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By

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Professor Yuriy Gorodnichenko
Professor Martin Lettau

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Abstract

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One of the ultimate goals of financial economics is to understand the mechanisms that drive asset prices, both on the macroeconomic level, and on the more granular level that involves interactions between groups of investors. In my dissertation, I study the settings in which monetary policy announcements act as a source of exogenous shocks. The heterogeneous cross-sectional response of asset prices to such shocks could be used to understand the channels through which the policy affects the market, and also to study the effects of market frictions on prices.

In the first chapter, I focus on the movements of the stock prices in anticipation of monetary policy announcements. Lucca and Moench (2015) document a significant upward drift in the stock market in the 24 hours preceding meetings of the Federal Open Market Committee (FOMC). This drift is not conditional on realized monetary policy shocks. My first chapter offers an explanation for this finding that is based on disagreement and short-selling constraints. When investors hold heterogeneous beliefs about the content of the upcoming monetary policy announcement and for some market participants it is costly or impossible to short-sell, speculative demand from optimistic investors can drive up prices before the announcement. This can be especially the case for stocks that are more sensitive to the monetary policy shocks, more expensive to short-sell, and during periods of high disagreement about the FOMC decisions. I confirm this intuition in a series of empirical tests using the cross-section of U.S. equities.

In the second chapter, my coauthor Christian Jauregui and I seek to understand what could monetary policy shocks tell us about optimal bank capital requirements. We find news following U.S. FOMC announcements can be viewed as quasi-natural "stress-tests" impacting U.S. banks depending on their equity capital ratios. The heterogeneous response of banks' equity returns and bond yields to surprises in interest rates reveal how financial markets favorably value excess equity capital. We show the equity return of a bank in the 75th percentile of total equity capital ratio is roughly 1/6 less sensitive to monetary policy shocks than a bank in the 25th percentile. Similarly, corporate bond yields of banks with larger equity capital ratios are better insulated against unexpected changes in the "slope", or rate of change, of monetary policy. We conclude that higher capital requirements are viewed positively by market participants.

To Darya

Contents

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Chapter 1

Pre-FOMC Announcement Drift and Speculative Trading

1.1 Introduction

The Federal Open Market Committee (FOMC) has eight scheduled meetings per year in which the decision about the U.S. monetary policy is made. Since 1994 the outcome is announced through the press-release, usually around 2 PM on the second day of the meeting. The 24-hour period that precedes the announcement is part of a larger blackout period, during which no communication about monetary policy is supposed to happen between members of the FOMC and outsiders. Standard asset pricing theory predicts that no significant price movements should occur when there is no new information. Yet, Lucca and Moench (2015), henceforth LM, show that between 1994 and 2011 stock markets around the world have experienced significant positive returns during the 24-hour period preceding FOMC announcements. In the US, this pre-FOMC drift of the S&P 500 index is on average 49 basis points, which corresponds to about 80% of the of the annual realized excess returns in the stock market.

What explains the pre-FOMC announcement drift? LM argue that it is not likely to be the premium that investors require for holding stocks during the period when non-diversifiable risk is high because the returns are realized before the announcement, while the post-announcement market movement is zero on average. An alternative explanation involves the reallocation of market risk due to inattentive investors leaving the market before the announcement. Yet, there is no empirical evidence supporting this hypothesis: for instance there is indication of active sell-off before FOMC meetings. Another potential explanation is related to the leakage of information from the Federal Reserve to market participants, who could trade on this information before the announcement. Several recent papers study leakage ahead of FOMC meetings, though none focuses explicitly on the 24-hour pre-announcement period. Cieslak et al. (2018) provide evidence of systematic communication of private information by the Federal Reserve officials and show that this leads to the bi-weekly cycles in the stock market risk premia. Bernile et al. (2016) use data from the futures market to show evidence of informed trading in the 30 minutes before FOMC press-release, which they explain by leakage of embargoed information by news outlets. Ai and Bansal (2018) develop a revealed preference theory in which recursive preferences give rise to the announcement premium, but their explanation of the pre-FOMC drift still requires traders to receive informative signals before the announcement. An important limitation of the leakage explanation is that the pre-FOMC drift is not related to the monetary policy shock realized at the announcement: whether rates surprisingly increase or decrease, the drift remains positive. If market participants had advance knowledge of Fed decision, their trading would lead the market to move in the direction of the monetary policy shock. However, this is not what happens in the data.

In this chapter, I argue that a significant part of the pre-FOMC drift could be attributed to speculative trading by investors who are overly optimistic about the upcoming FOMC announcement. Miller (1977) describes a setting in which market participants hold heterogeneous expectations about future returns of a risky asset, and face short-selling constraints. When shorting is prohibited or costly, the pessimistic investors have less capacity to trade in line with their beliefs than the optimistic investors. As a result, the equilibrium price of the risky asset is above its fundamental valuation. I apply this intuition to explain the pre-FOMC drift. I develop a static model in which an announcement determines the future payoff of a stock, and investors hold heterogeneous beliefs about the outcome of this announcement. Short-selling is costly for some investors, and not available at all for other investors[1]. The model generates positive returns in the period leading to the announcement and offers a series of cross-sectional predictions: (i) pre-announcement returns are increasing with disagreement, and this effect is stronger for stocks that are more exposed to the monetary policy shocks, (ii) pre-announcement drift should be more pronounced for stocks with higher short-selling costs, and (iii) post-announcement returns should be smaller for stocks that have highest pre-announcement returns.

Using a cross-section of stocks, I document a series of empirical findings that are consistent with the hypothesis of speculative trading ahead of FOMC announcements. First, stocks that are more exposed to monetary policy shocks should be more attractive to optimistic investors, because they allow betting on the FOMC outcome at lower cost, so the pre-announcement drift should be higher for such stocks. I use time-series regressions of intraday returns on the unexpected innovations in the Federal Funds Futures prices to measure the sensitivity of individual stocks to monetary policy shocks as "betas", similar to Bernanke and Kuttner (2005). Consistent with the prediction, stocks in the top monetary policy beta decile by absolute value tend to have higher pre-FOMC announcement drift by 25-35 basis points, compared to stocks in the bottom decile.

Second, in the speculative trading framework, the pre-FOMC drift should be higher when the dispersion in investors' beliefs about the content of the upcoming announcement is larger. In order to test this prediction empirically, I follow the literature that uses the standard deviation of forecasts as a measure of the divergence of opinions (Diether et al. (2002), Hong and Sraer (2016)). I assemble a novel dataset of near-term professional forecasts for the Federal Funds Rate that come from surveys of economists at large financial institutions. These surveys are conducted by business news outlets to report on Wall Street expectations of the upcoming FOMC announcement. The primary finding regarding the interaction between disagreement and exposure to monetary policy shocks is documented in Figure 1.1, which

[1] Strict short-selling constraint is not necessary, as main results hold with only the short-selling costs.

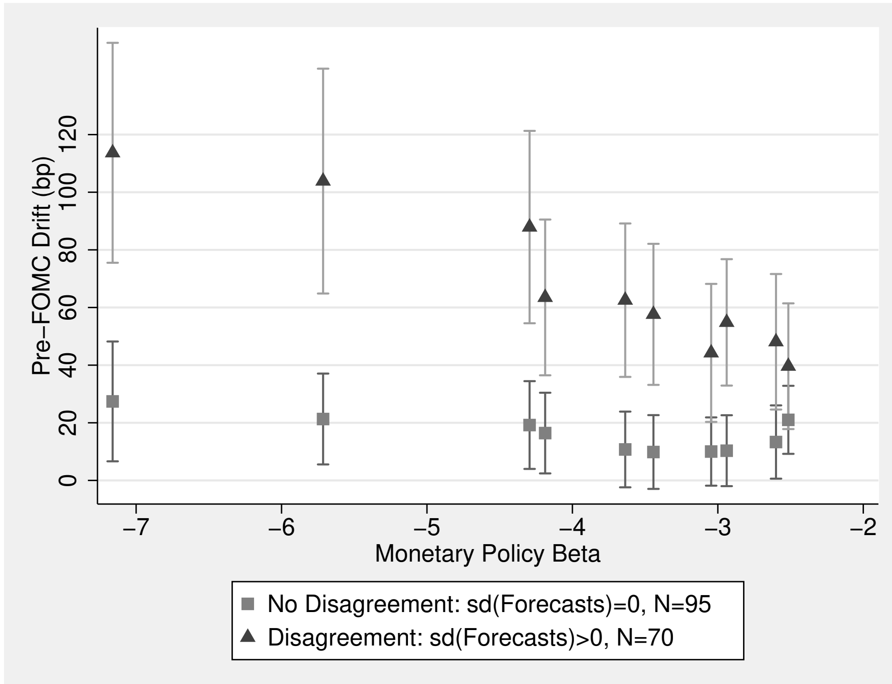

Figure 1.1: Average pre-FOMC returns of ten portfolios sorted on monetary policy beta, announcements separated on level of disagreement. Monetary policy betas computed using a 30-period rolling window time series regressions. Disagreement measured as standard deviation of forecasts for the next FOMC decision. Vertical bars show the 90% confidence intervals.

plots the average pre-FOMC returns of 10 value-weighted portfolios sorted on monetary policy betas. When disagreement about the upcoming FOMC decision is low, the average pre-annnouncement return is about 20 basis points, and flat across all portfolios. However, when disagreement is high, the portfolios with more negative beta tend to earn much higher returns, which is consistent with the first prediction of the model.

The distinctive feature of the speculative trading hypothesis is that it also makes two additional predictions about the positive relationship between short-selling costs and pre-announcement returns, and about return reversal after the announcement. I find empirical support for both predictions. For short-selling constraints, I follow the approach of Boehme et al. (2006) and use relative short interest (computed at monthly or bi-weekly intervals as a fraction of all shares outstanding that are held short on the last day of the interval; I use the most recent observation within 30 days before FOMC announcement) as a proxy for the cost of shorting. I find that increasing relative short interest by one standard deviation is associated with a higher pre-FOMC return by an average of 5-7 basis points at the stock level, and up to 14 basis points at the portfolio level. I also find evidence of negative returns in the 30-minute window around the announcements, especially for assets with higher sensitivity to shocks during periods of more substantial investor disagreement about the outcome of the FOMC meeting.

This chapter is related to work of Kaul and Watanabe (2018), who study the cross-section of stock returns before the FOMC announcements and show that pre-announcement drift is increasing with market beta, and also that buying pressure is largest for high-beta stocks. They interpret it as evidence of stock cross-pumping by institutional investors, who have the incentive to bid up high-beta assets to improve their short-term performance. They support this explanation by showing that drift is primarily driven by buying orders of large size, which indicates institutional trading. In essence, this goes along the lines of the speculative trading explanation, and my chapter complements their work by showing the role of monetary policy beta, disagreement and short-selling constraints in the pre-FOMC announcement drift.

On a broader scale, this chapter builds upon the literature that examines the cross-sectional heterogeneity in response of stock prices to monetary policy shocks. Chava and Hsu (2015) show that stocks of more financially constrained companies are more sensitive to unexpected monetary policy tightenings. Weber (2015) and Gorodnichenko and Weber (2016) investigate the role of price rigidity in the reaction of stock prices to the monetary policy surprises. Ippolito et al. (2018) describe floating rate channel in the transmission of monetary policy, and conduct empirical analysis in the cross-section of stocks. Several recent papers also focus on the resolution of uncertainty on FOMC announcement days (Kroencke et al. (2017), Amengual and Xiu (2018), Gu et al. (2018)). This chapter is also related to the vast literature on the effects of policy uncertainty and on asset prices and economy on the aggregate level (Pastor and Veronesi (2012), Baker et al. (2016), Creal and Wu (2017), Husted et al. (2017)), and in the cross-section of assets (Bali et al., 2017). I also contribute to the literature that studies the effects of differences of opinions and short-selling constraints on asset prices (Duffie et al. (2002), Atmaz and Basak (2018), Diether et al. (2002), Berkman et al. (2009)). In constructing the model I also employ insights from the literature on constrained arbitrage (Shleifer and Vishny (1997), De Long et al. (1990)).

The remainder of this chapter is organized as follows. Section 1.2 presents the model and outlines empirical predictions. Section 1.3 describes the data. Section 1.4 provides the principal empirical analysis. Section 1.5 performs a series of robustness checks. Section 1.6 discusses policy implications of the findings. Section 1.7 concludes.

1.2 Model

1.2.1 Setup and Equilibrium

The economy is described by a continuum of investors of mass 1. There are three periods $t = 0, 1, 2$, and trading only occurs at $t = 1$. There is a single risky asset in unitary supply, and a risk-free asset in infinite supply that pays exogenous return r. At date $t = 2$ the risky asset pays the dividend:

$$\tilde{d} = d + b\tilde{z}$$

where d is the fixed payout, $\tilde{z}$ is the exogenous "macro" factor with $\mathbb{E}[\tilde{z}] = 0$ and $Var(\tilde{z}) = \sigma_z^2$. The parameter b is the cash-flow sensitivity to the factor. This payoff structure is chosen to highlight the fact that payoff of the stock around announcements are likely to be driven by the exposure to the exogenous factor. This setup also could be naturally extended to the case of multiple stocks.

There are three groups of investors in the market. Groups A and B represent constrained investors, that are prohibited from short-selling the risky asset, and also disagree about the mean of the "macro" factor. Assuming $b > 0$, group A would be labeled as optimists with $\mathbb{E}^A[\tilde{z}] = \lambda > 0$, and group B are pessimists with $\mathbb{E}^B[\tilde{z}] = -\lambda < 0$. Group hf represents arbitrageurs (hedge funds), who are allowed to short-sell the risky asset but have to pay a shorting fee $0 < c < 1$ per every unit of the asset if they decide to have negative holdings.[2] Arbitrageurs hold correct beliefs about the mean of the common factor $\mathbb{E}^{hf}[\tilde{z}] = 0$. The fraction of constrained investors is α, split equally between groups A and B. The fraction of arbitrageurs hf is $1 - \alpha$, so on average investors hold correct beliefs about the mean of the "macro" factor. Figure 1.2 illustrates the setup of the model with three groups of investors, their weights, constraints and beliefs.

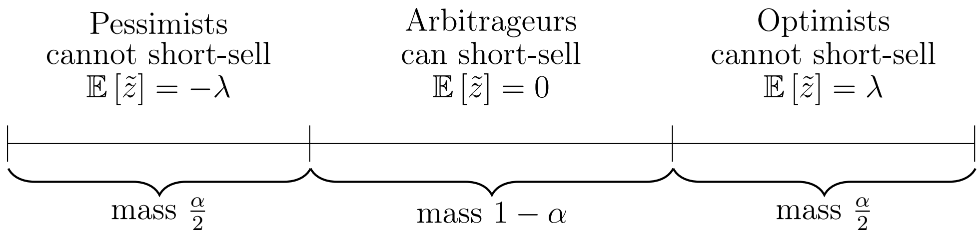

Figure 1.2: The three types of investors in the model.

The timing of the model is as follows:

- At $t = 0$ there is no disagreement and the benchmark price of the risky asset equal to the rational valuation. I assume that at $t = 0$ all agents are myopic and disagreement at $t = 1$ is a surprise for them.[3]

- At $t = 1$ the tree types start to disagree, as described above. Investors trade with endowment of 1, and market-clearing condition determines price of a risky asset.

- Between $t = 1$ and $t = 2$ the announcement is made that reveals the realization of $\tilde{z}$.

- At $t = 2$ investors consume the dividend from the risky asset.

When investors trade at $t = 1$, all types $k \in \{A, B, hf\}$ maximize their mean-variance preferences:

$$U\left(\tilde{W}^k\right) = \mathbb{E}^k\left[\tilde{W}^k\right] - \frac{1}{2\gamma} Var\left(\tilde{W}^k\right)$$

where $\tilde{W}^k$ is the final-period wealth and γ is a risk tolerance parameter.

Theorem 1 (Equilibrium at $t = 1$): If $\lambda > \frac{dc}{b(1-c)} + \frac{2b\sigma_z^2}{\gamma\alpha}$, then at $t = 1$ the model has a unique equilibrium in which optimists are long the risky asset, arbitrageurs are short, and pessimists have zero holdings. The price of the risky asset is given by:

[2] In other words, c is the fraction of the price of the risky asset that short-sellers have to forego. If the price of going long on one unit of risky asset is P, then by shorting one unit an arbitrageur receives $(1 - c)P$.

[3] The rationale behind this assumption is that until publication of the working paper by Lucca and Moench in 2011, the pre-FOMC drift was not known to academics. The publication was also widely discussed in business news outlets, which suggests that the discovery of this phenomenon was a surprise to many market participants as well.

$$P_1(1+r) = \left[d\left(1-\frac{\alpha}{2}\right) - \frac{1}{\gamma}b^2\sigma_z^2\right] \times \frac{1}{\left(1-\frac{\alpha}{2}\right) - c(1-\alpha)} + \frac{b\lambda\frac{\alpha}{2}}{\left(1-\frac{\alpha}{2}\right) - c(1-\alpha)}$$

Proof: See Appendix A.

Corollary 1: Define $\theta = \frac{\frac{\alpha}{2}}{1-\frac{\alpha}{2}}$. Then, the first order approximation in c for the price of a risky asset at $t = 1$:

$$P_1(1+r) = \underbrace{d - \frac{1}{\gamma}b^2\sigma_z^2}_{\text{rational valuation}} + \underbrace{\theta\left(b\lambda - \frac{1}{\gamma}b^2\sigma_z^2\right)}_{\text{speculative premium}} + \underbrace{c(1-\theta)\left[d - \frac{1}{\gamma}b^2\sigma_z^2 + \theta\left(b\lambda - \frac{1}{\gamma}b^2\sigma_z^2\right)\right]}_{\text{costly arbitrage premium}} \tag{1.1}$$

Proof: See Appendix A.

