary policy announcements. Since regime 1 falls on the low return periods, in comparison to even weeks, a large fraction of under-performance can be assigned to high sensitivity to macroeconomic uncertainty

**Table 4.5:** Regime switching model for corporate bond returns estimates.
This table provides the estimates of the model described by equation 4.5. Robust standard errors are reported in brackets. The data covers the period from 01 October 2004 until 31 December 2014. ***, ** and * indicate significance at 1%, 5% and 10% level, respectively.

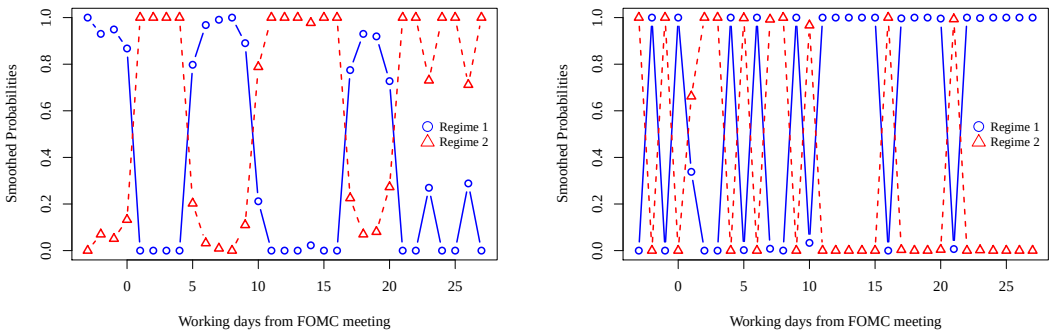
| | Investment Grade | | | Junk Grade | | |
|---|---|---|---|---|---|---|
| | OLS | Regime 1 | Regime 2 | OLS | Regime 1 | Regime 2 |
| (Intercept) | −0.025* | −0.038*** | 0.003 | 0.084 | 0.692*** | −0.026 |
| | (0.013) | (0.002) | (0.185) | (0.065) | (0.008) | (0.019) |
| TERM | 0.088* | 0.038** | 0.066 | −0.021 | −1.204*** | −0.053 |
| | (0.043) | (0.016) | (0.061) | (0.204) | (0.082) | (0.063) |
| DEF | 1.334*** | 0.955*** | 1.086* | 3.930* | 7.404*** | 2.031*** |
| | (0.330) | (0.150) | (0.435) | (1.523) | (0.890) | (0.407) |
| ILLIQ | −0.002 | −0.013*** | 0.013 | 0.006 | −0.016 | −0.045*** |
| | (0.005) | (0.002) | (0.009) | 0.029 | (0.014) | (0.009) |
| SNR | 0.025 | 0.038*** | −0.003 | −0.092 | −0.744*** | 0.022 |
| | (0.014) | (0.002) | (0.019) | (0.068) | (0.009) | (0.020) |
| | | Transition probabilities: | | | | |
| | | Regime 1 | Regime 2 | | Regime 1 | Regime 2 |
| Regime 1 | | 0.77 | 0.20 | | 0.28 | 0.37 |
| Regime 2 | | 0.23 | 0.80 | | 0.72 | 0.63 |

and shift in adverse selection ahead of the announcements.

Junk bonds do not experience steady periods as $p = 0.28$ and $q = 0.63$. This suggests that shocks related macroeconomic announcements disappear faster than in the case of investment grade bonds. This could be the effect of a larger proportion of credit risk in these bonds and the fact that the policy effect cannot be easily disentangled from non-investment grade bond returns.

So far I have identified two purely statistical regimes which differ across two bond categories. Junk bond returns vary regarding term premium, liquidity risk and monetary policy uncertainty between the two regimes. On the other hand, the good credit quality bonds show a greater sensitivity to liquidity and more persistent periods. Moreover, the investment grade bond implied probabilities of regimes present strong evidence that patterns in returns are the effect of macroeconomic news releases as the signal-to-noise ratio is only priced in weeks with low bond returns.

**Figure 4.4:** Smoothed probabilities of Markov model states.
The plots present smoothed Markov regime switching model (Equation 4.5) probabilities of two regimes across days in a FOMC cycle. The data covers the period from 1 Oct 2004 to 31 Dec 2014.




**(a)** Investment grade bonds **(b)** Junk bonds

The results also support the hypothesis that macro-related fundamentals lead to increased uncertainty. (Bollerslev et al. 2018) point out, using high frequency data, that agents in the US stock and bond futures markets agree-to-disagree ahead of the most important public news announcements. They find a disparity in volume/volatility discrepancy between periods before and after announcements, notably those with negative sentiment. As the $ILLIQ$ factor is directly related to the elasticity measured in their study, it is likely that returns in regime 1 are driven by uncertainty and disagreement among market participants.