Intuitively, the price of a risky asset at $t = 1$ could be split into three parts, as shown in eq. (1.1). The "rational valuation" term shows that in absence of disagreement or short-selling constraints, the equilibrium price would be linear in expected return and risk, which is the common result in the models with mean-variance preferences. When investors hold heterogeneous beliefs, and some of them are unable to short-sell, the price of a risky asset is driven up by optimistic investors. This is captured in the "speculative premium" term that is increasing in the interaction between disagreement λ, and exposure of the risky asset to the "macro" risk b. Importantly, "speculative premium" is always positive for the values of λ that satisfy the condition for the equilibrium. Finally, the fact that short-selling is costly for arbitrageurs implies that optimistic investors would face even less opposition from short-sellers, which is captured in the last term of eq. (1.1). The "costly arbitrage premium" is increasing in shorting costs c, as well as in both "rational valuation" and "speculative premium" terms inside the brackets.

Corollary 2 (Returns): Given that at $t = 0$ the market-maker sets the price of an asset equal to the rational valuation, the "pre-announcement" return between periods 0 and 1 is given by:

$$R^{0-1} = \underbrace{\theta\left(b\lambda - \frac{1}{\gamma}b^2\sigma_z^2\right)}_{\text{speculative premium}} + \underbrace{c(1-\theta)\left[d - \frac{1}{\gamma}b^2\sigma_z^2 + \theta\left(b\lambda - \frac{1}{\gamma}b^2\sigma_z^2\right)\right]}_{\text{costly arbitrage premium}} \tag{1.2}$$

Consequently, the return between periods 1 and 2 is given by:

$$R^{1-2} = b\tilde{z} - \theta\left(b\lambda - \frac{1}{\gamma}b^2\sigma_z^2\right) - c(1-\theta)\left[d - \frac{1}{\gamma}b^2\sigma_z^2 + \theta\left(b\lambda - \frac{1}{\gamma}b^2\sigma_z^2\right)\right] \tag{1.3}$$

Moreover, the expected return between periods 0 and 2 is positive, because announcement eliminates risk:

$$\mathbb{E}\left[R^{0-2}\right] = \frac{1}{\gamma} b^2 \sigma_z^2 \tag{1.4}$$

Proof: Follows from corollary 1 and rational valuation of the asset at $t = 0$.

Intuitively, the return of a risky asset between periods $t = 0$ and $t = 1$ is increasing in speculative premium and costly arbitrage premium, because these two terms capture the overpricing of a risky asset due to speculative trading and costly short-selling. The realized return between periods $t = 1$ and $t = 2$ is primarily driven by the realization of the "macro" factor $\tilde{z}$ multiplied by stock sensitivity to the shock b, and by reversal of overpricing created at $t = 1$. Finally, expected return between periods $t = 0$ and $t = 2$ is positive, because announcement resolves uncertainty.

1.2.2 Discussion and Testable Predictions

The model makes a series of assumptions. First, I assume that a sizable fraction of the market participants has short-selling constraints. In the real world markets, the largest group of investors are mutual funds, who are prohibited from shorting, and as of 2017 have over $18 trillion in assets in the US. Individual investors often do not have access to shorting as well. The largest group that has access to short-selling are hedge funds with $3.2 trillion in assets in 2017. Even for them shorting is often costly, both in terms of the fees that have to be paid to the owner of the stock, and in terms of indirect costs of finding a counterparty in the decentralized short-selling market. Moreover, most of the predictions could be generated in the model that does not have strict short-selling restrictions, but has short-selling costs. The asymmetry between short-selling and going long is what drives overpricing.

Second, I assume that investors disagree about the mean of the "macro" factor, but I am agnostic about the nature of this disagreement. The FOMC announcements often reveal important private information of the Federal Reserve system about the state of the economy, which moves the market (Gürkaynak et al., 2005). Naturally, before the announcements market participants would disagree about economic conditions, either due to the heterogeneous beliefs or due to difference in learning (for example different agents might have different models for the economy).

It is worth noting that the model has several shortcomings. It considers only one risky asset, while the following empirical analysis relies on the cross-section of stocks. The structure of the model could easily be extended to multiple risky assets that may vary in terms of their exposure to the "macro" factor, short-selling costs, and potentially have an idiosyncratic shock in the dividend as well. The primary reason why I focus on the one-asset case is that it allows deriving a tractable solution that has a simple interpretation. The model also has only one trading period, so in order to apply this intuition to the case of the pre-FOMC drift, I have to assume that investors only trade on their beliefs in the last 24 hours before the monetary policy announcement. Potentially, this pattern could be explained by either myopia or lack of attention of the investors, who only form their beliefs about the FOMC once multiple news outlets start to talk about the upcoming announcement.

Using Corollary 2, I derive testable predictions for the pre-FOMC announcement drift in the cross-section of stocks:

Prediction 1: The pre-FOMC announcement returns should be positively related to the speculative premium, which is driven by the interaction between the sensitivity of the stock to the monetary policy shock b and disagreement of investors about the mean of the shock λ.

Prediction 2: The pre-FOMC announcement drift should be higher for stocks that are more costly to short sell, i.e., have higher c, as indicated by the costly arbitrage premium.

Prediction 3: The post-announcement return should be decreasing in the interaction between the sensitivity of the stock to the monetary policy shock b and disagreement of investors about the mean of the shock λ, and also in shorting cost c.

1.3 Data

1.3.1 Stock and Announcement Data

I collect intraday price data for U.S. stocks from the TAQ database and daily characteristics such as the number of shares outstanding and split adjustment factors from CRSP. The sample includes all U.S. ordinary stocks, from which I eliminate micro-cap stocks (below the 20th percentile of NYSE market capitalization) and penny stocks (with the closing price below \$5 on the day prior to the announcement date) in order to make sure that results are not driven by price fluctuations of small stocks.

The period that I study is 1994-2016, with the starting point corresponding to the year in which the Federal Reserve began making monetary policy announcements. The dates and times of the FOMC press-releases come from Gürkaynak et al. (2005) and I extend their sample using information from the Federal Reserve website. For each scheduled announcement, the primary dependent variable in my analysis is the log stock return in the 24-hour window that ends 10 minutes prior to the release of the statement, excess of the risk-free rate from Kenneth French website. There are a few extreme returns in the sample, most likely due to the misrecorded prices or stock-specific events, so I drop 24-hour returns that are larger than 50% in absolute value. I also compute similar 24-hour returns for the previous and next trading days relative to the announcement, to use them as a placebo test. Panel A of Table 1.1 contains summary statistics for stock-level returns.

In order to measure the surprise component of the monetary policy announcement, I use the changes in the prices of the Federal Funds futures contracts, as suggested by Kuttner (2001). These contracts are traded at CME and data is obtained from CQG, and the settlement at the end of each month depends on the average effective Federal Funds rate in that month. The monetary policy shock is then computed as:

$$MP1_t = \frac{D}{D-d}\left(\Delta FF_t\right) \tag{1.5}$$

where ΔFF_t is the change in the in the rate implied by the Federal Funds futures contract in the 30-minute window around the time of the FOMC announcement, D is the total number of days in the month t, and d is the number of days between the announcement day and end of the month. Intuitively, the shock is scaled up in order to account for the fact that the new rate revealed at the announcement would only be in effect for d remaining days of the month. Following previous literature, for the ΔFF_t term I use the change in the current month contract if the announcement is more than seven days away from the end of the month. For the cases when the announcement is made in the last seven days of the month, the price of the contract might suffer from rollover distortions, and the large scaling factor could blow up those distortions even further. Therefore, for such announcements, I use the second Federal Funds futures contract with the scaling factor of 1. Panel B of Table 1.1 shows the summary statistics for the time-series of the monetary policy shocks.

1.3.2 Measuring Sensitivity to Monetary Policy Surprises

In order to measure the exposure of individual stocks to the monetary policy surprises, I use time-series regressions, similar to Bernanke and Kuttner (2005). Specifically, I first compute returns of each stock in the 30-minute window that starts 10 minutes before the exact time of FOMC announcement release and ends 20 minutes after. I then estimate time-series regressions of these returns on monetary policy shocks:

$$r_{i,t}^{tight} = \beta_0 + \beta_i^{MP1} MP1_t + \varepsilon_t \tag{1.6}$$

where $r_{i,t}^{tight}$ is the return of the stock i around announcement t, and $MP1_t$ is the monetary shock, computed as described in eq. (1.5). Since the period that I study contains roughly 175 FOMC announcements, in most of my analysis, I compute betas using the full sample data to improve precision. When computing full sample betas, I drop companies that have data for less than 40 announcements and also trim monetary policy betas at 99th and 1st percentiles to eliminate outliers. For the portfolio construction, I also use betas computed within a rolling window of 30 announcements. The summary statistics for the full sample monetary policy betas is shown in Panel C of Table 1.1. Notably, the average beta is -3.15 which is not far from -4, that is consistent with findings of Bernanke and Kuttner (2005) who find that an unexpected 25 basis points tightening leads to a -1% return in the stock market.

1.3.3 Disagreement about FOMC Announcements

A common approach in the literature is to measure disagreement of investors with the dispersion of analyst forecasts. The primary policy tool of the Federal Reserve is the Federal Funds Rate (FFR); therefore I focus on the FFR forecasts in my analysis. I assemble a novel dataset of professional forecasts for the upcoming monetary policy move. These forecasts come from two sources. First, I use the surveys conducted by three business news outlets (Reuters, Dow Jones Newswires and Market News International) that are available through the Factiva database. In these surveys, journalists poll economists at the primary dealer institutions (20-30 large financial companies that are authorized to trade directly with the Federal Reserve) at irregular intervals, with at least one poll available within the 30-day period before each announcement. In the surveys economists provide their forecasts for the Federal Funds rate at the next FOMC meeting, which I record in the form of the basis points change relative to the current value of the FFR, for example "+25" means that a forecaster expects a 25 basis points tightening at the next meeting. Some forecasts mention two possible outcomes, and in those cases, I record an average of the two. The surveys often include forecasts about the FFR at meetings after the next one, and also questions on other topics related to the wording of the FOMC press-release and macroeconomic conditions. However, those additional questions often vary across surveys, so I do not include them in my analysis. I use Factiva forecasts for the 1995-2008 period because surveys collected after 2008 usually do not include questions about the Federal Funds Rate, due to the zero lower bound.

The second source of the FFR forecast data is Bloomberg, which collects forecasts made by economists at large financial institutions, think-tanks, and universities, with 30-150 respondents per survey. For each FOMC meeting, the data includes the expected change in the FFR and the date on which the forecast was submitted to Bloomberg. I clean this data to exclude the forecasts with the record date more than 30 days before the FOMC, or after the meeting. The Bloomberg data is available for the 1999-2016 period. I merge Factiva and Bloomberg forecasts, and for the overlapping meetings and companies, I use the most recent forecast out of the two sources[4].

In order to verify that the collected forecasts correctly gauge the opinions of market participants about the Federal Funds rate, I compare the surprises in the forecast data with the Kuttner (2001) surprises calculated from the Federal Funds futures data, as described in eq. (1.5). The forecast surprise is defined as a difference between the actual change in the FFR and mean forecast. If the forecasts and the futures market agree, there should exist a close relationship between the two types of surprises. Figure 1.3 shows that this is indeed true: the futures-based and forecast-based surprises are strongly correlated, and follow the 45-degree line quite closely.

Additionally, I estimate a time-series regressions of aggregate stock returns on the forecast surprises and futures-based surprises, described by eq 6. Table 1.2 shows that for the tight 30-minute window the impact of the forecast-implied shock is not significant at 10% level. However, with the wide 60-minute window, the forecast-implied shock has a similar and highly significant effect on the stock market, as the surprise computed from the futures data. This analysis shows that my novel forecast data is consistent with the Federal Funds futures data, with a primary advantage being that it allows estimating investor disagreement.

The primary proxy for investor disagreement that I use is the standard deviation of forecasts, $DisagFcst_t$. The forecast data is available for 165 announcements, and for 90 of them the value of $DisagFcst_t$ is zero because forecasters are unanimous about the outcome of the FOMC meeting. However, I do not interpret this as a complete lack of disagreement about the outcome of the FOMC meeting, because the forecasts are often collected from as little as 25 participants, which are all big institutional investors. There still could be a certain degree of disagreement among smaller market participants, so I interpret cases of

[4]It is worth noting there exist at least two other sources of Federal Funds Rate forecasts that I do not use due to the limitations of the data. Blue Chip Financial Forecasts is a survey of professional forecasters that includes questions about the Federal Funds Rate. These surveys are conducted monthly, but the questions about the Federal Funds Rate are worded in terms of quarters. For example, a survey released in early January would ask a question about the FFR at the end of the first quarter, a period that includes two upcoming meetings: in January and in March. Since it is not possible to disentangle forecasts for the two meetings in such cases, I do not use the Blue Chip data. The other source is the survey of primary dealers that is conducted by the Federal Reserve, which is similar to the data that Factiva contains. However, Federal Reserve only began to collect this data in 2005, with publicly available data starting in 2011, so I omit this source of data as well.

unanimous forecasts as an indication of the periods when the aggregate disagreement is low, rather than completely zero.

1.3.4 Short-Selling Constraints

The ideal data to measure the costs of short-selling a stock would be the fees that an investor has to pay to borrow the stock for shorting. Jones and Lamont (2002) use data from the Great Depression and show that borrowing fees are the primary impediment to short-selling. I do not have access to the data on the fees; therefore I proxy it with RSI – relative short interest, computed as a ratio of shares shorted to the total number of shares outstanding on a given date. Earlier work by D'avolio (2002) showed that shorting fees are usually higher for stocks that have higher relative short interest, although this relationship could be non-monotonic. Some stocks might have very high fees, so the overall quantity shorted and RSI might be low. This evidence was revised by Boehme et al. (2006) who show that when stocks with no observed short interest are excluded from the sample, the borrowing rebates are on average a monotonically increasing function of the relative short interest.

The short interest data is available on monthly (and sometimes bi-weekly) basis through Compustat Supplemental Short Interest File. For each announcement, I merge the last observed short interest (but not further than 31 days before the announcement) with the number of shares outstanding from CRSP by matching CUSIP codes and dates. On average, the matches are produced for about two thirds of CRSP stocks on each announcement date. The summary statistics for the RSI_t variable is shown in Panel B of Table 1.1.

1.4 Empirical Results

1.4.1 Preliminary Evidence

I start the empirical analysis by replicating the main result of Lucca and Moench (2015) in Panel A of Figure 1.4, which shows the cumulative return of the value-weighted sample of CRSP stocks, cleaned as described in Section 1.3.1. To create this figure, I sample stock prices at the 10-minute intervals and compute value-weighted returns. The average drift is around 42 basis points, which is lower than 49 bp reported by LM. The difference is likely due to my sample ending in 2016, rather than 2011 in LM.

Next, I separate FOMC announcements into three groups based on realized monetary policy shocks (computed with Federal Funds futures). Tightening shocks and easing shocks are defined as having $MP1_t^{tight}$ greater than 0.5 basis points or less than -0.5 bp, respectively, while the remaining announcements are classified as zero shocks. Panel B of Figure 1.4 shows that the pre-announcement drift is similar for all three groups. There is no statistically significant difference between drift that precedes tightening shocks and easing shocks. This suggests that leakage of information about the upcoming FOMC decision is not likely to be a primary driver of the pre-announcement drift. If this was the case, informed trading should push the market in the direction of the shock that is revealed at the announcement. I discuss how my theory differs from the leakage explanation for the pre-FOMC announcement drift in Section 1.5.3.

In Panel C of Figure 1.4, I split the data into five value-weighted portfolios sorted on monetary policy betas, computed using a rolling window of 30 announcements. The lowest beta portfolio contains stocks that are most sensitive to the monetary policy shocks. The speculative trading explanation predicts that such stocks are more likely to be overpriced prior to the announcement, and the plot supports this result: the portfolio of stocks that are the most sensitive to the monetary policy shocks on average enjoys pre-announcement drift of about 65 basis points, while the least sensitive stocks on average grow by about 40 bp. To evaluate the significance of this result, in Table 1.3 I compare the pre-FOMC drift among 10 portfolios sorted on monetary policy betas, as well as returns of these portfolios one day before and one day after the FOMC day. In the 24 hours before the announcement, all portfolios earn a return that is significantly different from zero, and the spread between the most sensitive (portfolio 1) and least sensitive (portfolio 10) is 36 basis points for value-weighted portfolios and 25 basis points for equal-weighted portfolios. Both numbers are highly statistically significant. No similar pattern is observed for the previous or next day relative to the pre-FOMC period.

Finally, I investigate how the average pre-FOMC drift depends on the disagreement of investors about the FOMC decision on the Federal Funds rate. Panel D of Figure 1.4 shows that the average drift for the announcements that have a non-zero standard deviation of forecasts is higher by 44 basis points, compared to the announcements without disagreement in forecasts, which is statistically significant at 5% level.

1.4.2 Cross-sectional Regressions: Stock Level

Prediction 1 states that the pre-FOMC announcement drift should be increasing in the interaction between the sensitivity to the monetary policy shocks and disagreement about the upcoming FOMC decision. I use eq. (1.2) from Section 1.2.1 in order to motivate the specification for cross-sectional regressions. In the setup of the model, the standard deviation of investor opinions would be estimated as $\lambda\sqrt{\alpha}$, while the monetary policy betas proxy for parameter b. For now, I assume that short-selling costs are constant across all stocks, so the "costly arbitrage premium" term in eq. (1.2) is constant. This gives the following simplification for the pre-announcement returns:

$$R^{0-1} = \frac{\frac{\sqrt{\alpha}}{2}}{1-\frac{\alpha}{2}} \times \left(b\lambda\sqrt{\alpha}\right) + const. \tag{1.7}$$

where $\frac{\frac{\sqrt{\alpha}}{2}}{1-\frac{\alpha}{2}}$ is positive, hence the model predicts a positive slope coefficient on the interaction term between the monetary policy beta and standard deviation of forecasts. In the regression form this translates into:

$$r_{i,t}^{k} = \gamma_0 + \gamma_1 \times Z\left(-\beta_i^{MP1} \times DisagFcst_t\right) + \gamma_2 X_{i,t} + \varepsilon_{it} \tag{1.8}$$

where the dependent variable is the log excess return of the stock i in the 24-hour window preceding the FOMC announcement t. I also conduct placebo tests with previous day and next day returns, so $k \in \{$-1 Day, Pre-FOMC, +1 Day$\}$.

I construct the main explanatory variable as the product of the full-sample monetary policy beta and disagreement, computed as the standard deviation of forecasts. Since the majority of the monetary policy betas are negative, I also multiply this product by -1, in order to make it qualitatively comparable to the $b\lambda\sqrt{\alpha}$ term in eq. (1.7). Additionally, I normalize the interaction term by subtracting the mean from each observation and dividing it by standard deviation, to simplify interpretation. I use notation $Z\left(-\beta_i^{MP1} \times DisagFcst_t\right)$ for the resulting variable. The $X_{i,t}$ term captures controls, which in the baseline specification include levels of the monetary policy beta β_i^{MP1} and disagreement $DisagFcst_t$. In a more broad specification, I also use additional controls: logarithm of the market capitalization, value of the VIX index two days prior to the announcement, returns of the stock and market at the previous FOMC announcement[5], the average forecast for the FOMC move, and Federal Funds futures surprise. Finally, I also estimate a specification with stock and announcement fixed effects. For all regressions I use ordinary least squares estimation, and in order to account for potential serial and cross-sectional correlation I compute standard errors using two-way clustering on the stock and announcement level[6].

Table 1.4 presents the results for the stock-level estimation. The middle panel shows the coefficients for the pre-FOMC announcement return. The baseline specification (4) suggests that when the interaction between monetary policy beta and disagreement increases by one standard deviation, the pre-FOMC return grows by an extra 18 basis points, which is statistically significant at 1% level. For the specification with fixed effects (5) the coefficient is somewhat smaller, at 9 basis points. Dropping the fixed effects and adding more controls, still shows a significant effect at 14.2 basis points in specification (6). The left and right panels do not show a strong relationship between the returns and the interaction term, except for a small positive post-announcement return, which is likely to be a part of a "relief rally" described by Gu et al. (2018).

The cross-sectional regressions presented in Table 1.4 also allow me to recover the structural parameter α, the share of investors that have short-selling constraints and biased expectations. In order to do so, I convert coefficients on the interaction term $-\beta_i^{MP1} \times DisagFcst_t$ to the raw form (i.e. not normalized). The coefficients in the specifications (4), (5), and (6) are 0.81, 0.40, and 0.64 respectively. This gives the range for the parameter α between 0.41 and 0.85, which is close to the value of 0.66 that Hong and Sraer (2016) use in their calibration of the similar model. Importantly, Hong and Sraer (2016) motivate their choice of α by stating that share of mutual funds and retail investors is roughly $2/3$, while I am able to confirm this value through estimation of the cross-sectional regression.

1.4.3 Cross-Sectional Results: Portfolios

A natural concern about the analysis of the previous section is that the monetary policy betas are estimated, which could introduce an errors-in-variables problem. Therefore, I reproduce the previous analysis using portfolios, as it improves the precision of the estimated variables. I start by computing monetary policy betas using a rolling window of 30 announcements, and for each announcement I trim betas at 1st and 99th percentile to eliminate outliers. I

[5]Lucca and Moench (2015) used a time series of aggregate returns to show that pre-FOMC announcement drift is increasing in the VIX index, and also has positive autocorrelation.

[6]Petersen (2009) argues that in financial applications, two-way clustering delivers similar, and sometimes even more robust results, than the commonly used Fama-Macbeth regression.

use the remaining betas to create 10 value-weighted portfolios. I proceed by estimating the cross-sectional regressions described by eq. (1.7), with the only difference that all variables are now computed on the portfolio level. Table 1.5 presents the results of this exercise. The middle panel shows that one standard deviation increase in the normalized interaction between the monetary policy beta and the disagreement predicts pre-FOMC drift that is on average higher by about 30 basis points. Placebo tests in the right and left panels show that the relationship between the interaction term and returns is only significant in the pre-FOMC period, rather than the day before or day later.

The obtained results are consistent with the evidence that was presented earlier in Figure 1.1. The portfolios of stocks that are more sensitive to the monetary policy shocks tend to have higher pre-FOMC drift, especially when investors disagree about the outcome of the FOMC announcement. I conclude that there is strong evidence in favor of Prediction 1 of the model.

1.4.4 The Role of Short-selling Constraints

In this section, I test Prediction 2 of the model, which states that the stocks with higher shorting costs should earn higher pre-announcement return because arbitrageurs are less inclined to correct mispricing in such stocks. Earlier studies show that relative short interest (RSI) is positively related to short-selling costs c, so I assume $c = f(RSI)$ hence the reduced form of eq. (1.2) is:

$$R^{0-1} = \frac{\frac{\sqrt{\alpha}}{2}}{1 - \frac{\alpha}{2}} \times \left(b\lambda\sqrt{\alpha}\right) + A \times f(RSI) + const. \tag{1.9}$$

where constant A is positive[7], as it captures all terms of the "costly arbitrage premium" except parameter c. This motivates the cross-sectional regressions on the stock level:

$$r_{i,t}^{k} = \gamma_0 + \gamma_1 \times Z(RSI_t) + \gamma_2 \times Z\left(-\beta_i^{MP1} \times DisagFcst_t\right) + \gamma_3 X_{i,t} + \varepsilon_{it} \tag{1.10}$$

Where $Z(RSI_t)$ is the normalized short interest, and $Z\left(-\beta_i^{MP1} \times DisagFcst_t\right)$ is the normalized interaction between monetary policy beta and disagreement, as described earlier. Table 1.6 reports the estimation results. In the middle panel, the baseline specification (4) suggests that with a one standard deviation increase in RSI the pre-FOMC drift increases by 7.7 basis points on average. Adding announcement and stock fixed effects reduces the estimate to around 4.5 basis points, but it remains statistically significant at the 5% confidence level. Importantly, the coefficient on the interaction between monetary policy beta and investor disagreement is of similar magnitude as reported earlier in Table 1.4, and significant at the 5% level. This implies that shorting costs create a separate channel for overpricing prior to the announcement, as suggested by the model. Noticeably, short-selling constraints do not seem to influence returns on the days before or after the FOMC announcement.

[7]More precisely, A would also partially depend on $b\lambda\sqrt{\alpha}$, which would motivate inclusion of the triple interaction term between shorting costs, monetary policy beta, and disagreement. I tested specifications with such term, and did not obtain robustly significant results, so they are not reported.

Next, I repeat the tests on the portfolio level. For each announcement, I sort stocks into 10 value-weighted portfolios on RSI and repeat regressions described by eq. (1.10). Table 1.7 reports results. Consistent with previous findings, the middle panel shows that stocks with higher RSI tend to earn higher returns in the 24 hours that precede the FOMC announcement: a one standard deviation increase in RSI predicts drift higher by about 14 basis points, which is statistically significant on 10% level and higher.

Overall, I conclude that there is strong evidence in favor of the empirical prediction 2. Consistent with the model, stocks with higher shorting costs tend to have higher drift in the 24-hours before the FOMC announcement.

1.4.5 Reversal at the Announcement

Prediction 3 of the model states that the overpricing should be corrected after the FOMC announcement, as investors learn the true value of the shock and prices revert to the rational valuation. While Panel A of Figure 1.4 suggests that there is no reversal on the aggregate level, the cross-section might offer a deeper insight into this question. Using eq. (1.3) from Section 1.2.1, and again assuming that short-selling constraints are uniform, the post-announcement return is reduced to:

$$R^{1-2} = b\tilde{z} - \frac{\frac{\sqrt{\alpha}}{2}}{1-\frac{\alpha}{2}} \times \left(b\lambda\sqrt{\alpha}\right) + const. \tag{1.11}$$

Which motivates the cross-sectional regression:

$$r_{i,t}^{tight} = \gamma_0 + \gamma_1 \times Z\left(-\beta_i^{MP1} \times DisagFcst_t\right) + \gamma_2 \times \left(\beta_i^{MP1} \times MP1_t\right) + \gamma_3 X_{i,t} + \varepsilon_{it} \tag{1.12}$$

where the dependent variable $r_{i,t}^{tight}$ is the return in the 30-minute window around the announcement. Similar to previous analysis, the main explanatory variable $Z\left(-\beta_i^{MP1} \times DisagFcst_t\right)$ is the normalized interaction between the monetary policy beta and disagreement, and this time the model predicts a negative coefficient on this variable. I also include the product between the monetary policy beta β_i^{MP1} and the monetary policy shock $MP1_t$, revealed at the announcement, which stand for the $b\tilde{z}$ term in eq. (11). The model predicts coefficient of 1 on this term. For brevity, I only estimate regressions (12) with returns of the 10 portfolios sorted on monetary policy betas, with results at the stock level being qualitatively similar, and available from the author upon request.

The results presented in the Table 1.8 suggest that there is indeed a negative relationship between the interaction term and the announcement returns: one standard deviation increase in the explanatory variable predicts returns lower by about 14 basis points (in the full sample, left panel), which is slightly less than half of the pre-FOMC return increase reported for the portfolios in Table 1.5. The coefficients in the middle panel and right panel are of similar magnitude, which suggests that result holds in shorter subsamples as well. I conclude that data supports Prediction 3 of the model.

1.5 Robustness Checks

1.5.1 Subsample Analysis

One concern about the results presented earlier is that they might be driven by the post-2008 period when the Federal Funds rate was at the zero lower bound (ZLB), and there was almost no disagreement about the monetary policy moves of the FOMC. Additionally, the original sample of Lucca and Moench (2015) ends in 2011, and Cieslak et al. (2018) report that pre-FOMC drift is not significantly different from zero in the 2012-2016 period. Therefore, I repeat the portfolio cross-sectional regressions[8] for the 1995-2011 period (almost identical to the period studied by LM), and also for the subsample that excludes the zero lower bound period.

The robustness checks presented in Table 1.9 suggest that earlier findings hold in shorted sample periods as well. Panel A repeats analysis with the 10 portfolios sorted on monetary policy betas, and the estimates for the coefficient on the interaction term fall slightly in magnitude and significance for the 1995-2011 and no ZLB subsamples, but remain significant at 10% level. Panel B shows the results for the 10 portfolios sorted on the relative short interest. Compared to the full sample, the effect of short-selling constraints seems to be even higher in shorter samples, with t-values increasing as well.

1.5.2 Alternative Measures of Disagreement

I conduct additional robustness checks with the two alternative measures of investor disagreement. Panel A of Table 1.10 presents results of portfolio return regressions with the *DisagBinary*, which is the dummy version of the disagreement variable developed from the forecast data: it takes values 1 when the standard deviation of forecasts is different from zero, and a value of 0 otherwise. Panel B of the same table shows the results for the third disagreement variable *DisagRvol*, measured as the realized volatility of the nearest month Federal Funds futures contract. The realized volatility computed using daily data over the period of 22 trading days that end 2 days before the announcement. For both alternative measures, the results are similar to the previous findings: one standard deviation increase in the interaction between the monetary policy beta and disagreement predicts significantly higher pre-FOMC announcement drift. The placebo tests in the right and left panels of Table 1.10 confirm that this effect is only limited to the pre-announcement period.

1.5.3 Test for the Evidence of Leakage ahead of FOMC Announcements

In this section, I conduct a simple empirical test of an explanation for the drift that is alternative to my hypothesis of speculative trading. Cieslak et al. (2018) document frequent communication between officials of the Federal Reserve and outsiders, and argue that the flow of information from the Fed creates a bi-weekly pattern of the returns in the stock market. They suggest that the equity risk premium tends to fall when market learns about

[8] Stock-level regressions deliver qualitatively similar results, and available from the author upon request.

the promise of the Federal Reserve to provide accommodating monetary policy if economy encounters a downturn because the potential outcome in the bad state of the world improves.

Could the pre-FOMC drift be driven by leaks as well? Cieslak et al. (2018) favor this explanation and argue that the monetary policy news is on average good, and could be driving the returns in the 24 hours prior to the FOMC announcement if they are known to some market participants. However, the exact nature of the information that leaks from the Fed remains questionable. Using my data, I conduct a simple test on whether the information about the changes of the Federal Funds rate could move prices in the direction of the revealed shock prior to the announcement. In Table 1.11 I estimate cross-sectional regressions with 10 value-weighted portfolios, sorted on the monetary policy beta. The dependent variable is the 24-hour pre-announcement return. Along with previously discussed explanatory variables, I also include two measures of stock reaction to the announcement: an interaction between the monetary policy beta and the shock (similar to the $b\tilde{z}$ term in the model), and returns of the stock in the tight window around the announcement. Both these variables are ex-post, which means that they use the information revealed at the announcement.

Table 1.11 reports the results of this test. In various specifications and subsamples, the ex-post return is either negatively related to the pre-FOMC return, or has no statistical significance. This finding suggests that the decision of the Fed about the interest rates is not likely to be known to the market participants before the announcement. Although I could not rule out the hypothesis that other types of information could leak from the Fed (for example, the market might be relieved knowing that FOMC is not going to "blow up" the economy), I conclude that the pre-FOMC drift is not likely to be driven by the informed trading. Together with evidence on the reversal of the drift that I presented in Section 1.4.3, this lends additional credibility to the speculative trading hypothesis.

1.6 Policy Implications

What are the policy implications of the findings presented above? First, it is important to note that returns on announcement days should be unconditionally positive even without speculative trading, if the announcement resolves uncertainty. This holds in the model that I discuss in Section 1.2: the expected return between starting period $t = 0$ and post-announcement period $t = 2$ is positive, because announcement eliminates risk. Moreover, this intuition is supported empirically in recent work by Amengual and Xiu (2018) and Gu et al. (2018) who show that FOMC announcements resolve a significant portion of aggregate uncertainty which drives up asset prices. In this context, speculative trading only changes the timing, such that most of the return is realized prior to the announcement rather than after it. Therefore, pre-FOMC drift could be interpreted as a major short-term deviation of prices from their fundamental values, which is corrected after the announcement. Even though this deviation is short-lived, its significant magnitude might make it undesirable for policy makers, especially in light of the debate of how Federal Reserve is concerned with not surprising the financial markets (Stein and Sunderam (2018), Cieslak et al. (2018)).

The results presented in previous sections could be used to provide policy advice for the Federal Reserve that is aimed at reducing price movements prior to the FOMC announcements. While short-selling constraints and sensitivity of stocks to monetary policy shocks are mostly beyond control of the Fed, certain actions could be taken to reduce disagreement about the upcoming decision of the FOMC. Historically Federal Reserve have been changing the policy rate using discrete steps of at least 25 basis points. This feature naturally amplifies the disagreement among market participants, as they will flock towards two (or more) most probable alternatives for the next FOMC decision rather than form their expectations on the continuum of outcomes. For example if the most optimistic investors believe that the optimal change for the Federal Funds Rate is -15 basis points, they would assume that Fed is very likely to ease by 25 basis points and would trade accordingly. In the model described in Section 1.2, this would correspond to disagreement parameter $\lambda = 25$ bp. In a counterfactual scenario, if Fed were to adopt a continuous approach to changing in the Federal Funds rate, this would reduce disagreement to $\lambda = 15$ bp. According to my empirical findings, this is likely to reduce the pre-FOMC drift by more than 20 basis points for a stock with average monetary policy beta.[9]

Federal Reserve could also change their communication schedule to directly reduce disagreement among market participants. Steps could be taken to increase transparency about the future FOMC moves, similar to how forward guidance was implemented at the zero lower bound. Additionally, Federal Reserve might consider amending the blackout period, and allowing communication of intentions of the FOMC several days prior to the meeting, especially if the disagreement about the future policy decision is high.

1.7 Conclusion

In this chapter, I describe the mechanism that explains a significant part of the cross-sectional variation in the pre-FOMC announcement drift. I argue that assets that are most sensitive to the monetary policy shocks are more likely to be overpriced before the announcement due to speculative demand from optimistic investors, especially during periods of high disagreement about the upcoming FOMC decisions. Arbitrage in such cases is often costly due to short-selling constraints. The empirical analysis shows that interaction between the monetary policy beta and investor disagreement is positively related to the pre-FOMC drift, and so is the proxy for the short-selling costs. Additionally, I show that the most overpriced assets tend to have negative returns after the announcement, which I interpret as a price correction. Importantly, the speculative trading story does not seem to explain the entirety of the pre-FOMC drift, as most assets still tend to earn about 20 basis points of returns before announcements when the disagreement is low. Other explanations for this puzzle should be explored in further research.

[9] I use coefficient of 0.64 on the raw $-\beta_i^{MP1} \times DisagFcst_t$ interaction term, obtained from a regression with controls, similar to specification (6) in Table 1.4. Average monetary policy beta is 3.15 and change in disagreement is 10 bp in this counterfactual scenario.