(Nagel 2012) argues that a given shock generates greater effects on asset prices following negative shocks to market maker capital. In normal times, liquidity shocks can be absorbed by financial intermediaries as the costs of liquidity provision are lower; yet in times of high economic uncertainty and financial sector stress, liquidity providers become more capital-constrained and risk averse. Then, a liquidity shock leads to a larger effect on asset prices due to all market makers being constrained at the same time. The estimated Markov model coefficients suggest a market-wide jump in sensitivity to liquidity risk ahead of information sensitive weeks. As a result, all dealers should require a higher premium, thus greater asset price discount for a given liquidity shock. Additionally, the findings highlight that the corporate bond participants are more risk averse ahead of any monetary policy announcements.

(Bao et al. 2011) examine the impact of illiquidity on bond valuation. Using price reversals as captured by the negative of the autocovariance of prices changes, they show that their illiquidity measure is related to bond characteristics and is both statistically

and economically significant. Moreover, in aggregate, it moves together with the general market conditions. They argue that illiquidity is the most significant factor in explaining the monthly variation in the US aggregate yield spreads of high-rated bonds (A and above). Building on this argument, I estimate their *illiquidity* factor, and demonstrate that all bonds are more liquid in odd weeks with the coefficients 0.46 as opposed to 0.57 for even weeks. The variable supports the Markov model results that there are two distinct liquidity regimes during FOMC cycles. The measure implies that the bid-ask spread should be about 1.36% and 1.51% for the two periods, respectively[8]. A further decomposition of the illiquidity measure shows that non-investment grade bonds experience a larger shock to their liquidity between odd and even weeks. The coefficient rises from 0.65 to 0.88 between the two periods with implied bid-ask spreads being equal to 1.88% and 1.61%. The investment grade bonds illiquidity increases from 0.43 in odd weeks to 0.59 in even weeks and the implied spreads surge from 1.31% to 1.54%. Empirically, there is a little difference in volume traded between odd and even weeks. Therefore, these results suggest that the liquidity providers' inventory capacity is limited due to significant uncertainty in odd weeks. The dealers are under pressure to provide more favourable prices to investors to revert their inventories more efficiently.

The above analysis leads to the following conclusions. First, there are two distinct liquidity regimes where the market participants' sensitivity to main risk factors varies substantially. Key drivers of this variation are disagreement and uncertainty about the future policy. Second, the liquidity level also fluctuates between the periods with non-investment grade bonds being most impacted by this shift. As the findings present a large disparity in implied bid-ask spreads across the two regimes a deeper study of liquidity is required in order to quantify the US corporate bonds transaction costs during FOMC cycles.

## 4.3 Trading Costs and FOMC cycle

Having established that there are two distinct statistical states for investment grade bonds during the FOMC cycle, an important question is whether and how such variation impacts the trading costs on the corporate bond market. It is pertinent to study whether changes in sensitivity to liquidity risk are driven by change in liquidity provision costs or by shifts in demand. For example, (Ruzza and Zurowski 2017) report that corporate bond transaction prices tend to be shifted in relation to mid prices such that it is easier for the market makers to adjust their inventory position (lower effective bids) a few days before the FOMC announcements.

It is still unclear whether overall trading costs rise or fall. The dealers might poten-

[8] As presented by (Roll 1984), $2\sqrt{illiquidity}$ can be interpreted as implied bid-ask spread.

tially widen bid-ask spreads in weeks ahead of macroeconomic news and provide a better price to customers at the same time (by lowering offer prices as well). The transaction costs can increase because of greater risk aversion ahead of important upcoming news or lower demand from liquidity traders due to elevated information asymmetry in the same period. Yet, this uncertainty may oblige capital constrained dealers to provide better prices due to risk management requirements.

### 4.3.1 Transaction costs model

I employ (Edwards et al. 2007)'s regression model to calculate trading costs. The methodology is adjusted such that the transactions are split into odd and even FOMC cycle weeks, i.e. week 0 - days 0 to 4 from a meeting, week 1 - days 5 to 9 etc.. Both groups are almost identical in terms of trade numbers and volume traded; there are 30,358 and 30,373 thousand trades with \$16,690 and \$17,040 billion of volume in even and odd weeks, respectively. Next, I compute transaction costs for the two groups separately allowing for all coefficients to vary. In order to estimate the model, transaction level data described in Table 4.2 is used.