1.8 Figures

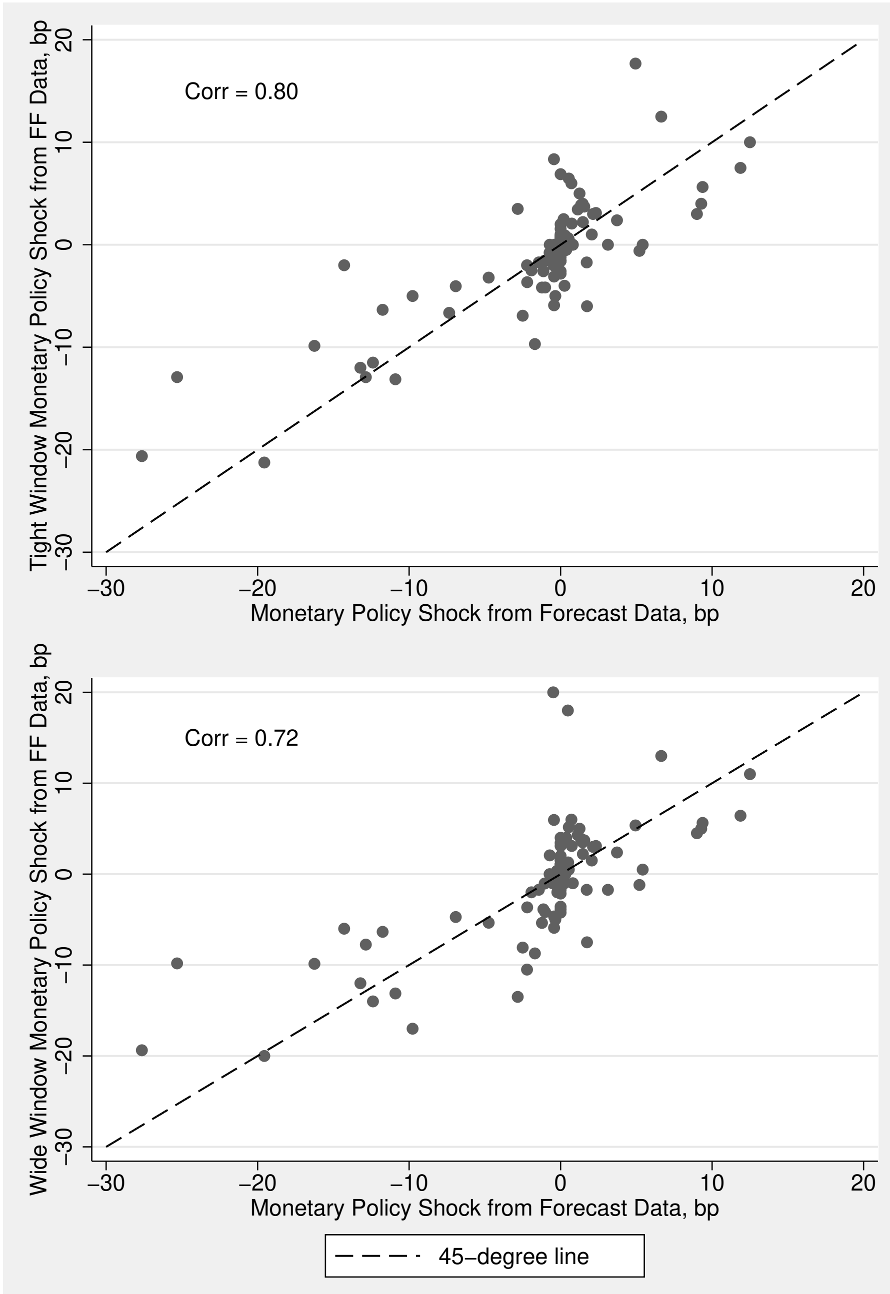

Figure 1.3: Monetary policy shocks from forecast data vs. futures data. The horizontal axis shows shocks computed as average error in the forecasts collected from Factiva and Bloomberg, as described in the text. The vertical axis in the upper panel shows surprises calculated from the changes in prices of the Federal Funds Futures in the narrow 30-minute window around the announcement. In the lower panel surprises for the wide 60-minute window are shown.

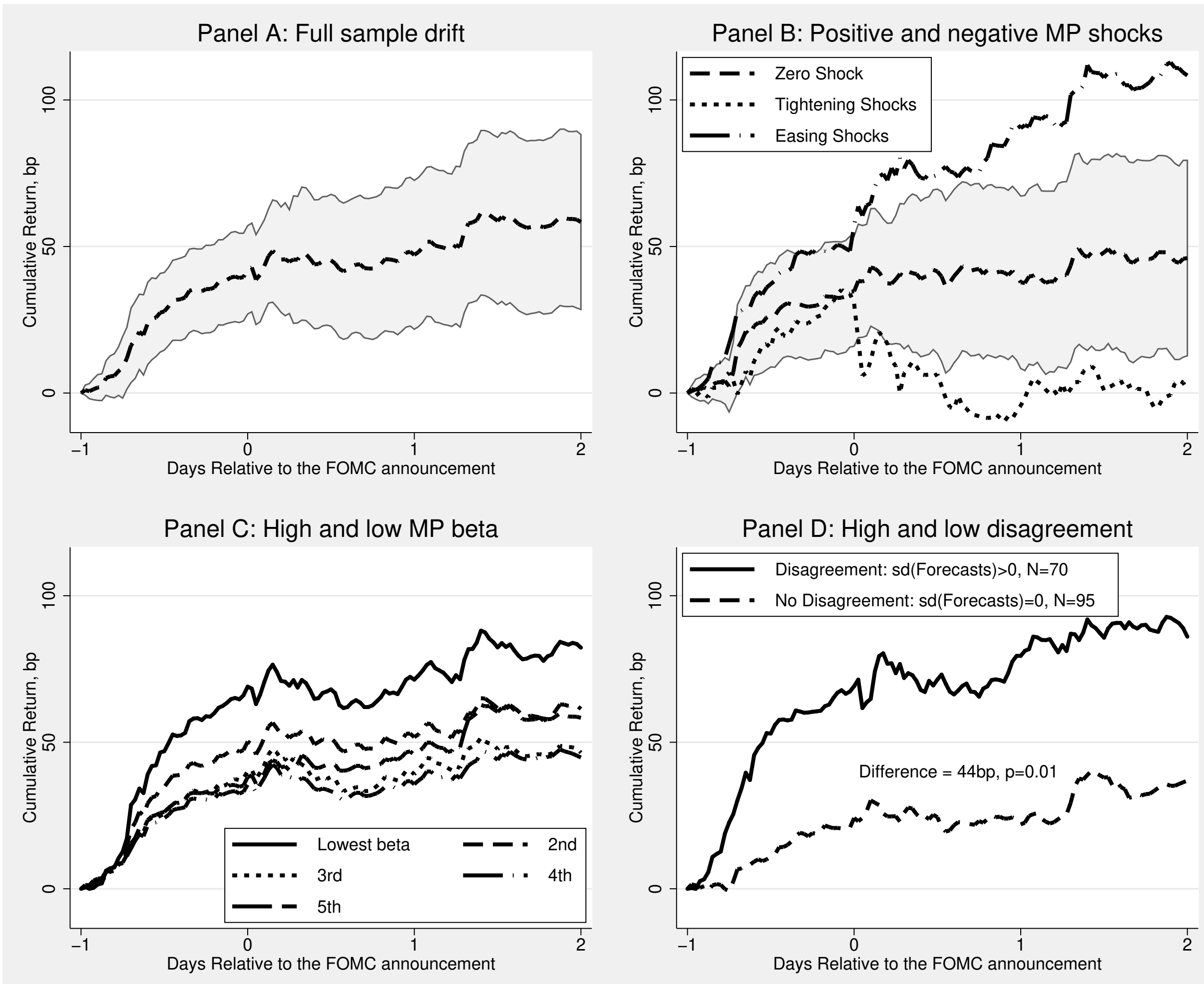

Figure 1.4: Pre-FOMC Announcement Drift. Panel A shows cumulative value-weighted stock return in the whole sample together with 95% confidence bands. Panel B shows returns separately for the announcements with tightening shocks and easing shocks, as determined by the 30-minute change in the Federal Funds Futures. Panel C shows cumulative returns of five value-weighted portfolios sorted on monetary policy betas. Panel D shows cumulative value-weighted stock returns on days with positive disagreement in forecast data (solid line) and no disagreement (dashed line). Sample period is 1994-2016.

1.9 Tables

Table 1.1: Summary Statistics. Panel A shows summary statistics for variables measured at stock-announcement level. $r_{i,t}^{PreFOMC}$, $r_{i,t}^{-1Day}$, $r_{i,t}^{+1Day}$ are the excess stock returns in the 24-hour widow before FOMC announcement, and similar widows on previous and next trading days respectively. $r_{i,t}^{tight}$ is the stock return in the tight 30-minute window around the announcement. $RSI_{i,t}$ is the relative short interest. Panel B describes data measured at announcement level. $MP1_t$ is the monetary policy shock calculated from Federal Funds futures data in the tight 30-minute window around FOMC announcement. VIX_t is the VIX index. $DisagFcst_t$ and $MeanFcst_t$ are standard deviation and mean of the forecasts for the FOMC move, respectively. $DisagRvol_t$ is the realized volatility of the nearest-month Federal Funds futures contract in the 22 trading days that precede the FOMC announcement. β_i^{MP1} is the full-sample monetary policy beta, computed using time-series regressions. Products denote respective cross-terms, and Z denotes normalized variables. Sample period is 1994-2016.

Panel A: Stock-Announcement Level								
	Count	Mean	SD	P25	P50	P75	Min	Max
$r_{i,t}^{-1Day}$	372265	0.74	283.96	-111.36	-1.80	115.80	-4721.23	4867.22
$r_{i,t}^{PreFOMC}$	373028	33.44	283.30	-83.33	15.56	136.14	-4874.45	4988.21
$r_{i,t}^{+1Day}$	371753	1.37	325.77	-126.93	-1.70	132.03	-4926.96	4774.73
$r_{i,t}^{tight}$	372657	-3.34	91.40	-37.99	0.00	34.26	-4712.11	2852.87
$\beta_i^{MP1} \times DisagFcst_t$	317315	-10.38	22.23	-13.84	0.00	0.00	-415.32	223.40
$\beta_i^{MP1} \times DisagRvol_t$	336193	-49.30	129.14	-43.85	-16.42	-6.25	-3669.16	2008.70
$Z\left(-\beta^{MP1} \times DisagFcst\right)$	317315	-0.00	1.00	-0.47	-0.47	0.16	-10.52	18.22
$Z\left(-\beta^{MP1} \times DisagRvol\right)$	336193	-0.00	1.00	-0.33	-0.25	-0.04	-15.94	28.03
$\beta_i^{MP1} \times MP1_t$	336193	1.61	19.82	-1.33	0.00	3.17	-327.77	430.56
$RSI_{i,t}$	233815	0.04	0.04	0.01	0.03	0.06	0.00	0.25
$Z\left(RSI_{i,t}\right)$	233815	0.00	1.00	-0.70	-0.35	0.35	-0.96	4.62
Panel B: Announcement Level								
	Count	Mean	SD	P25	P50	P75	Min	Max
$MP1_t$	184	-0.47	5.10	-1.00	0.00	0.50	-22.55	18.67
VIX_t	184	20.38	8.59	14.30	18.68	23.94	10.61	80.06
$DisagFcst_t$	172	3.23	4.80	0.00	0.00	5.89	0.00	20.50
$MeanFcst_t$	172	-0.54	16.91	0.00	0.00	0.31	-74.56	47.67
$DisagRvol_t$	184	15.62	27.65	2.89	5.84	16.20	0.00	181.09
Panel C: Stock Level								
	Count	Mean	SD	P25	P50	P75	Min	Max
β_i^{MP1}	4773	-3.15	4.17	-5.18	-2.93	-1.05	-22.14	16.05

Table 1.2: Aggregate stock market reaction to the monetary policy shocks. The table presents results of the time-series regressions of the aggregate market returns on the monetary shocks computed from the forecast data $MP1_t^{fcst}$, and from the Federal Funds Futures data in the 30-minute tight window $MP1_t^{tight}$ and in the 60-minute wide window $MP1_t^{wide}$. The dependent variable in Panel A is the 30-minute value-weighted return, in Panel B the 60-minute value weighted return around the FOMC announcement.

Panel A: Tight Window Returns

	All CRSP				S&P 500			
	1994-2016		1994-2011		1994-2016		1994-2011	
$MP1_t^{fcst}$	-1.83		-1.96		-1.79		-1.92	
	(-1.57)		(-1.62)		(-1.44)		(-1.49)	
$MP1_t^{tight}$		-3.73***		-3.83***		-3.69***		-3.78***
		(-3.24)		(-3.27)		(-3.03)		(-3.05)
Constant	-4.38	-5.33	-9.36**	-10.41**	-4.69	-5.64	-9.81**	-10.87**
	(-1.18)	(-1.51)	(-2.13)	(-2.52)	(-1.22)	(-1.54)	(-2.15)	(-2.52)
Observations	172	172	132	132	172	172	132	132
R^2	0.03	0.11	0.04	0.13	0.03	0.10	0.04	0.12

Panel B: Wide Window Returns

	All CRSP				S&P 500			
	1994-2016		1994-2011		1994-2016		1994-2011	
$MP1_t^{fcst}$	-3.66***		-3.66***		-3.68***		-3.67***	
	(-3.74)		(-3.61)		(-3.69)		(-3.55)	
$MP1_t^{wide}$		-3.30***		-3.31***		-3.24***		-3.24***
		(-3.06)		(-2.99)		(-2.93)		(-2.86)
Constant	4.42	4.95	-0.37	0.08	4.83	5.38	0.21	0.68
	(0.93)	(1.05)	(-0.06)	(0.01)	(1.00)	(1.12)	(0.04)	(0.12)
Observations	172	170	132	130	172	170	132	130
R^2	0.08	0.07	0.09	0.08	0.08	0.06	0.08	0.07

Robust t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.3: Ten portfolios sorted on monetary policy betas. I estimate time-series regressions of 30-minute stock returns on the monetary policy shocks in the same interval and use a rolling window of 30 announcements to sort stocks into 10 portfolios. Left panel shows results for the value-weighted portfolios, right panel shows equal-weighted portfolios. In each panel, full-sample monetary policy betas, and average returns in three consecutive 24-hour windows are shown, with the middle column corresponding to the pre-FOMC announcement return. t-statistics reported in parentheses.

	Value-Weighted				Equal-Weighted			
Portfolio	β^{MP1}	Day −1	Pre-FOMC	Day +1	β^{MP1}	Day −1	Pre-FOMC	Day +1
1	-7.16	2.96	63.71	-3.48	-5.66	-2.97	53.93	3.92
		(0.20)	(5.04)	(-0.20)		(-0.25)	(4.67)	(0.23)
2	-5.71	-3.00	56.04	-5.58	-4.73	-3.09	45.18	-0.76
		(-0.26)	(4.73)	(-0.38)		(-0.29)	(4.40)	(-0.06)
3	-4.29	-0.10	48.12	-3.01	-4.15	-2.83	40.95	0.36
		(-0.01)	(4.62)	(-0.24)		(-0.29)	(4.29)	(0.03)
4	-4.19	6.99	36.23	-3.81	-3.98	-1.63	37.88	0.72
		(0.75)	(4.18)	(-0.35)		(-0.18)	(4.24)	(0.06)
5	-3.64	4.16	32.54	-0.61	-3.78	-1.99	37.70	-0.32
		(0.52)	(3.84)	(-0.06)		(-0.22)	(4.25)	(-0.03)
6	-3.44	5.52	29.96	-5.95	-3.42	-0.85	33.74	1.62
		(0.69)	(3.78)	(-0.58)		(-0.10)	(4.23)	(0.15)
7	-2.94	10.56	29.05	-5.46	-3.26	0.30	33.20	-0.84
		(1.41)	(3.98)	(-0.56)		(0.04)	(4.06)	(-0.08)
8	-3.05	7.52	24.42	-4.23	-3.42	2.52	30.95	1.84
		(1.01)	(3.25)	(-0.40)		(0.30)	(3.83)	(0.18)
9	-2.52	4.54	28.85	4.70	-2.88	1.24	30.15	1.95
		(0.62)	(4.13)	(0.54)		(0.15)	(3.96)	(0.19)
10	-2.60	4.73	27.96	-0.88	-2.92	0.84	29.62	1.28
		(0.59)	(3.67)	(-0.09)		(0.10)	(3.60)	(0.12)
1-10		-1.77	35.75	-2.61		-3.81	24.32	2.64
		(-0.16)	(3.62)	(-0.22)		(-0.75)	(4.30)	(0.32)

Table 1.4: Cross-sectional Regressions of 24-hour stock returns:

$$r_{i,t}^{k} = \gamma_0 + \gamma_1 \times Z\left(-\beta_i^{MP1} \times DisagFcst_t\right) + \gamma_2 X_{i,t} + \varepsilon_{it}$$

Where $r_{i,t}^{k}$ is the 24-hour excess return of individual stock in the window ending at announcement time, in the day preceding FOMC announcement (left panel), on the day of announcement (middle panel), and next day after the announcement (right panel). $Z\left(-\beta_i^{MP1} \times DisagFcst_t\right)$ is the normalized interaction between the full-sample monetary policy beta and disagreement from forecast data, multiplied by -1 to simplify interpretation. $X_{i,t}$ is the vector of controls, that could include: $ln(Mktcap)_t$ – the natural logarithm of the market capitalization, $r_{i,t-1}^{FOMC}$ – pre-FOMC return of the same stock at the previous announcement date, $MktR_{t-1}^{FOMC}$ – pre-FOMC return of the market at the previous announcement date, and other variables described in Table 1.1. Columns (2), (5) and (8) also include announcement and stock fixed effects. Regressions are estimated using OLS and standard errors are two-way clustered at announcement and stock level. Sample period is 1995-2016.

	–1 Day Return			Pre-FOMC Return			+1 Day Return		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Z\left(-\beta^{MP1} \times DisagFcst\right)$	-6.71	-4.10	-6.03	17.98***	8.99***	14.18***	8.81*	2.77	8.25*
	(-1.46)	(-1.20)	(-1.35)	(2.87)	(2.93)	(2.75)	(1.75)	(0.75)	(1.95)
β_i^{MP1}	-0.41		-0.22	-0.23		-0.81	1.77*		1.80*
	(-0.52)		(-0.24)	(-0.32)		(-1.13)	(1.85)		(1.68)
$DisagFcst_t$	-1.22		0.46	3.38		0.97	0.81		-1.60
	(-0.81)		(0.27)	(1.57)		(0.59)	(0.36)		(-0.66)
$ln(Mktcap)_t$			3.03*			2.88			0.27
			(1.67)			(1.39)			(0.12)
VIX_t			-2.59*			6.40***			-0.16
			(-1.75)			(2.81)			(-0.08)
$r_{i,t-1}^{FOMC}$			0.01			0.00			-0.02*
			(0.97)			(0.07)			(-1.82)
$MktR_{t-1}^{FOMC}$			0.14*			-0.02			0.20*
			(1.90)			(-0.19)			(1.67)
$MP1_t$			1.40			0.78			-6.52**
			(0.65)			(0.34)			(-2.07)
$MeanFcst_t$			0.35			0.46			-0.45
			(0.78)			(0.78)			(-0.53)
Date and Portfolio FE	No	Yes	No	No	Yes	No	No	Yes	No
Observations	314915	314781	303253	315308	315172	303496	314687	314552	303072

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.5: Cross-sectional Regressions of 24-hour portfolio returns:

$$r_{i,t}^{k} = \gamma_0 + \gamma_1 \times Z\left(-\beta_i^{MP1} \times DisagFcst_t\right) + \gamma_2 X_{i,t} + \varepsilon_{it}$$

Where $r_{i,t}^{k}$ is the 24-hour excess return of value-weighted monetary policy beta-sorted portfolio in the window ending at announcement time, in the day preceding FOMC announcement (left panel), on the day of announcement (middle panel), and next day after the announcement (right panel). $Z\left(-\beta_i^{MP1} \times DisagFcst_t\right)$ is the normalized interaction between the full-sample monetary policy beta of the portfolio and disagreement from forecast data, multiplied by -1 to simplify interpretation. $X_{i,t}$ is the vector of controls, that could include: $r_{i,t-1}^{FOMC}$ – pre-FOMC return of the same portfolio at the previous announcement date, $MktR_{t-1}^{FOMC}$ – pre-FOMC return of the market at the previous announcement date, and other variables described in Table 1.1. Columns (2), (5) and (8) also include announcement and portfolio fixed effects. Regressions are estimated using OLS and standard errors are clustered at announcement level. Sample period is 1995-2016.

	–1 Day Return			Pre-FOMC Return			+1 Day Return		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Z\left(-\beta^{MP1} \times DisagFcst\right)$	-8.75	-8.75	-6.83	31.70**	31.70**	31.14**	5.51	5.51	9.15
	(-0.74)	(-0.74)	(-0.56)	(2.53)	(2.52)	(2.33)	(0.42)	(0.42)	(0.66)
β_i^{MP1}	0.13		-0.29	-3.86*		-3.74*	1.65		0.86
	(0.05)		(-0.12)	(-1.67)		(-1.72)	(0.64)		(0.33)
$DisagFcst_t$	0.97		2.24	0.34		-3.58	-0.34		-3.04
	(0.70)		(1.33)	(0.18)		(-1.54)	(-0.20)		(-1.10)
VIX_t			-1.58			6.64***			-0.46
			(-1.12)			(3.00)			(-0.25)
$r_{i,t-1}^{FOMC}$			-0.08			0.02			-0.15
			(-0.79)			(0.20)			(-0.78)
$MktR_{t-1}^{FOMC}$			0.15			-0.04			0.29
			(1.47)			(-0.32)			(1.44)
$MP1_t$			-0.11			0.46			-5.94**
			(-0.05)			(0.17)			(-2.08)
$MeanFcst_t$			0.53			0.55			-0.35
			(1.20)			(0.96)			(-0.48)
Date and Portfolio FE	No	Yes	No	No	Yes	No	No	Yes	No
Observations	1640	1640	1640	1640	1640	1640	1640	1640	1640

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.6: Cross-sectional Regressions of 24-hour stock returns:

$$r_{i,t}^{k} = \gamma_0 + \gamma_1 \times Z\left(RSI_t\right) + \gamma_2 \times Z\left(-\beta_i^{MP1} \times DisagFcst_t\right) + \gamma_3 X_{i,t} + \varepsilon_{it}$$

Where $r_{i,t}^{k}$ is the 24-hour excess return of individual stock in the window ending at announcement time, in the day preceding FOMC announcement (left panel), on the day of announcement (middle panel), and next day after the announcement (right panel). $Z\left(RSI_t\right)$ is the normalized relative short interest. $Z\left(-\beta_i^{MP1} \times DisagFcst_t\right)$ is the normalized interaction between the full-sample monetary policy beta and disagreement from forecast data, multiplied by -1 to simplify interpretation. $X_{i,t}$ is the vector of controls, that could include: $ln(Mktcap)_t$ – the natural logarithm of the market capitalization, r_{t-1}^{pre} – pre-FOMC return of the same stock at the previous announcement date, $MktR_{t-1}^{pre}$ – pre-FOMC return of the market at the previous announcement date, and other variables described in Table 1.1. Columns (2), (5) and (8) also include announcement and stock fixed effects. Regressions are estimated using OLS and standard errors are two-way clustered at stock and announcement level. Sample period is 1995-2016.

	−1 Day Return			Pre-FOMC Return			+1 Day Return		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Z\left(RSI_t\right)$	-4.93	-1.78	-4.33	7.72**	4.46**	6.90**	1.04	-1.10	-0.34
	(-1.56)	(-1.18)	(-1.34)	(2.13)	(2.51)	(2.23)	(0.23)	(-0.48)	(-0.08)
$Z\left(-\beta^{MP1} \times DisagFcst\right)$	-12.15**	-7.04*	-10.65*	20.83**	9.37**	15.79**	11.34	2.37	8.84
	(-2.08)	(-1.91)	(-1.92)	(2.41)	(2.58)	(2.22)	(1.59)	(0.57)	(1.53)
β_i^{MP1}	-0.74		-0.54	0.15		-0.51	1.30		1.17
	(-0.92)		(-0.62)	(0.19)		(-0.68)	(1.42)		(1.19)
$DisagFcst_t$	-1.17		0.97	4.12		0.64	1.19		-2.02
	(-0.84)		(0.56)	(1.63)		(0.38)	(0.57)		(-0.84)
$ln(Mktcap)_t$			1.39			0.88			0.21
			(0.87)			(0.48)			(0.11)
VIX_t			-3.01*			6.83***			-0.10
			(-1.80)			(2.89)			(-0.04)
$r_{i,t-1}^{FOMC}$			0.01			0.01			-0.04**
			(0.74)			(1.09)			(-1.98)
$MktR_{t-1}^{FOMC}$			0.11			-0.05			0.21*
			(1.40)			(-0.44)			(1.69)
$MP1_t$			0.55			-0.21			-5.58**
			(0.25)			(-0.08)			(-2.52)
$MeanFcst_t$			0.35			0.54			-0.94
			(0.77)			(1.05)			(-1.39)
Date and Stock FE	No	Yes	No	No	Yes	No	No	Yes	No
Observations	206955	206863	201783	207094	207001	201881	206871	206779	201717

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.7: Cross-sectional Regressions of 24-hour relative short interest-sorted portfolio returns:

$$r_{i,t}^{k} = \gamma_0 + \gamma_1 \times Z\left(RSI_t\right) + \gamma_2 \times Z\left(-\beta_i^{MP1} \times DisagFcst_t\right) + \gamma_3 X_{i,t} + \varepsilon_{it}$$

Where $r_{i,t}^{k}$ is the 24-hour excess return of a value-weighted relative short interest sorted portfolio in the window ending at announcement time, in the day preceding FOMC announcement (left panel), on the day of announcement (middle panel), and next day after the announcement (right panel). $Z\left(RSI_t\right)$ is the normalized relative short interest. $Z\left(-\beta_i^{MP1} \times DisagFcst_t\right)$ is the normalized interaction between the full-sample monetary policy beta of the portfolio and disagreement from forecast data, multiplied by -1 to simplify interpretation. $X_{i,t}$ is the vector of controls, that could include: $r_{i,t-1}^{FOMC}$ – pre-FOMC return of the same stock at the previous announcement date, $MktR_{t-1}^{FOMC}$ – pre-FOMC return of the market at the previous announcement date, and other variables described in Table 1.1. Columns (2), (5) and (8) also include announcement and portfolio fixed effects. Regressions are estimated using OLS and standard errors are clustered at announcement level. Sample period is 1995-2016.

	−1 Day Return			Pre-FOMC Return			+1 Day Return		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Z\left(RSI_t\right)$	-10.28*	10.15	-9.44	14.35*	13.95**	13.43**	3.81	6.70	5.16
	(-1.66)	(1.30)	(-1.56)	(1.93)	(2.04)	(2.25)	(0.47)	(0.77)	(0.70)
$Z\left(-\beta^{MP1} \times DisagFcst\right)$	-27.36**	-24.47*	-27.35**	27.60**	27.54**	27.50**	22.57*	22.98*	24.12
	(-2.20)	(-1.88)	(-2.20)	(2.36)	(2.38)	(2.36)	(1.77)	(1.80)	(1.65)
β_i^{MP1}	-10.92		-9.63	14.53		13.35*	9.36		7.33
	(-1.40)		(-1.29)	(1.52)		(1.69)	(0.97)		(0.81)
$DisagFcst_t$	4.26**		6.29**	0.20		-3.20	-3.93**		-6.87**
	(2.16)		(2.52)	(0.08)		(-1.23)	(-2.09)		(-2.18)
VIX_t			-1.82			6.64***			0.05
			(-1.34)			(2.96)			(0.03)
$r_{i,t-1}^{FOMC}$			0.03			-0.01			-0.33
			(0.24)			(-0.06)			(-1.48)
$MktR_{t-1}^{FOMC}$			0.07			-0.02			0.45*
			(0.66)			(-0.15)			(1.82)
$MP1_t$			0.63			0.45			-4.77**
			(0.28)			(0.19)			(-2.01)
$MeanFcst_t$			0.74			0.46			-0.64
			(1.55)			(0.93)			(-0.97)
Date and Portfolio FE	No	Yes	No	No	Yes	No	No	Yes	No
Observations	1690	1690	1690	1690	1690	1690	1690	1690	1690

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.8: Cross-sectional regressions of tight-window portfolio returns:

$$r_{i,t}^{tight} = \gamma_0 + \gamma_1 \times Z\left(-\beta_i^{MP1} \times DisagFcst_t\right) + \gamma_2 \times \left(\beta_i^{MP1} \times MP1_t\right) + \gamma_3 X_{i,t} + \varepsilon_{it}$$

Where $r_{i,t}^{Pre-FOMC}$ is the return of value-weighted portfolio sorted on monetary policy betas, in the 30-minute window around the FOMC announcement time. $Z\left(-\beta_i^{MP1} \times DisagFcst_t\right)$ is the normalized interaction between the full-sample monetary policy beta of the portfolio and disagreement from forecast data, multiplied by -1 to simplify interpretation. $\beta_i^{MP1} \times MP1_t$ is the product of sensitivity to the monetary policy shock by the realization of the shock at the particular announcement. $X_{i,t}$ is the vector of controls. Regressions are estimated using OLS and standard errors are clustered at announcement level. Subsamples are 1995-2016, 1995-2011, and no zero lower bound (ZLB), which includes 1995-2008 and 2016.

	1995-2016		1995-2011		No ZLB	
	(1)	(2)	(3)	(4)	(5)	(6)
$Z\left(-\beta^{MP1} \times DisagFcst\right)$	-11.97**	-12.93***	-12.69**	-14.16***	-12.95**	-12.23**
	(-2.50)	(-2.62)	(-2.54)	(-2.72)	(-2.47)	(-2.36)
$\beta_i^{MP1} \times MP1_t$	1.10***	1.08***	1.07***	1.03***	1.09***	1.12***
	(4.00)	(3.88)	(3.90)	(3.70)	(3.96)	(3.99)
β_i^{MP1}		0.53		1.41		0.39
		(0.61)		(1.26)		(0.30)
$DisagFcst_t$		0.77		1.38		1.46
		(0.86)		(1.47)		(1.55)
VIX_t		-1.19**		-0.91		-1.39***
		(-2.19)		(-1.55)		(-3.10)
$r_{i,t-1}^{FOMC}$		0.04		0.07		-0.04
		(0.54)		(0.87)		(-1.49)
$MktR_{t-1}^{FOMC}$		0.05		0.03		0.14***
		(0.69)		(0.45)		(3.58)
$MP1_t$		0.08		-0.03		0.25
		(0.10)		(-0.04)		(0.32)
$MeanFcst_t$		-0.00		0.11		0.12
		(-0.01)		(0.40)		(0.46)
Date and Porfolio FE	Yes	No	Yes	No	Yes	No
Observations	1640	1640	1240	1240	1080	1080

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.9: Sub-sample cross-sectional regressions of 24-hour portfolio returns:

$$r_{i,t}^{PreFOMC} = \gamma_0 + \gamma_1 \times Z\left(RSI_t\right) + \gamma_2 \times Z\left(-\beta_i^{MP1} \times DisagFcst_t\right) + \gamma_3 X_{i,t} + \varepsilon_{it}$$

Where $r_{i,t}^{PreFOMC}$ is the 24-hour excess return value-weighted portfolio the window ending at FOMC announcement time. $Z\left(RSI_t\right)$ is the normalized relative short interest. $Z\left(-\beta_i^{MP1} \times DisagFcst_t\right)$ is the normalized interaction between the full-sample monetary policy beta and disagreement from forecast data, multiplied by -1 to simplify interpretation. $X_{i,t}$ is the vector of controls. Panel A shows results for 10 monetary policy beta sorted portfolios. Panel B shows results for 10 portfolios sorted on the relative short interest. Regressions are estimated using OLS and standard errors are clustered at announcement level. Specifications (1), (3), and (5) include date and portfolio fixed effects, while specifications (2), (4), and (6) include additional controls, same as in Table 1.7 (not shown). Subsamples are 1995-2016, 1995-2011, and no zero lower bound (ZLB), which includes 1995-2008 and 2016.

	1995-2016		1995-2011		No ZLB	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Monetary policy beta-sorted portfolios						
$Z\left(-\beta^{MP1} \times DisagFcst\right)$	31.70**	31.14**	29.23**	29.03*	28.84**	28.69*
	(2.52)	(2.33)	(2.09)	(1.96)	(2.00)	(1.97)
β_i^{MP1}		-3.74*		-6.16**		-4.00
		(-1.72)		(-2.04)		(-1.33)
$DisagFcst_t$		-3.58		-2.94		-4.10
		(-1.54)		(-1.20)		(-1.49)
Date and Portfolio FE	Yes	No	Yes	No	Yes	No
Panel B: RSI-Sorted portfolios						
$Z\left(RSI_t\right)$	13.95**	13.43**	21.98***	18.73**	18.88**	23.22***
	(2.04)	(2.25)	(2.85)	(2.42)	(2.56)	(2.67)
$Z\left(-\beta^{MP1} \times DisagFcst\right)$	27.54**	27.50**	24.85**	24.74*	19.84	19.90
	(2.38)	(2.36)	(2.01)	(1.98)	(1.58)	(1.62)
β_i^{MP1}		13.35*		15.95		21.57**
		(1.69)		(1.65)		(2.00)
$DisagFcst_t$		-3.20		-2.46		-2.94
		(-1.23)		(-0.87)		(-0.98)
Date and Porfolio FE	Yes	No	Yes	No	Yes	No

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.10: Cross-sectional Regressions of 24-hour portfolio returns:

$$r_{i,t}^{k} = \gamma_0 + \gamma_1 \times Z\left(-\beta_i^{MP1} \times Disag_t\right) + \gamma_2 X_{i,t} + \varepsilon_{it}$$

Where $r_{i,t}^{k}$ is the 24-hour excess return of value-weighted monetary policy beta-sorted portfolio in the window ending at announcement time, in the day preceding FOMC announcement (left panel), on the day of announcement (middle panel), and next day after the announcement (right panel). $Z\left(-\beta_i^{MP1} \times Disag_t\right)$ is the normalized interaction between the full-sample monetary policy beta of the portfolio and disagreement from forecast data, multiplied by -1 to simplify interpretation. $X_{i,t}$ is the vector of controls. Panel A shows results for the binary version of the forecast-based disagreement proxy. Panel B shows results for the realized volatility of the nearest-month Federal Funds futures contract as the proxy for the disagreement. Regressions are estimated using OLS and standard errors are clustered at announcement level. Sample period is 1995-2016.