Let $P_t$ be equal to the unobserved *true value*, $V_t$, of a bond at the transaction time, $t$, plus or minus a price concession that depends on whether the trade initiator is a buyer or a seller. The model separately estimates the sizes of these price concessions for customer and interdealer trades. The absolute customer transaction cost, $c(S_t)$, measured as a fraction of price, depends on the dollar notional value of the trade, $S_t$. The model analyses relative transaction costs and total dollar trade price because these are the quantities that are ultimately important to market participants. The split between odd and even weeks adds a dimension, which enables to study whether different liquidity and policy regimes presented in the previous sections cause transaction costs to vary in any significant way.

The percentage price cost associated with interdealer trades, $\delta_t$, is assumed to be random with zero mean and variance, $\sigma_\delta^2$.

Denoting, $Q_t$ to mark whether the customer is a buyer ($Q_t = 1$), a seller ($Q_t = -1$), or interdealer trade ($Q_t = 0$), and $I_t^D$ to indicate whether the trade is an interdealer trade ($I_t^D = 1$) or not ($I_t^D = 0$). Above assumptions generate the following equation:

$$P_t = V_t + Q_t P_t c(S_t) + I_t^D P_t \delta_t = V_t \left(1 + \frac{Q_t P_t c(S_t) + I_t^D P_t \delta_t}{V_t}\right). \tag{4.7}$$

Part B.3 presents the additional steps needed to obtain the trading cost regression in

the following form:

$$\begin{aligned} & r_{ts}^{P} - Days_{ts}(5\% - coupon) \\ & \quad = c_0 Q_t + c_1 \left( Q_t \frac{1}{S_t} - Q_s \frac{1}{S_s} \right) + c_2 (Q_t \log S_t - Q_s \log S_s) + c_3 (Q_t S_t - Q_s S_s) \\ & \quad + c_4 (Q_t S_t^2 - Q_s S_s^2) + \beta_1 Index_{ts} + \beta_2 Duration_{ts} + \beta_3 Credit_{ts} + \epsilon_{ts}, \end{aligned} \tag{4.8}$$

where $r_{ts}^{P}$ is the continuously compounded observed bond price return between trades $t$ and $s$, and $r_{ts}^{V}$ is the unobserved value return between trades $t$ and $s$. $Days_{ts}$ counts the number of calendar days between trades $t$ and $s$, $Index_{ts}$ is the index return for the average bond between trades $t$ and $s$ (estimated using all available trades), and $Duration_{ts}$ and $Credit_{ts}$ are the corresponding differences between index returns for long- (maturity above 15 years) and short-term (maturity under 2 years) bonds and high (ratings AAA to AA-) and low (ratings B+ and lower) credit risk bonds[9]. The first term accounts for the continuously compounded bond price return that traders expect when interest rates are constant and the bonds coupon interest rate differs from 5%. The three factor returns account for bond value changes in a similar way to daily frequency factors - $TERM$, $DEF$ and $ILLIQ$, namely, they capture shifts in interest rates and credit spreads.

The error of equation 4.8 is distributed with mean 0 and variance equal to:

$$\sigma_{ts}^2 = N_{ts}^{Days} \sigma_{Days}^2 + D_{ts} \sigma_{\delta}^2 + (2 - D_{ts}) \sigma_{\kappa}^2, \tag{4.9}$$

where $N_{ts}^{Days}$ counts the number of trading days between trades $t$ and $s$, $\sigma_{Days}^2$ is a variance of a trading day, $\sigma_{\delta}^2$ and $\sigma_{\kappa}^2$ correspond to volatility of interdealer and customer transactions, respectively. $D_{ts}$ represents the number of interdealer trades and $D \in \{0, 1, 2\}$.

I calculate iterated weighted least-squares regressions in which the weights are given by the inverse of the error variance from equation 4.9. This procedure ensures that results reflect the information available in the data sample. In particular, the weighting procedure permits the use of all bonds. If trading in a bond cannot provide useful information, its cost estimate error variance will be large and the bond will have essentially no effect on the results. On the other hand, for some bonds, despite meeting the minimum trade number, the regression results are perfectly fitted due to repeating transaction sizes. These regression would lead to bias in weightings thus are removed from analysis. Such bonds consist no more than 0.25% per trade volume.

Using the above time series results I compute transaction costs across dollar volumes

[9] The choice of maturities and credit ratings does not impact the results significantly.

in the cross section. For a given trade size $S$, the estimated cost implied by the model is a linear combination of the obtained coefficients:

$$\hat{c}(S) = \hat{c}_0 + \hat{c}_1 \frac{1}{S} + \hat{c}_2 \log S + \hat{c}_3 S + \hat{c}_4 S^2. \tag{4.10}$$

The obtained error variance of this estimation is given by:

$$\mathrm{Var}[\hat{c}(S)] = \mathbf{S}\hat{\Sigma}_{\hat{c}}\mathbf{S'}, \tag{4.11}$$

where $\hat{\Sigma}_{\hat{c}}$ is the computed variance-covariance matrix of the coefficient estimators and $\mathbf{S} = \begin{bmatrix} 1 & \frac{1}{S} & \log S & S & S^2 \end{bmatrix}$. The linear combination of the coefficients is typically well identified for trade sizes that are common in the data. If trade volumes are larger than the trades upon which the computations are based, the cost estimate error variance explodes with $S^4$. For trade sizes that are smaller than the trades upon which the numbers are based, the obtained error variance rises with $1/S^2$.