	−1 Day Return		Pre-FOMC Return		+1 Day Return	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Binary forecast disagreement proxy						
$Z\left(-\beta^{MP1} \times DisagBinary\right)$	-4.19	-2.46	29.07***	28.45***	-1.43	1.59
	(-0.41)	(-0.25)	(3.08)	(2.98)	(-0.13)	(0.13)
β_i^{MP1}		0.25		-2.88		-0.17
		(0.09)		(-1.55)		(-0.06)
$DisagBinary_t$		20.32		-39.26*		-4.17
		(1.28)		(-1.95)		(-0.20)
Date and Portfolio FE	Yes	No	Yes	No	Yes	No
Panel B: Realized volatility disagreement proxy						
$Z\left(-\beta^{MP1} \times DisagRvol\right)$	-5.09	-2.06	53.28***	53.42***	16.38	23.27
	(-0.62)	(-0.24)	(3.05)	(2.83)	(0.68)	(0.89)
β_i^{MP1}		0.53		-2.42		1.98
		(0.23)		(-1.25)		(0.63)
$DisagRvol_t$		0.42		-0.23		-0.91
		(0.97)		(-0.52)		(-1.45)
Date and Portfolio FE	Yes	No	Yes	No	Yes	No

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.11: Cross-sectional regressions of 24-hour portfolio returns:

$$r_{i,t}^{PreFOMC} = \gamma_0 + \phi \times r_{i,t}^{announcement} + \gamma_1 \times Z\left(-\beta_i^{MP1} \times DisagFcst_t\right) + \gamma_2 X_{i,t} + \varepsilon_{it}$$

Where $r_{i,t}^{PreFOMC}$ is the 24-hour excess return value-weighted portfolio sorted by monetary policy beta in the window ending at FOMC announcement time. $r_{i,t}^{announcement}$ is the return that is realized in the narrow window around the announcement, measured as product of monetary policy beta and tight-window monetary policy shock (Panel A) or as 30-minute return (Panel B). $Z\left(-\beta_i^{MP1} \times DisagFcst_t\right)$ is the normalized interaction between the full-sample monetary policy beta and disagreement from forecast data, multiplied by -1 to simplify interpretation. Regressions are estimated using OLS and standard errors are clustered at announcement level. Subsamples are 1995-2016, 1995-2011, and no zero lower bound (ZLB), which includes 1995-2008 and 2016.

	1995-2016		1995-2011		No ZLB	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Tight window shock and sensitivity as measure of announcement return						
$\beta_i^{MP1} \times MP1_t$	-0.71*	-0.73*	-0.69*	-0.70	-0.68*	-0.69*
	(-1.75)	(-1.74)	(-1.67)	(-1.63)	(-1.66)	(-1.68)
$Z\left(-\beta^{MP1} \times DisagFcst\right)$	33.63***	33.02**	30.83**	30.54**	30.36**	30.10**
	(2.73)	(2.53)	(2.25)	(2.12)	(2.15)	(2.12)
β_i^{MP1}		-3.84*		-6.29**		-4.18
		(-1.79)		(-2.11)		(-1.42)
$DisagFcst_t$		-3.94*		-3.24		-4.37
		(-1.77)		(-1.38)		(-1.64)
Date and Portfolio FE	Yes	No	Yes	No	Yes	No
Panel B: Tight window return as measure of announcement return						
$r_{i,t}^{tight}$	-0.21	-0.25*	-0.22	-0.24	-0.26**	-0.28*
	(-1.43)	(-1.96)	(-1.19)	(-1.51)	(-2.05)	(-1.90)
$Z\left(-\beta^{MP1} \times DisagFcst\right)$	29.78**	28.56**	26.99**	26.16*	26.15*	25.94*
	(2.46)	(2.20)	(1.99)	(1.82)	(1.93)	(1.86)
β_i^{MP1}		-3.64*		-5.87*		-3.97
		(-1.69)		(-1.95)		(-1.33)
$DisagFcst_t$		-3.52		-2.71		-3.82
		(-1.63)		(-1.20)		(-1.50)
Date and Porfolio FE	Yes	No	Yes	No	Yes	No

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 2

Bank Capital and Monetary Policy Shocks

2.1 Introduction

In the aftermath of a 2007-2008 financial crisis central banks around the world are facing a dilemma of optimal regulation of the banking sector. On the one hand, excessive leverage of many financial institutions was one of the key factors behind the fast propagation of the crisis. In order to improve stability and ensure that financial institutions have more "skin in the game", it is reasonable for the regulators to raise the capital requirements. On the other hand, conventional wisdom suggests that equity financing is more expensive than debt, so higher capital requirements could be costly. If the banks shift these costs onto their consumers, this could result in dampened access to credit, which is a very undesirable effect in the environment when central banks seek to stimulate economy with the interest rates near zero.

The recent academic literature gives support to the both sides of the debate. Admati et al. (2013) argue that banks do not need high leverage to perform the socially beneficial role of the financial intermediary. Moreover, along the lines of Modigliani and Miller (1958) authors suggest that tighter capital requirements would actually make equity cheaper, as it will become less risky, so the "costly equity" argument is simply invalid. They conclude that the capital requirements introduced after the financial crisis (Tier 1 capital ratio of 11% with Basel III agreement in 2010) should be made even stricter, up to 20-30% Tier 1 capital ratio, as this would greatly improve stability of the financial system and bring significant social benefit. On the other side of the debate, Baker and Wurgler (2015) argue that lower risk bank equity actually leads to higher returns and higher cost of capital. They suggest that the primary explanation of this phenomenon is the Low-Risk Anomaly, a well-known tendency of low-risk stocks to outperform high-risk stocks in the long term. According to their estimates, raising Tier 1 capital requirement from 8% to 11% could result in costs of capital raising by 85 basis points. As a conclusion, Baker and Wurgler (2015) suggest that the increased costs of equity are not something to be ignored in the policy debate on the capital requirements.

In this chapter we seek to contribute to the debate on the optimal bank regulation by addressing the question from a new angle. One could argue that regulators are likely to put stability of banking sector above profitability, while bank managers tend to care more about the bottom line. However, there is also a third group of agents with more balanced views – investors. Indeed, it is reasonable to assume that a person who buys bank's stocks or bonds would care about both profitability and stability of their investment. Such approach has an additional advantage, as prices in the financial markets could be used to gauge changes in investor expectations in response to various shocks with high precision.

Our empirical estimation strategy uses monetary policy announcements of the Federal Open Market Committee (FOMC) as a source of exogenous variation in the interest rates, or quasi-natural "stress-tests" for the banking sector. The heterogeneous response of bank equity prices and bond yields to these shocks could be linked to the total capital ratio to investigate whether better-capitalised banks respond differently to the monetary policy shocks. Importantly, due to the potential trade-off between stability and profitability, we do not make ex ante prediction as to whether higher amounts of capital are viewed positively or negatively by the investors.

Our results suggest that banks with more capital are better insulated against unexpected changes in the interest rates. In line with English et al. (2018) we find that an unanticipated increase in the level of Federal Funds Rate has negative effects on the stock prices of banks. However, we also show that this effect is roughly 1/6 smaller for a bank in the 75th percentile of the total capital ratio, as compared to the bank in the 25th percentile. We find similar effects for the squared returns, which we interpret as reduced stock price volatility of the better-capitalised banks around the time of the FOMC announcements. Finally, we also consider changes in the yields of the bonds issued by the banks: we show that they are sensitive to the unexpected innovations in the slope of the U.S. Treasury yield, but this sensitivity is lower for better-capitalised banks.

The remainder of this chapter is organized as follows. Section 2.2 describes the data. Section 2.3 presents the main empirical results. Section 2.4 concludes.

2.2 Data

2.2.1 Monetary Policy Shocks

Our empirical estimation strategy relies on the accurate measurement of the monetary policy shocks. We employ the approach pioneered by Kuttner (2001) and Bernanke and Kuttner (2005), and use intraday changes in the prices of futures contracts to estimate the unanticipated component of the monetary policy announcements. The shock to the level of the yield curve is measured by a scaled change in the price of the futures contracts on the Federal Funds Rate:

$$MP1_t = \frac{D}{D-d}\left(\Delta ff1_t\right) \tag{2.1}$$

where $\Delta ff1_t$ is the change in the price of the nearest-month Federal Futures Contract in the narrow 30-minute window around the exact time when the press-release of the Federal Open Market Committee becomes available to the public, D is the total number of days in the month of the announcement, and d is the number of days that remain in the month after the day of the announcement. The scaling factor here accounts for the fact that the futures contract settles at the end of each month at the average effective Federal Funds Rate during the month.

Since banks engage in maturity transformation, it is reasonable to expect that their profitability and asset prices would be sensitive not only to the shocks to level of the yield curve, but also to changes in its slope. One monetary policy announcement can contain both level and slope shocks, so to disentangle them we regress the changes in long-term U.S. Treasury rates on the level surprise, and treat the residuals as the unanticipated change in the slope of the yield curve:

$$\Delta y_t^m = \alpha + \beta MP1_t + SLOPE_t^m \tag{2.2}$$

where Δy_t^m is the change in the m-year U.S. treasury yields in the narrow 30-minute window around the monetary policy announcement, and $MP1_t$ is the level surprise described earlier. Following English et al. (2005), we consider $m = \{2, 5, 10\}$ year slope surprises.

For our sample we use all scheduled and unscheduled FOMC announcements between 02/04/1994 and 12/17/2014. The data for the exact dates and times of monetary policy announcements comes from Gürkaynak et al. (2005) and Federal Reserve web site. The intraday prices of futures contracts and U.S. Treasury yields are obtained from CQG and Bloomberg. Panel A of Table 2.1 shows the summary statistics for the level and slope monetary policy shocks (all measured in basis points). In line with the previous literature, we find that the average level shock is very small, less than 1.5 basis points. The means of slope surprises on all three horizons are even closer to zero. This evidence suggests that the shocks are not biased in any direction, and our interpretation of them as "quasi-natural stress tests" is valid.

Figure 2.1 shows the time series of monetary policy shocks. Panel A contains the level surprises, while Panel B shows the slope surprises for the $m = \{2, 5, 10\}$ year horizons. We note that there is a substantial variation in both types of shocks, especially prior prior to 2009. During the period when the interest rates were at the zero lower bound, the level surprise flattens out, while the three slope surprises remain quite volatile.

2.2.2 Bank Financial Information

In order to identify the sample of banks for our analysis, we start with the Call Reports, also known as FR Y-9C forms. These reports are filed quarterly by the domestic bank holding companies (BHC) and other financial institutions to the Federal Reserve. The reports contain various financial data, including balance sheet, income statements, and off balance-sheet items of the financial institutions, and serve the purpose of monitoring financial conditions of the banking sector firms between the on-site inspections. The coverage of the FR Y-9C is not uniform, as only the financial institutions with consolidated assets above a certain threshold (ranging from \$150 million before 2006 to \$1 billion in 2015) are required to file the FR Y-9C.

We obtain the FR Y-9C data from the Federal Reserve Board's Freedom of Information Office. In order to match this data with the data from other sources, we use the linking table provided by NY Federal Reserve, that establishes the match between unique bank identifier in the FR Y-9C data and unique company identifier used in the CRSP dataset. We eliminate all duplicate matches, and end up with 1,569 banks[1] in our main sample, that spans 20 years between 1994 and 2014. We then proceed by merging the financial holdings data from FR Y-9C with Compustat data, using the CRSP-Compustat linking table provided by WRDS.

Our primary variable of interest is the item "caprtq"[2] in Compustat, which measures the total capital ratio. Compustat defines this variable as the ratio of the sum of tier 1 and tier 2 capital to the average risk-weighted assets, where:

$$\begin{aligned}
\text{Tier 1 capital} &= \text{Shareholder's Equity-Goodwill}+\text{Retained Earnings} \\
&\quad -\text{NonMortgage Servicing Rights (MSR) Intangibles} \\
&\quad +\text{Qualified Hybrid Securities and Noncontrolling Interests} \\
\text{Tier 2 capital} &= \text{Subordinated Debt}+\text{NonQualified Hybrid Securities} \\
&\quad +\text{Qualifying Allowance for Loan Losses} \\
\text{Average Risk-Weighted Assets} &= \text{Mean}^{\text{Risk-Weighted}}(\text{Cash and Equivalents,} \\
&\quad \text{Residential Mortgages, Credit/Auto Loans,} \\
&\quad \text{Commercial Real Estate, Sovereign debt,} \\
&\quad \text{Interbank Loans, Corporate Loans, etc.})
\end{aligned}$$

Henceforth, we use notation TTC for the total capital ratio. Figure 2.2 plots the time series of the TTC[3]. We notice two important things about this variable. First, for each time period there is a substantial variation in the capital ratios of the banks in our sample, as interquartile range is around 1.5%. Second, the financial crisis of 2008 and subsequent Basel III and Dodd-Frank regulation of 2010 led to a significant increase in the average and median total capital ratios.

Using Compustat and FR Y-9C data we construct a number of controls that are meant to capture other dimensions of heterogeneity in the capital structure that banks have, in addition to variability in the total capital ratio:

- Market Equity (ME), Book-to-Market Ratio (BM), and Return on Equity (ROE).
- Loans-to-Assets ratio (LOANS), savings deposits as a share of total liabilities (SDEP), demand deposits as a share of total liabilities (DDEP) – all computed as described by English et al. (2018).
- Income gap (IGAP) which measures the mismatch between assets and liabilities in sensitivity to the interest rate changes – computed as described by Gomez et al. (2016).

We are also concerned that banks might be seeking to hedge their exposure to the interest rate innovations. If there is a systematic relationship between hedging and capitalisation, this could distort the relationship between sensitivity to the monetary policy shocks and TTC. Hence, add controls for banks' holdings of interest rate derivatives:

[1] This number includes name changes, mergers, and acquisitions, so the actual number of unique companies is smaller.

[2] In older versions of Compustat database this item was named "capr3q".

[3] We exclude observations with negative values of TTC, and also trim bottom 1st and upper 99th percentiles to clean for the mis-coded values and outliers.

- Swap contracts (SWAPS), Futures contracts (FUT), Forward contracts (FOR), written exchange-traded options (ET OPT (w)), purchased exchange-traded options (ET OPT (p)), written over-the-counter options (OTC OPT (w)), purchased over-the-counter options (OTC OPT (p)) – all computed as described by English et al. (2018).

The summary statistics for the variables outlined above is presented in Panel B and Panel D of Table 2.1. For all variables we trim outliers at the 1st and 99th percentiles.

2.2.3 Bank Stock Prices and Bond Yields

We turn to asset markets in order to construct the dependent variables that would measure the reaction of investors to the monetary policy shocks. Our first dependent variable is the simple net return in the 1-hour window around the exact time of the monetary policy announcement:

$$R_{i,t} = \frac{PRICE_{i,t,\tau+45\text{ minutes}}}{PRICE_{i,t,\tau-15\text{ minutes}}} - 1 \tag{2.3}$$

where $PRICE_{i,t,\tau-15\text{ minutes}}$ is the stock price of bank i, on day of the announcement t, 15 minutes prior to the exact time of the FOMC press-release τ, while $PRICE_{i,t,\tau-15\text{ minutes}}$ is the same price 45 minutes after the announcement, both from TAQ database. Similar to other variables, we trim the returns at the 1st percentile from below, and at the 99th percentile from above. Panel B of Table 2.1 presents the summary statistics for the stock returns in our sample.

We are also interested in how stock price volatility reacts to the monetary policy shocks, and what is the role of capitalisation in this relationship. Therefore, we follow Gorodnichenko and Weber (2016) and estimate stock price volatility as squared return $R^2_{i,t}$. Such approach is reasonable, because the mean return in the sample is 0.1 basis points, which is very close to zero.

Finally, we are also interested in the reaction of bond markets to the monetary policy shocks. We use data on bond prices from the TRACE database, to compute the change in the yields of the bonds issued by the banks in our sample. Since the bond market is less liquid than the stock market, we use the daily yield change:

$$\Delta Y_{i,t} = Y_{i,t+1day} - Y_{i,t-1day} \tag{2.4}$$

where $Y_{i,t-1day}$ is the yield of the commercial bond of bank i at the last transaction on the day prior to the FOMC announcement day t, and $Y_{i,t+1day}$ is the yield at the last transaction on the day after to the FOMC announcement day t. Panel C of Table 2.1 reports summary statistics for the recorded yield changes, together with the overall bond maturity T, remaining maturity $T - t$, and the aggregated credit rating obtained from Mergent FSID (RATING), with smaller values corresponding to higher-rated bonds. Similar to other variables, we trim the yield changes at the 1st and 99th percentiles.

2.3 Empirical Results

2.3.1 Stock Returns

The first regression model that we estimate is similar to the approach suggested by English et al. (2018). We estimate the panel regression of stock returns in the 1-hour window around the announcement on the level and slope monetary policy shocks, their interactions with total capital ratio TTC, and a number of controls:

$$\begin{aligned} R_{i,t} =& \alpha_i + \beta_0 MP1_t + \beta_1 SLOPE_t \\ & + \beta_2 \left(MP1_t \times TTC_{i,t}\right) + \beta_3 \left(SLOPE_t \times TTC_{i,t}\right) + \gamma \mathbf{X}_{i,t} + \epsilon_{i,t} \end{aligned} \tag{2.5}$$

Table 2.2 presents the results of this exercise. Columns (1)-(3) describe the coefficients of baseline model with three different variables for the slope shock (on the 2-, 5-, and 10-year horizons), but no controls. Columns (4)-(6) include balance sheet controls (ME, BM, LOANS, IGAP, ROE, SDEP, and DDEP), and their interactions with MP1. Finally, columns (7)-(9) add all of the controls for the holdings of interest rate derivatives outlined in Panel D of Table 2.1, and their interactions with MP1. All regressions are estimated via OLS with bank-fixed effects, and standard errors are clustered at the announcement level. Finally, the interactions between MP1, balance sheet items (specifications (4)-(6) in Table 2.2), and interest rate derivatives (specifications (7)-(9) in Table 2.2) are reported in Appendix B, Tables B1 and B2.

We notice that in all specifications in Table 2.2 we find the negative and highly significant reaction of returns to the level monetary policy shock MP1. According to the baseline specification (1), for a median bank with TTC of 13.70%, the unanticipated 25 basis points tightening on average leads to a -0.675% return, a noticeably smaller effect than 2-2.5% negative return reported by English et al. (2018). However, our sample covers longer period and a wider cross-section of banks, which potentially could explain this difference.

Turning to the differential effects of capitalization, we notice that the interaction between MP1 and TTC is significant on at least 10% level in all 9 specifications. The sign of this coefficient is positive which implies that better-capitalised banks are less sensitive to the monetary policy level shocks. The magnitude of this effect could be assessed from the observation that the difference between banks in the 25th and 75th percentiles of TTC is roughly 4%. According to the specification (1), the difference in reaction to the unanticipated 25 basis points tightening is about 0.111%, or 1/6 of the stock return of the median bank of -0.675%. All other specifications produce results of similar magnitude.

We also do not find the strong relationship between the shocks to the slope of the U.S. Treasury yield curve and bank stock returns, as in two out of nine specifications, the coefficient on the SLOPE variable is not statistically significant. Additionally, we notice that the interactions between the SLOPE variables and TTC are not statistically significant, so the capitalisation does not seem to play a role in relationship between bank stock prices and slope shocks.

2.3.2 Return Volatility

In order to investigate the relationship between return volatility and monetary policy shocks we regress the squared returns around the FOMC announcements on squared measures of level and slope surprises, following approach of Gorodnichenko and Weber (2016). Since our primary focus is to study the effects of capitalisation, we add interactions between the squared shocks and total capital ratio TTC, as well as other controls:

$$\begin{aligned} R^2_{i,t} =& \alpha_i + \beta_0 MP1^2_t + \beta_1 SLOPE^2_t \\ &+ \beta_2 \left(MP1^2_t \times TTC_{i,t}\right) + \beta_3 \left(SLOPE^2_t \times TTC_{i,t}\right) + \gamma \mathbf{X}_{i,t} + \epsilon_{i,t} \end{aligned} \tag{2.6}$$

Table 2.3 shows the results of this estimation. Specifications (1)-(3) are the baseline with no controls. Specifications (4)-(6) contain balance sheet controls (ME, BM, LOANS, IGAP, ROE, SDEP, and DDEP) and their interactions with $MP1^2$, while specifications (7)-(9) add interest rate derivative controls and their interactions with $MP1^2$. All of the models include bank-fixed effects, and we estimate them using OLS with standard errors clustered at the announcement level.

The coefficient on $MP1^2$ is positive and statistically different from zero in all specifications in Table 2.3, which suggests that with higher volatility of monetary policy level shocks, the volatility of stock prices in the 1-hour window around the announcement should also be higher. We also notice that the interaction between $MP1^2$ and TTC is negative and highly significant in all nine specifications, which means that the volatility of bank stock prices is decreasing with bank capitalisation. It should also be noted that we do not find conclusive evidence on the relationship between the slope shocks and volatility of stock returns at the announcement, which is consistent with the findings of the previous subsection. Additionally, we also report the coefficients on interactions between the balance sheet controls and $MP1^2$ in the Appendix B, Table B3 (for specifications (4)-(6) in Table 2.3), and the coefficients on the interactions on interactions between the interest rate derivatives controls and $MP1^2$ in the Appendix B, Table B4.

2.3.3 Split on TTC Median and Asymmetric Effects of Monetary Policy Shocks

Earlier, we established that stock prices of banks with higher capital ratios are less sensitive to the monetary policy level surprises. We are now interested whether this effect is uniform, or mostly driven by the observations on one side of the spectrum. To test for the potential non-linearity in the role of capital, we create the dummy variable for the banks that have TTC below the median value for a given announcement date: $1_{TTC<MED}$. We then add triple interaction terms with this indicator variable to the model described by eq. (2.5), and estimate:

$$\begin{aligned} R_{i,t} =& \alpha_i + \beta_0 MP1_t + \beta_1 SLOPE_t + \beta_2 \left(MP1_t \times TTC_{i,t}\right) + \beta_3 \left(SLOPE_t \times TTC_{i,t}\right) \\ &+ \beta_4 \left(MP1_t \times TTC_{i,t} \times 1_{TTC<MED}\right) + \beta_5 \left(SLOPE_t \times TTC_{i,t} \times 1_{TTC<MED}\right) \\ &+ \gamma \mathbf{X}_{i,t} + \epsilon_{i,t} \end{aligned} \tag{2.7}$$

Table 2.4 reports coefficients from this regression for the specification with balance sheet controls, interest rate derivative controls, and their interactions with the monetary policy level shock MP1. We notice that the interaction $MP1_t \times TTC_{i,t}$ is now no longer significant, while the triple interaction term $MP1_t \times TTC_{i,t} \times 1_{TTC<MED}$ is negative and statistically significant at 5% level in all three specifications. This suggests that less-capitalised banks are more sensitive to the monetary policy shocks, while better-capitalised institutions are not significantly different from the average, so most of the effect comes from the lower end of the TTC distribution.

Next, we are also interested in the differential effects of the contractionary and expansionary monetary policy shocks. We define contractionary shocks, as having $MP1_t > 0$ and create an indicator variable $1_{MP1>0}$. We add triple interaction terms to the model describe by eq. (2.5) and estimate:

$$\begin{aligned} R_{i,t} =& \alpha_i + \beta_0 MP1_t + \beta_1 MP1_t \times 1_{MP1>0} + \beta_2 SLOPE_t \\ &+ \beta_3 \left(MP1_t \times TTC_{i,t}\right) + \beta_4 \left(MP1_t \times TTC_{i,t} \times 1_{MP1>0}\right) + \beta_5 \left(SLOPE_t \times TTC_{i,t}\right) \\ &+ \gamma \mathbf{X}_{i,t} + \epsilon_{i,t} \end{aligned} \tag{2.8}$$

The estimated coefficients for this model are presented in Table 2.5. We notice that in all of the specifications the effects are coming from the expansionary monetary policy level shocks, because neither $MP1_t \times 1_{MP1>0}$ nor $MP1_t \times TTC_{i,t} \times 1_{MP1>0}$ terms have statistically significant coefficients.

2.3.4 Bond Yields

We now switch our focus to the bond market and study the 1-day response of the corporate bond yields to both level and slope monetary policy shocks, and investigate the role of capital in this relationship. Similar to our approach in the analysis of the stock market, we estimate panel regressions of yield changes on the level and slope shocks, their interactions with the total capital ratio TTC, and controls:

$$\begin{aligned} \Delta Y_{i,t} =& \alpha_i + \beta_0 MP1_t + \beta_1 SLOPE_t \\ &+ \beta_2 \left(MP1_t \times TTC_{i,t}\right) + \beta_3 \left(SLOPE_t \times TTC_{i,t}\right) + \gamma \mathbf{X}_{i,t} + \epsilon_{i,t} \end{aligned} \tag{2.9}$$

Estimation results are shown in Table 2.6. Columns (1)-(3) show the baseline specification with no controls. Columns (4)-(6) add balance sheet controls (ME, BM, LOANS, IGAP, ROE, SDEP, and DDEP), and their interactions with MP1 and SLOPE shocks. Columns (7)-(9) show the results for the model with a full set of controls, that includes balance sheet items, interest rate derivatives, and their interaction with level and slope surprises.

We notice that in all nine specifications in Table 2.6 the shock to the slope of the U.S. treasury curve has a more significant role than the shock to the level of the interest rates, as coefficients on SLOPE are statistically significant more often than coefficients on MP1. The role of capitalisation is similar to what we found for the stock market: having more capital dampens the response of yields to the level surprises, but it also makes yields less sensitive to the slope shocks, as suggested by negative and statistically significant coefficients on the interaction term $SLOPE_t \times TTC_{i,t}$ in the specifications (4)-(9).

2.4 Conclusion

We find that equity and bonds of banks with more capital are better insulated against monetary policy shocks. The difference of 4% in the total capital ratio (which is approximately the gap between the banks in the 25th and 75th percentiles of TTC) reduces the sensitivity of bank stock to the unexpected changes in the interest rate level by approximately 1/6. We also find similar effects for the return volatility and bond yields. Our findings suggest that investors in the financial markets view excessive capital favourably, as it leads to more stable asset prices. While we do not rule out the possibility that raising the capital requirements above the historic levels could lead to reduced profits of the financial institutions, our results suggest that stability gains would outweigh the losses.

2.5 Figures

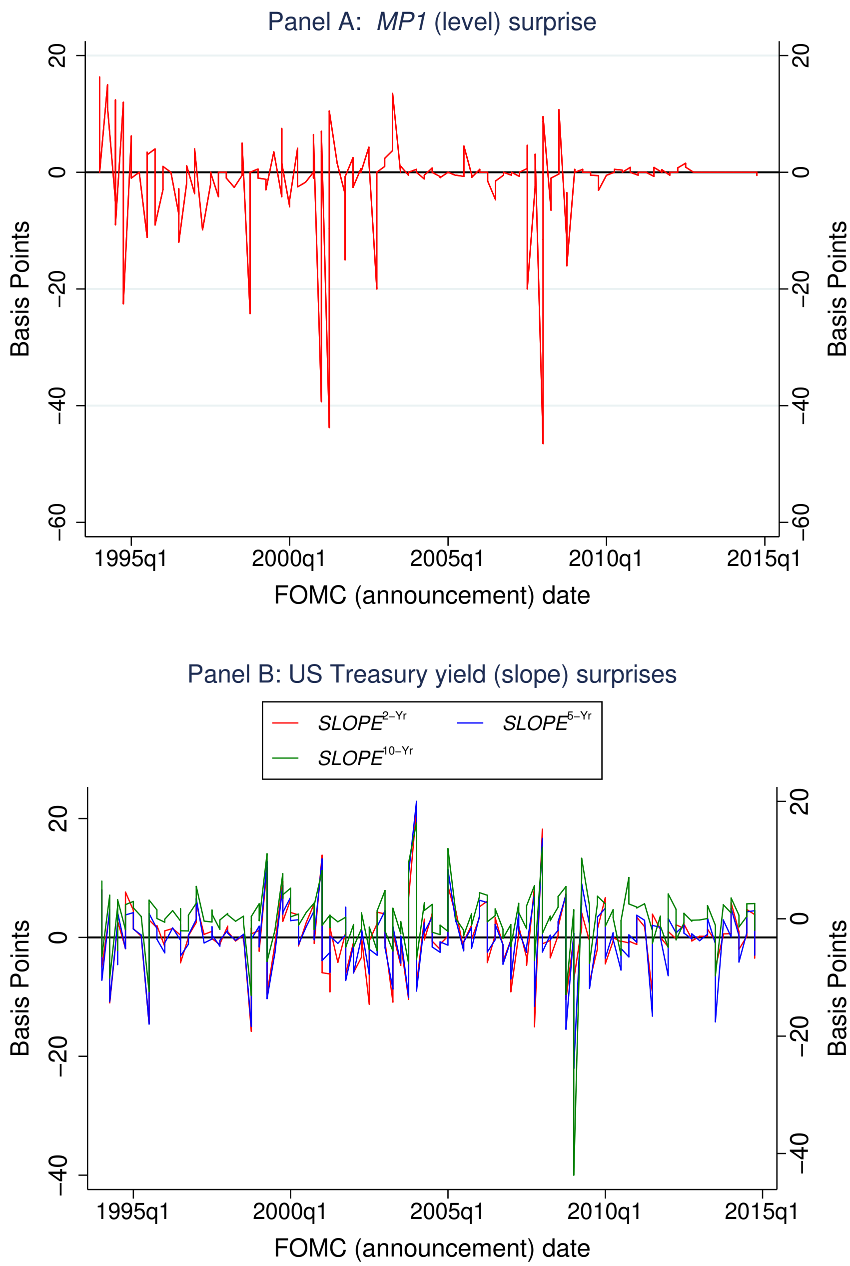

Figure 2.1: Monetary policy shocks. Panel A shows level surprises, computed as scaled price changes of Federal Funds Futures contracts in the narrow 30-minute window around the FOMC announcements. Panel B shows U.S. treasury yield slope surprises for 2-, 5-, and 10-year horizons. The shocks are computed as residuals from the OLS regression of the changes in Treasury yields in the narrow 30-minute window around the announcement on the level surprises. Sample period is 1994-2014.

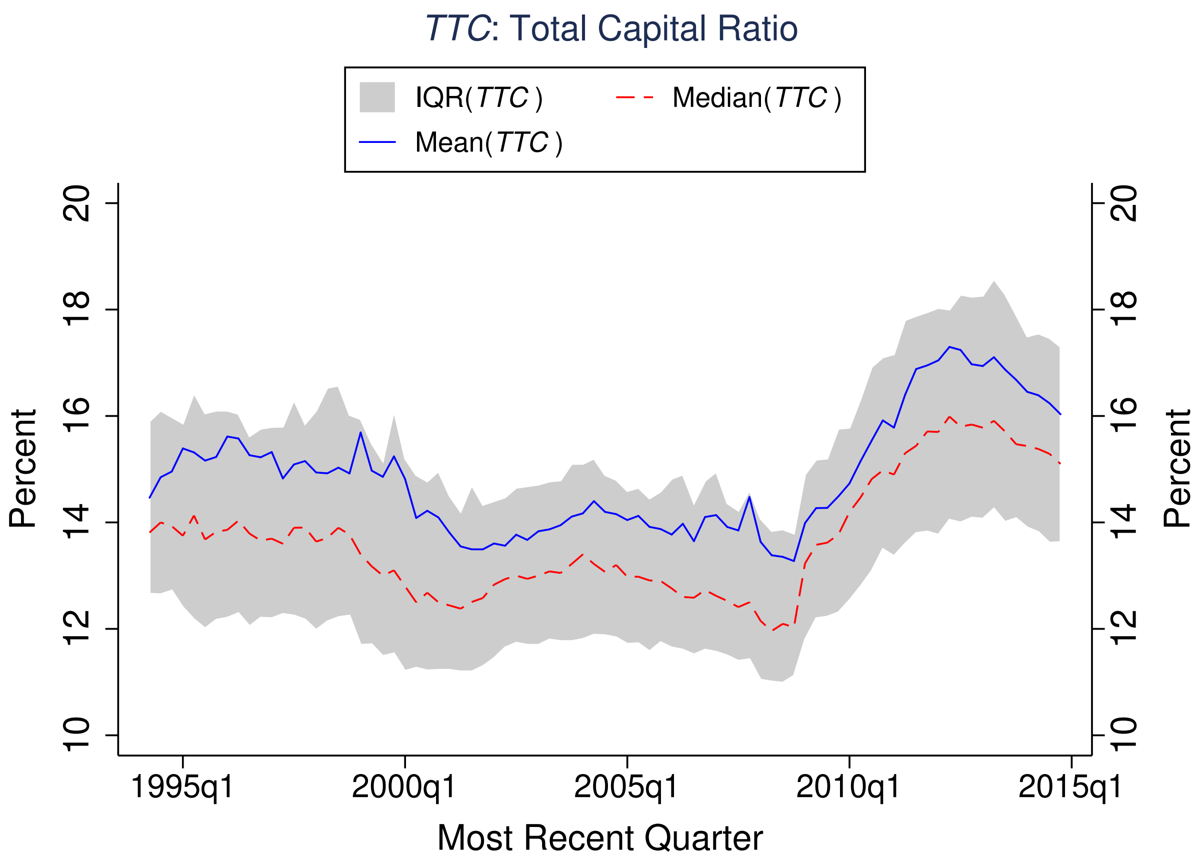

Figure 2.2: Time-series of the Total Capital Ratio of banks in the sample. Total capital ratio is computed as a ratio of tier 1 capital and tier 2 capital to average risk-weighted assets. Outliers above 99th and below 1st percentile at each date are excluded. Sample period is 1994-2014.

2.6 Tables

Table 2.1: Summary Statistics. MP1 is the level surprise; SLOPE variables are the unexpected changes in slope of the U.S. Treasury yield curve, computed as OLS residuals. TTC is the total capital ratio; R is the percentage return of bank equity in the 30-minute window around the FOMC announcement; BM is book-to-market ratio; LOANS is the loans-to-assets ratio; IGAP is the income gap; ROE is the return on equity; SDEP and DDEP are saving and demand deposits respectively. ΔY is the change in the yield in the 2-day window around the announcement; T and T - t are overall and remaining maturity respectively; RATING is the aggregated credit rating obtained via Mergent FISD (lower values encode higher rating). SWAPS, FUT, FOR are swap, futures and forward contracts respectively; ET and OTC are the exchange-trades and over-the-counter options respectively; (w) and (p) denote written and purchased options respectively. Sample period is 1994-2014.