Next, the average costs are calculated for each category using the same weighting approach. Standard errors of the cost estimates are obtained using the following formula:

$$\sigma_{\bar{c}S} = \sqrt{\frac{1}{\sum_{i=1}^{n} \mathrm{Var}[\hat{c}(S)]_i^{-1}}}. \tag{4.12}$$

My results are in line with previous studies. The obtained half-spreads are very similar to the simple round trip costs computed in Section 4.1. During both even and odd weeks average costs fall with the transaction size, the half spreads range from 2bps for \$10 million notional to 65bps for a \$5 thousand trade size. However, there is a large gap between transaction costs in even and odd weeks. Effective half-spreads for both even and odd weeks are plotted in Figure 4.5a.

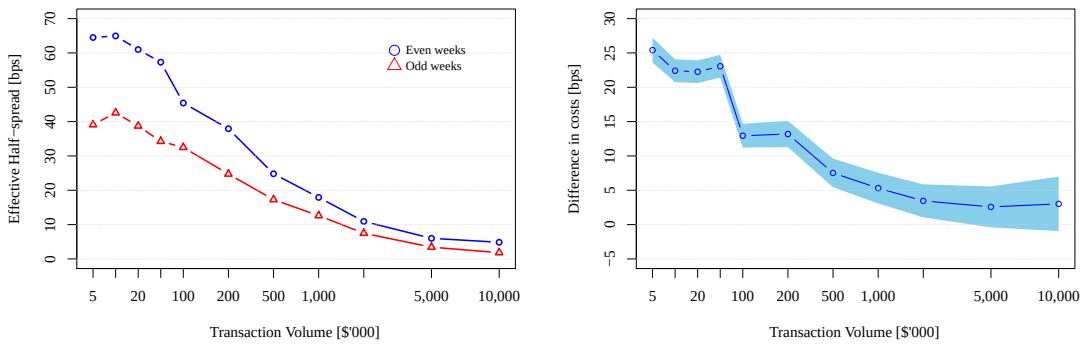
Surprisingly, trading in even weeks (after fundamental news reach the market) is more costly. The difference is both statistically and economically significant. All differences are significant at the 99% confidence level with the exception of the transactions above \$5 million, which are significant at the 95% level. The reason for that is that largest transactions both experience lowest transaction costs (per unit traded) and are more likely to be prearranged. The difference in effective half-spreads ranges from 3 to 25 basis points. Furthermore, the gap is almost monotonically decreasing with size. There is also an 11 basis points decrease in the difference between 50 thousand (retail) and 100 thousand (small institutional) trade sizes. Detailed results together with the difference between the two groups are displayed in Table 4.6 and are plotted, together with the 99% confidence interval, in 4.5b. The findings demonstrate that dealers provide better quotes to customers before the information-rich weeks despite facing larger information asymmetry. At least part of the reason for the excess market liquidity during periods

**Table 4.6:** Estimated transaction costs
This table presents cross-sectional statistics that characterize average trade costs for various trade sizes in odd and even FOMC cycle weeks implied by the estimated coefficients of the transaction cost estimation model (Equation 4.8). The dependent variable is the continuously compounded return. The cost estimates, which are effective half-spreads, are obtained from time-series regressions estimated separately for each of the 32,304 bonds in the sample. The estimated costs for a trade of size $S$ are computed from $\hat{c}(S) = \hat{c}_0 + \hat{c}_1 \frac{1}{S} + \hat{c}_2 \log S + \hat{c}_3 S + \hat{c}_4 S^2$. The weights used to compute the weighted means are the inverses of the computed variances of the respective costs estimates. Standard errors of obtained means are reported in brackets. T-stats are for hypothesis that the two subsamples have the same mean. $^{***}$, $^{**}$ and $^{*}$ denote significance at 1%, 5% and 10% levels, respectively.

| Trade Size [$'000] | Weighted mean cost even [bps] | Weighted mean cost odd [bps] | Difference [bps] | T-stat |
|---|---|---|---|---|
| 5 | 64.5 | 39.1 | 25.4 | 36.2*** |
| | (0.5) | (0.5) | | |
| 10 | 65.0 | 42.6 | 22.4 | 34.7*** |
| | (0.5) | (0.4) | | |
| 20 | 61.0 | 38.7 | 22.3 | 34.8*** |
| | (0.5) | (0.4) | | |
| 50 | 57.3 | 34.3 | 23.1 | 36.0*** |
| | (0.4) | (0.4) | | |
| 100 | 45.4 | 32.5 | 12.9 | 19.3*** |
| | (0.5) | (0.4) | | |
| 200 | 37.9 | 24.7 | 13.2 | 17.8*** |
| | (0.6) | (0.5) | | |
| 500 | 24.8 | 17.3 | 7.5 | 9.3*** |
| | (0.7) | (0.5) | | |
| 1,000 | 17.9 | 12.6 | 5.3 | 6.1*** |
| | (0.7) | (0.6) | | |
| 2,000 | 10.9 | 7.5 | 3.5 | 3.7*** |
| | (0.7) | (0.6) | | |
| 5,000 | 6.0 | 3.4 | 2.6 | 2.23** |
| | (0.9) | (0.7) | | |
| 10,000 | 4.9 | 1.8 | 3.0 | 1.96** |
| | (1.2) | (0.9) | | |

ahead of important announcements seems to be that liquidity providers face a mismatch in their inventory levels. In order to effectively adjust their inventories, they need to decrease the transaction costs. Furthermore, (Brunnermeier and Pedersen 2009) show that the funding of liquidity suppliers can dry up when volatility is high, they need to prevent this by offering more favourable quotes to their clients. This is further supported by (Adrian and Shin 2010), who argue that variations in financial intermediaries risk

**Figure 4.5:** Transaction costs between odd and even FOMC cycle weeks.
The charts display estimated effective half-spreads split into even and odd FOMC cycle weeks and the difference together with a 99% confidence interval between the two groups for all TRACE transactions from 1 Oct 2004 to 31 Dec 2014.



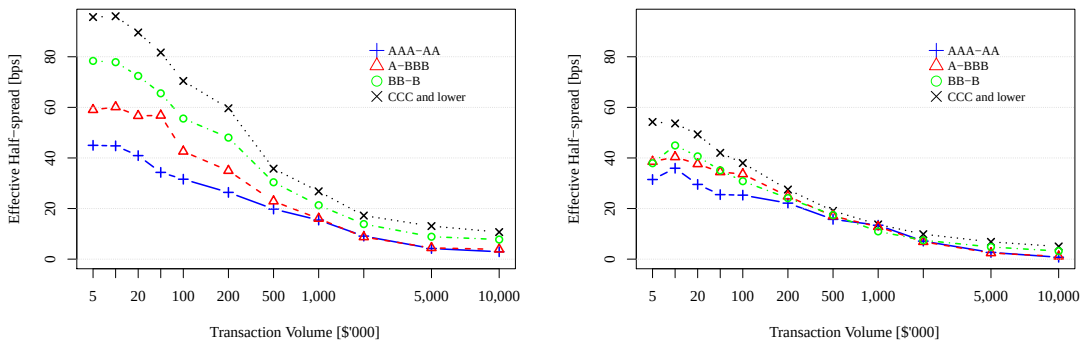

**(a)** Effective half-spreads **(b)** Difference in effective half-spreads

appetite are driven by risk management constraints, which are more likely to be binding just ahead of scheduled announcements.

### 4.3.2 Credit ratings

Further split of the transaction costs, as estimated by equation 4.8, into credit ratings categories shows more diversity in the cross-sectional behaviour of the effective spreads between the two periods. Plots 4.6a and 4.6b display these results.

**Figure 4.6:** Effective half-spreads by credit rating.
The graphs display estimated effective spreads for all TRACE transactions from 1 Oct 2004 to 31 Dec 2014 split into even and odd FOMC cycle weeks across four credit rating groups.




**(a)** Even FOMC cycle weeks **(b)** Odd FOMC cycle weeks

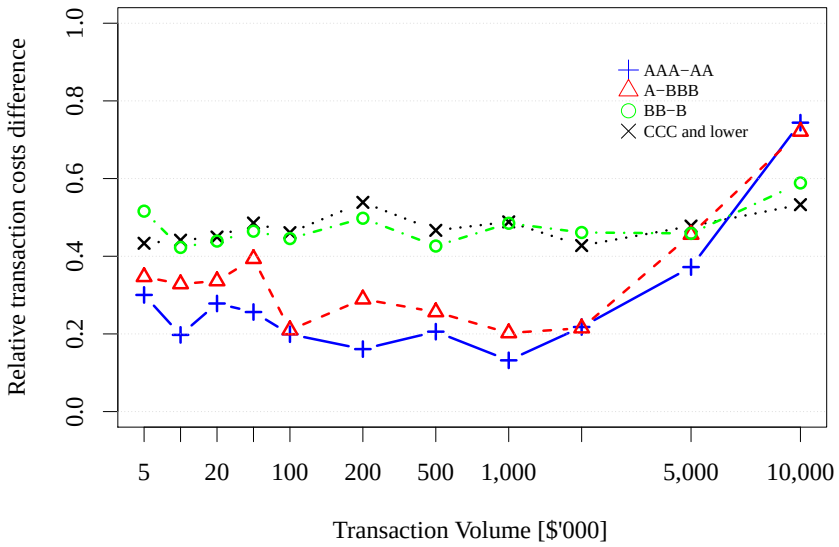
All groups display similar patterns with costs declining as transaction volume rises.

However, the largest drop in the trading costs comes from low credit quality bonds. Half spreads for assets with ratings below CCC fall from about 90 to under 60 basis points for the smallest trades. For the same category high grade bonds costs fall only by about 20 basis points (60 to 40 basis points). A-BBB category (more than 60% of the trades in sample) display the largest decline in expenses when moving from retail to institutional trade sizes.

Similar conclusions can be drawn when assessing relative changes in the transaction costs. Figure 4.7 presents the relative variation in effective spreads. Non-investment grade bonds effective spreads are about 40% greater in even cycle weeks. The relative difference is almost flat across all trade sizes. This result is possibly caused by flight to quality found in the regime switching model. Increased price pressure ahead of announcements causes dealers to provide much better prices for this group. Investment grade transaction costs are between 20%-40% higher in the same period for retail trades and 15-30% for institutional transaction sizes. Yet, trades above $2 million of face value experience a relative costs increase to almost 80%. The elevated effect is partially driven by wider standard errors and small values in absolute terms for these bonds and transaction volumes.

Returning to the implied spreads from Section 4.2 two observations can be made. First, the change in both effective and implied spreads shows the same effect of the FOMC cycle - inflated transaction costs in even weeks. Second, the relative rise in implied trading costs oscillates around 17% which is considerably lower than the value computed in this section. Since the aggregate illiquidity measure captures a more general state of the world, it indicates that the contemporaneous market conditions are not sufficient in explaining the variation in effective spreads. Rather, the expectations about future monetary policy news announcements play a relevant role in explaining the differences between odd and even weeks. It also suggests that market makers bear non negligible risk ahead of the news releases such that they need to offer more favourable prices than implied by the market conditions. Overall, my results highlight that both liquidity and monetary policy uncertainty are important drivers of transaction costs.

**Figure 4.7:** Relative difference in transaction costs.
The plot presents relative transaction costs difference between trading in odd and even FOMC cycle weeks for all TRACE transactions from 1 Oct 2004 to 31 Dec 2014.




## 4.4 Conclusion

I use more than 10 years of the US corporate bond and 30 day FF futures trade data to evaluate the behaviour of market participants in the bond market during FOMC cycles. Through a theoretical model I show how market makers are able to infer and incorporate monetary policy uncertainty in prices. Building on a stylized fact that bond returns behave very differently in odd and even cycle weeks, I develop a hidden Markov regime switching model. Both investment and non-investment grade bonds exhibit two statistically distinct liquidity regimes; one with high sensitivity to price pressure and policy measures, the other with low response to liquidity risk and no clear reaction to news from the FF market. Moreover, in the case of investment grade bonds, Markov model implied probabilities align closely with the bi-weekly return pattern further suggesting a significant impact of monetary policy on corporate bond market participants. The macroeconomic news uncertainty ahead of announcements increases inventory risks borne by intermediaries providing liquidity to facilitate continuous market clearing.

I also estimate effective trading costs in the two regimes to test the inventory risk hypothesis. This study shows that it is considerably cheaper to trade in weeks ahead of announcements due to disagreement about upcoming fundamental news. The difference is the largest for low credit quality bonds and retail size transactions. Absolute and relative differences in costs vary between 3 bps and 25bps, and from about 15% to more

than 70% in relative terms, respectively.

Large transactions are often being prearranged thus allow liquidity providers to manage their inventory, funding capital and risk more efficiently. The significant disparity in transaction costs, notably for small transactions, suggests that the OTC market participants are impacted by upcoming monetary policy news. This creates shifts in risk aversion and inventory capacity capabilities.

A possible solution could be to further increase transparency of the bond market. This would lead to small investor trading being more active in times of high disagreement, reducing the duration of price pressure by allowing intermediaries to mean-revert their inventories more efficiently. Another way could be achieved through release of news in smaller and more frequent fashion, which would make possible policy shocks limited thus easier to absorb for the risk-bearing capacity of liquidity providers.

# Appendix B

# Appendix to Costs of Monetary Policy Uncertainty

## B.1 30 Day FF Futures and Macroeconomic Announcements

As the monetary policy is limited not only to the setting of the short term rate but also it drives the expectations of forward rates, the 30 day Fed funds futures respond to several macroeconomic variables.

30 day FF futures pay an average effective Federal funds rate, $ff$, over the current month. Thus, immediately before an important macroeconomic announcement, at time $t-\epsilon$ the implied rate from the current-month futures contract, $FUT$, is simply a weighted average of the effective rate that has dominated so far in the month, and the expectations for the rest of the month:

$$FUT_{t-\epsilon,T} = \int_0^{t-\epsilon} ff_s ds + \mathbb{E}_{t-\epsilon}\left[\int_{t-\epsilon}^{T} ff_s ds\right] + risk\ premium \tag{B.1}$$

Then, by shifting this equation to time $t+\epsilon$ (30 minutes after an announcement)[1] and differencing, the surprise component of the change in the federal funds rate target is equal to:

$$unexpected\ change_t = (FUT_{t+\epsilon,T} - FUT_{t-\epsilon,T}) \times \frac{T}{T-t}. \tag{B.2}$$

In order to be able to define *unexpected change* as the surprise change in monetary policy expectations, I have to assume that the *risk premium* remains constant, or at least that is relatively small compared to the change in expectations over the short

[1] Similar results can be also obtained on $\epsilon = 15$ minutes.

announcement window.

Next, I use all macroeconomic announcements data downloaded from Bloomberg[2]. The data spans from 11 Nov 2003 to 30 Nov 2016 and includes an announcement name, hour stamp as well as surveyed and actual indicator values.

I run the following regressions for each announcement type, $i$, separately:

$$unexpected\ change_t^i = \beta^i(survey - actual)_t + \xi_t^i. \tag{B.3}$$

Unsurprisingly, the most significant results are related to FOMC meetings. Nonetheless, there are numerous other macroeconomic news, which impact monetary policy expectations. $\beta$ from equation B.3 is statistically significant for following announcements:
ISM Manufacturing (ticker:NAPMPMI Index)
ISM Prices Paid (NAPMPRIC Index)
Change in Nonfarm Payrolls (NFP TCH Index)
Initial Jobless Claims (INJCJC Index)
Philadelphia Fed Business Outlook (OUTFGAF Index)
CPI Ex Food and Energy MoM (CPUPXCHG Index).

Additional analysis done on contracts expiring further out in the future shows that macroeconomic announcements are also important for longer maturity expectations.

## B.2 Model

The model is a particular case of (Cespa and Foucault 2014)'s liquidity spillover model. Consider dealers in one asset, a bond - $B$, who have perfect information about the fundamental value $\gamma_B$ but use, as a signal, the price of some other asset, a future contract - $F$. The price is informative because it demonstrates information about fundamentals known to dealers in asset $F$ - $\gamma_F$. Nonetheless, the price of asset $F$ is also affected by transient demand pressures, and even more so when the cost of liquidity provision for dealers rises. Therefore, the price of asset $F$ is a noisy signal for dealers in asset $B$, and the informativeness of this signal falls when the price of $F$ becomes more sensitive to demand shocks, i.e. when asset $F$ is less liquid. Accordingly, if a shock specific to dealers in asset $F$ (e.g., a decline in these dealers risk appetite) leads to increased costs of liquidity provision in this asset, uncertainty for dealers in asset $B$ becomes higher and their cost of liquidity provision surges too. Therefore, the drop in liquidity for asset $F$ propagates to asset $B$ and the value, $V_i$, can be depicted as a sum of a fundamental value and extra information from another asset:

[2] I am grateful to Anna Cieslak for providing me with this dataset.

$$\begin{aligned} V_B &= \gamma_B + d_B \times \gamma_F + \xi_B, \\ V_F &= \gamma_F + d_F \times \gamma_B + \xi_F \end{aligned} \tag{B.4}$$

Assuming that unlike in the case of government bonds the corporate bonds fundamentals do not impact monetary policy or the Fed rate and the dealers infer the monetary policy future outcomes from 30 day Fed futures, $0 < d_B \leq 1$ and $d_F = 0$.

Each dealer $k$, operating in asset $j$, has a CARA utility with risk tolerance $\alpha$:

$$\mathbb{E}\left[U(V_j - p_j)x_{kj}|\gamma_j, \mathcal{F}_j\right] = \mathbb{E}\left[-\exp(-\alpha_j^{-1}(V_j - p_j)x_{kj})|\gamma_j, \mathcal{F}_j\right], \tag{B.5}$$

where $x_{kj}$ is the amount of asset $j$ held by a dealer $k$ and $\mathcal{F}_j$ is the information set, $\mathcal{F}_j$ includes prices, $p$, of assets $B$ and $F$ and:

$$x_{kj}(\gamma_j, \mathcal{F}_j) = \alpha_j \left( \frac{\mathbb{E}[V_j|\gamma_j, \mathcal{F}_j] - p_j}{\mathbb{V}[V_j|\gamma_j, p_{-j}]} \right). \tag{B.6}$$

Under an assumption that dealers in bonds extract information about the macro-factor unknown to them from the futures price, liquidity providers must form beliefs on the relationship between clearing prices and risk factors. The dealers trade with and take the opposite side of liquidity traders.

Denoting an aggregate dealers demand for an asset $i$ as $u_i$ and assuming $u_i \sim \mathcal{N}(0, \sigma_{u_i}^2)$, $\mathbb{E}[u_B u_F] = 0$, $\mathbb{E}[u_i \gamma_j] = 0$, and $\mathbb{E}[u_i \xi_j] = 0$ for $i, j \in \{B, F\}$. A linear rational expectations equilibrium is a set of prices $p_B^*$, such that :

$$p_B^* = \gamma_B + B_B u_B + H_B \gamma_F + C_B u_F, \tag{B.7}$$

where

$$B_B = f(B_F, \alpha_B, \sigma_{\xi_B}, d_B, \sigma_{u_F}) = \frac{\sigma_{\xi_B}}{\alpha_B} + \frac{d_B^2 B_F^2 \sigma_{u_F}}{\alpha_B(1 + B_F^2 \sigma_{u_F})}, \tag{B.8}$$

and

$$B_F = \alpha_F^{-1} \mathbb{V}[V_F|\gamma_F]. \tag{B.9}$$

Coefficients

$$H_B = \frac{u_B B_B d_B \alpha_B}{d_B^2 B_F^2 \sigma_{u_F}^2 + \sigma_{\xi_B}(1 + B_F^2 \sigma_{u_F}^2)} \tag{B.10}$$

and $C_B = H_B B_F$ are fully characterised once $B_B$ and $B_F$ are known.

$p_B^*$ clears the market of for each realization of $\{u_B, \gamma_B, u_F, \gamma_F\}$ when dealers anticipate that clearing prices satisfy equation B.7 and choose their positions to maximize their expected utility (equation B.5). Furthermore, it can be shown that the precision

of the bond's payoff using signal $S_F \equiv \gamma_F + B_F u_F$ from the Fed funds futures is:

$$\frac{1}{\mathbb{V}\left[V_B|\gamma_B, S_F\right]} = \frac{1}{\mathbb{V}\left[V_B|\gamma_B\right](1-\rho_B)}, \tag{B.11}$$

where:

$$\rho_B = \frac{\mathbb{E}[V_B S_F|\gamma_B]^2}{\mathbb{V}\left[V_B|\gamma_B\right]\mathbb{V}\left[S_F\right]}, \tag{B.12}$$

$$\rho_B = \frac{d_B^2}{\sigma_{\xi_B}^2 + d_B^2} \times SNR_F. \tag{B.13}$$

Variable $\rho_B$ quantifies the informativeness of the asset $F$ price about the payoff of a bond ($B$) for intermediaries in the corporate bond market. The higher $\rho_B$, the greater is the precision of the signal revealed by the price of asset $F$.

## B.3 Trading Costs

Starting with the equation 4.7 and taking logs of both sides I get:

$$\log(P_t) = \log\left[V_t + Q_t P_t c(S_t) + I_t^D P_t \delta_t\right]. \tag{B.14}$$

Next, building on the fact that transaction costs are typically small fraction of value, and the price mostly is close to the fundamental value I make two approximations:

$$\log(P_t) \approx \log(V_t) + Q_t c(S_t) + I_t^D \delta_t, \tag{B.15}$$

and subtract the same expression for trade at time $s$,

$$\log(P_t) - \log(P_s) \approx \log(V_t) + Q_t c(S_t) + I_t^D \delta_t - \log(V_s) - Q_s c(S_s) - I_s^D \delta_s. \tag{B.16}$$

Lastly, I drop the approximation sign, which yields:

$$r_{ts}^P = r_{ts}^V + Q_t c(S_t) - Q_s c(S_s) + I_t^D \delta_t - I_s^D \delta_s. \tag{B.17}$$

$r_{ts}^V$ from the above equation is further decomposed as

$$r_{ts}^V = Days_{ts}(5\% - coupon) + \beta_1 Index_{ts} + \beta_2 Duration_{ts} + \beta_3 Credit_{ts} + \epsilon_{ts}, \tag{B.18}$$

which directly leads to the equation 4.8.

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