Panel A: Monetary Policy Shocks								
	Mean	SD	P5	P25	Median	P75	P95	Obs
MP1	-1.23	7.89	-15.00	-1.00	0.00	0.65	9.54	177
SLOPE$^{\text{2-Yr}}$	0.08	5.14	-9.54	-1.55	0.19	2.29	7.63	172
SLOPE$^{\text{5-Yr}}$	0.12	5.53	-10.30	-1.85	0.42	2.86	8.06	172
SLOPE$^{\text{10-Yr}}$	0.06	5.40	-7.28	-1.69	0.42	2.44	7.03	172
Panel B: Bank Balance Sheet and Return Data								
	Mean	SD	P5	P25	Median	P75	P95	Obs
TTC	14.87	5.30	10.59	12.05	13.70	16.00	22.64	45309
R (%)	0.10	1.20	-1.82	-0.38	0.00	0.56	2.22	45463
ME [USD Mil]	1367.52	6524.38	15.00	49.15	132.37	478.04	4961.22	45458
BM	90.19	86.07	32.91	49.74	68.99	99.71	211.16	44320
LOANS (%)	65.57	12.58	43.53	59.63	67.07	73.56	83.12	39062
IGAP (%)	10.37	18.93	-19.66	-0.56	10.21	21.75	40.15	39061
ROE (%)	1.85	25.88	-1.28	1.53	2.66	3.66	5.13	45401
SDEP (%)	33.97	15.44	10.99	23.13	32.24	43.97	62.27	39062
DDEP (%)	5.86	5.91	0.36	1.62	3.64	8.57	17.65	39062
Panel C: Bank Bonds Data								
	Mean	SD	P5	P25	Median	P75	P95	Obs
ΔY (%)	0.01	0.30	-0.45	-0.12	0.00	0.12	0.51	4741
T	11.08	6.21	5.00	10.00	10.00	12.00	30.00	4738
T - t	7.12	6.15	1.00	3.00	6.00	9.00	25.00	4738
RATING	5.94	2.53	3.00	4.00	5.00	7.00	11.00	4738
Panel D: Interest Rate Derivative Data								
	Mean	SD	P5	P25	Median	P75	P95	Obs
SWAPS	0.06	0.27	0.00	0.00	0.00	0.03	0.22	39053
FUT	0.01	0.09	0.00	0.00	0.00	0.00	0.02	37918
FOR	0.02	0.12	0.00	0.00	0.00	0.00	0.06	37918
ET OPT (w)	0.00	0.05	0.00	0.00	0.00	0.00	0.00	37918
ET OPT (p)	0.01	0.05	0.00	0.00	0.00	0.00	0.00	37918
OTC OPT (w)	0.02	0.10	0.00	0.00	0.00	0.00	0.05	37918
OTC OPT (p)	0.02	0.09	0.00	0.00	0.00	0.00	0.06	37918

Table 2.2: Cross-sectional regressions of tight-window stock returns:

$$R_{i,t} = \alpha_i + \beta_0 MP1_t + \beta_1 SLOPE_t + \beta_2 \left(MP1_t \times TTC_{i,t}\right) + \beta_3 \left(SLOPE_t \times TTC_{i,t}\right) + \gamma \mathbf{X}_{i,t} + \epsilon_{i,t}$$

Where $R_{i,t}$ is the stock return of bank i in the narrow 30-minute window around FOMC announcement t. $MP1_t$ and $SLOPE_t$ are level and slope monetary policy surprises, respectively, $TTC_{i,t}$ is the total capital ratio of bank i prior to the announcement t, $\mathbf{X}_{i,t}$ is the vector of controls that includes balance sheet items and their interactions with $MP1_t$ (specifications (4), (5), and (6)), and additionally interest rate derivative holdings and their interactions with $MP1_t$ (specifications (7), (8), and (9)). All specifications include bank fixed effects. Regressions are estimated using OLS and standard errors are clustered at the announcement level. Sample period is 1994-2014.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MP1	-4.224***	-4.251***	-4.233***	-5.174***	-5.379***	-5.165***	-5.283***	-5.528***	-5.315***
	(-3.987)	(-3.943)	(-4.048)	(-4.855)	(-5.127)	(-5.034)	(-4.820)	(-5.113)	(-5.175)
MP1 * TTC	0.111***	0.112***	0.112***	0.122***	0.120***	0.120***	0.105**	0.103**	0.102***
	(2.973)	(3.017)	(3.233)	(2.781)	(2.858)	(3.036)	(2.352)	(2.418)	(2.638)
$\text{SLOPE}^{\text{2-Yr}}$	-1.995			-5.474**			-4.665*		
	(-1.229)			(-2.123)			(-1.752)		
$\text{SLOPE}^{\text{2-Yr}}$ * TTC	0.0584			0.0771			0.0724		
	(1.002)			(0.870)			(0.792)		
$\text{SLOPE}^{\text{5-Yr}}$		-2.654*			-5.011**			-4.275*	
		(-1.866)			(-2.213)			(-1.809)	
$\text{SLOPE}^{\text{5-Yr}}$ * TTC		0.0679			0.0796			0.0753	
		(1.218)			(0.956)			(0.883)	
$\text{SLOPE}^{\text{10-Yr}}$			-3.018***			-4.385**			-3.600
			(-2.613)			(-2.179)			(-1.619)
$\text{SLOPE}^{\text{10-Yr}}$ * TTC			0.0459			0.0208			0.0153
			(1.315)			(0.308)			(0.223)
R-squared	0.043	0.046	0.052	0.054	0.058	0.063	0.056	0.060	0.065
Observations	43880	43880	43880	37378	37378	37378	36232	36232	36232
Bank-Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Interactions with Balance-Sheet Items				Yes	Yes	Yes	Yes	Yes	Yes
Interactions with Interest Rate Derivatives							Yes	Yes	Yes

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.3: Cross-sectional regressions of tight-window squared stock returns:

$$R_{i,t}^2 = \alpha_i + \beta_0 MP1_t^2 + \beta_1 SLOPE_t^2 + \beta_2 \left(MP1_t^2 \times TTC_{i,t}\right) + \beta_3 \left(SLOPE_t^2 \times TTC_{i,t}\right) + \gamma \mathbf{X}_{i,t} + \epsilon_{i,t}$$

Where $R_{i,t}^2$ is the squared stock return of bank i in the narrow 30-minute window around FOMC announcement t. $MP1_t^2$ and $SLOPE_t^2$ are squared level and slope monetary policy surprises, respectively, $TTC_{i,t}$ is the total capital ratio of bank i prior to the announcement t, $\mathbf{X}_{i,t}$ is the vector of controls that includes balance sheet items and their interactions with $MP1_t^2$ (specifications (4), (5), and (6)), and additionally interest rate derivative holdings and their interactions with $MP1_t^2$ (specifications (7), (8), and (9)). All specifications include bank fixed effects. Regressions are estimated using OLS and standard errors are clustered at the announcement level. Sample period is 1994-2014.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$MP1^2$	33.15***	33.15***	35.23***	42.43***	37.26**	36.46**	39.68**	34.77**	34.54*
	(3.707)	(3.990)	(3.748)	(2.775)	(2.153)	(2.068)	(2.500)	(1.998)	(1.958)
$MP1^2$ * TTC	-1.008***	-0.982***	-0.984***	-0.755***	-0.976***	-1.064***	-0.766***	-1.000***	-1.080***
	(-3.904)	(-3.895)	(-3.782)	(-3.468)	(-4.504)	(-4.606)	(-3.798)	(-5.102)	(-5.088)
$(SLOPE^{2\text{-}Yr})^2$	58.90			19.80			34.29		
	(1.270)			(0.318)			(0.608)		
$(SLOPE^{2\text{-}Yr})^2$ * TTC	-0.620			-2.415			-2.564		
	(-0.515)			(-1.454)			(-1.536)		
$(SLOPE^{5\text{-}Yr})^2$		73.80			69.23			71.89	
		(1.647)			(0.991)			(1.046)	
$(SLOPE^{5\text{-}Yr})^2$ * TTC		-0.954			-0.514			-0.454	
		(-0.790)			(-0.309)			(-0.281)	
$(SLOPE^{10\text{-}Yr})^2$			43.50***			78.29***			78.67***
			(23.573)			(6.128)			(5.076)
$(SLOPE^{10\text{-}Yr})^2$ * TTC			-0.739***			-0.418			-0.433
			(-10.900)			(-0.674)			(-0.887)
R-squared	0.067	0.078	0.085	0.091	0.096	0.102	0.095	0.100	0.106
Observations	43880	43880	43880	37671	37671	37671	36522	36522	36522
Bank-Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Interactions with Balance-Sheet Items				Yes	Yes	Yes	Yes	Yes	Yes
Interactions with Interest Rate Derivatives							Yes	Yes	Yes

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.4: Cross-sectional regressions of tight-window stock returns. Dependent variable is $R_{i,t}$, the stock return of bank i in the narrow 30-minute window around FOMC announcement t. $MP1$ and $SLOPE$ are level and slope monetary policy surprises, respectively, TTC is the total capital ratio of bank prior to the announcement, $1_{\text{TTC} < \text{MED(TTC)}}$ is the indicator variable for the banks that have total capital ratio below the median in the sample of all banks at a time of an announcement. All specifications include balance sheet and interest rate derivative controls, and their interactions with $MP1$. All specifications include bank fixed effects. Regressions are estimated using OLS and standard errors are clustered at the announcement level. Sample period is 1994-2014.

	(1)	(2)	(3)
MP1	-4.734***	-5.021***	-4.808***
	(-4.406)	(-4.744)	(-4.950)
MP1 * TTC	0.0720	0.0717	0.0710
	(1.342)	(1.388)	(1.531)
MP1 * TTC * $1_{\text{TTC} < \text{MED(TTC)}}$	-0.0481**	-0.0453**	-0.0455**
	(-2.257)	(-2.108)	(-2.125)
SLOPE$^{\text{2-Yr}}$	-5.006*		
	(-1.730)		
SLOPE$^{\text{2-Yr}}$ * TTC	0.0974		
	(0.874)		
SLOPE$^{\text{2-Yr}}$ * TTC * $1_{\text{TTC} < \text{MED(TTC)}}$	0.0455		
	(1.043)		
SLOPE$^{\text{5-Yr}}$		-4.774*	
		(-1.762)	
SLOPE$^{\text{5-Yr}}$ * TTC		0.110	
		(1.003)	
SLOPE$^{\text{5-Yr}}$ * TTC * $1_{\text{TTC} < \text{MED(TTC)}}$		0.0572	
		(1.044)	
SLOPE$^{\text{10-Yr}}$			-4.402*
			(-1.695)
SLOPE$^{\text{10-Yr}}$ * TTC			0.0629
			(0.706)
SLOPE$^{\text{10-Yr}}$ * TTC * $1_{\text{TTC} < \text{MED(TTC)}}$			0.0587
			(1.480)
R-squared	0.057	0.061	0.066
Observations	36232	36232	36232
Bank-Fixed Effects	Yes	Yes	Yes
Interactions with Balance-Sheet Items	Yes	Yes	Yes
Interactions with Interest Rate Derivatives	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.5: Cross-sectional regressions of tight-window stock returns. Dependent variable is $R_{i,t}$, the stock return of bank i in the narrow 30-minute window around FOMC announcement t. $MP1$ and $SLOPE$ are level and slope monetary policy surprises, respectively, TTC is the total capital ratio of bank prior to the announcement, $1_{\mathrm{MP1}>0}$ is the indicator variable for the announcements with contractionary level monetary policy surprises. Some specifications include balance sheet and interest rate derivative controls, and their interactions with $MP1$. All specifications include bank fixed effects. Regressions are estimated using OLS and standard errors are clustered at the announcement level. Sample period is 1994-2014.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MP1	-3.930***	-3.974***	-3.988***	-4.657***	-4.993***	-4.759***	-4.554***	-4.940***	-4.723***
	(-3.007)	(-2.992)	(-3.127)	(-4.182)	(-4.469)	(-4.293)	(-4.343)	(-4.710)	(-4.605)
MP1 * $1_{\mathrm{MP1}>0}$	-1.516	-1.431	-1.269	-2.872	-2.282	-2.330	-3.806	-3.031	-2.896
	(-0.625)	(-0.574)	(-0.517)	(-0.797)	(-0.638)	(-0.657)	(-0.748)	(-0.607)	(-0.590)
MP1 * TTC	0.0951**	0.0972**	0.0986**	0.0990**	0.0968**	0.0978**	0.0910*	0.0884*	0.0887**
	(2.159)	(2.230)	(2.476)	(2.030)	(2.073)	(2.298)	(1.823)	(1.849)	(2.069)
MP1 * $1_{\mathrm{MP1}>0}$ * TTC	0.0836	0.0790	0.0704	0.143	0.140	0.131	0.0998	0.0973	0.0885
	(0.788)	(0.743)	(0.688)	(1.232)	(1.212)	(1.199)	(0.803)	(0.787)	(0.764)
$\mathrm{SLOPE}^{\text{2-Yr}}$	-2.028			-5.730**			-4.943*		
	(-1.261)			(-2.244)			(-1.867)		
$\mathrm{SLOPE}^{\text{2-Yr}}$ * TTC	0.0597			0.0769			0.0723		
	(1.034)			(0.898)			(0.813)		
$\mathrm{SLOPE}^{\text{5-Yr}}$		-2.666*			-5.184**			-4.449*	
		(-1.883)			(-2.268)			(-1.859)	
$\mathrm{SLOPE}^{\text{5-Yr}}$ * TTC		0.0683			0.0786			0.0751	
		(1.232)			(0.957)			(0.893)	
$\mathrm{SLOPE}^{\text{10-Yr}}$			-3.017***			-4.697**			-3.905*
			(-2.630)			(-2.304)			(-1.731)
$\mathrm{SLOPE}^{\text{10-Yr}}$ * TTC			0.0456			0.0238			0.0183
			(1.314)			(0.358)			(0.270)
R-squared	0.043	0.047	0.052	0.052	0.056	0.061	0.055	0.059	0.063
Observations	43880	43880	43880	37671	37671	37671	36522	36522	36522
Bank-Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Interactions with Balance-Sheet Items				Yes	Yes	Yes	Yes	Yes	Yes
Interactions with Interest Rate Derivatives							Yes	Yes	Yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.6: Cross-sectional regressions of two-day bond yield changes:

$$\Delta Y_{i,t} = \alpha_i + \beta_0 MP1_t + \beta_1 SLOPE_t + \beta_2 \left(MP1_t \times TTC_{i,t}\right) + \beta_3 \left(SLOPE_t \times TTC_{i,t}\right) + \gamma \mathbf{X}_{i,t} + \epsilon_{i,t}$$

Where $\Delta Y_{i,t}$ is the change of the yield of corporate bonds of bank i in the 2-day window around FOMC announcement t. $MP1_t$ and $SLOPE_t$ are level and slope monetary policy surprises, respectively, $TTC_{i,t}$ is the total capital ratio of bank i prior to the announcement t, $\mathbf{X}_{i,t}$ is the vector of controls that includes rating, maturity, and balance sheet items and their interactions with $MP1_t$ (specifications (4), (5), and (6)), and additionally interest rate derivative holdings and their interactions with $MP1_t$ (specifications (7), (8), and (9)). All specifications include bank fixed effects. Regressions are estimated using OLS and standard errors are clustered at the announcement level. Sample period is 1994-2014.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MP1	-0.808	-0.716	-1.077	-2.125	-2.828	-3.051	-7.012*	-7.529*	-7.483*
	(-0.608)	(-0.554)	(-0.904)	(-0.820)	(-0.977)	(-1.126)	(-1.853)	(-1.887)	(-1.879)
MP1 * TTC	0.113	0.106	0.132	0.196	0.241*	0.244*	0.290**	0.329**	0.351***
	(0.948)	(0.895)	(1.217)	(1.534)	(1.703)	(1.829)	(2.467)	(2.615)	(2.911)
$SLOPE^{2\text{-Yr}}$	1.705			3.168*			5.932**		
	(1.031)			(1.927)			(2.476)		
$SLOPE^{2\text{-Yr}}$ * TTC	-0.0705			-0.206**			-0.295**		
	(-0.536)			(-2.299)			(-2.491)		
$SLOPE^{5\text{-Yr}}$		2.112*			1.724			4.032**	
		(1.811)			(1.363)			(2.172)	
$SLOPE^{5\text{-Yr}}$ * TTC		-0.0981			-0.122*			-0.200**	
		(-1.076)			(-1.695)			(-2.142)	
$SLOPE^{10\text{-Yr}}$			2.518*			3.183			6.105**
			(1.901)			(1.643)			(2.331)
$SLOPE^{10\text{-Yr}}$ * TTC			-0.141			-0.224**			-0.328**
			(-1.478)			(-2.103)			(-2.425)
R-squared	0.048	0.056	0.050	0.064	0.073	0.073	0.063	0.071	0.070
Observations	4456	4456	4456	4362	4362	4362	4372	4372	4372
Bank-Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Interactions with Balance-Sheet Items				Yes	Yes	Yes	Yes	Yes	Yes
Interactions with Interest Rate Derivatives							Yes	Yes	Yes

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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Appendix A

Appendix to Chapter 1

Proof of Theorem 1

I posit that in the equilibrium the optimists are long in the risky asset $\mu_A > 0$, pessimists are sidelined $\mu_B = 0$ and arbitrageurs are short $\mu_{hf} < 0$. I would verify that in this case the unique equilibrium for the price of the risky asset is given by Theorem 1, and then I would derive the values of exogenous parameters that would generate this type of equilibrium.

The first order condition for the optimistic investor is:

$$d + b\lambda - P(1+r) = \mu_A \frac{1}{\gamma} b^2 \sigma_z^2$$

Arbitrageur is short the risky asset, and after paying the fee her proceedings are reduced by a factor of $(1-c)$:

$$d - P(1-c)(1+r) = \mu_{hf} \frac{1}{\gamma} b^2 \sigma_z^2$$

Since pessimists have zero holdings $\mu_B = 0$, the market clearing condition is:

$$\frac{\alpha}{2}\mu_A + (1-\alpha)\mu_{hf} = 1$$

Multiplying first equation by $\frac{\alpha}{2}$ and second equation by $(1-\alpha)$, and summing them up:

$$d\left(1 - \frac{\alpha}{2}\right) + b\lambda\frac{\alpha}{2} - P(1+r)\left(\frac{\alpha}{2} + (1-c)(1-\alpha)\right) = \frac{1}{\gamma} b^2 \sigma_z^2$$

Solving for the price yields:

$$P_1(1+r) = \left[d\left(1 - \frac{\alpha}{2}\right) - \frac{1}{\gamma} b^2 \sigma_z^2\right] \times \frac{1}{\left(1 - \frac{\alpha}{2}\right) - c(1-\alpha)} + \frac{b\lambda\frac{\alpha}{2}}{\left(1 - \frac{\alpha}{2}\right) - c(1-\alpha)}$$

Clearly, the solution is unique. Now, the three following inequalities determine conditions that need to hold for demands to satisfy $\mu_A > 0$, $\mu_{hf} < 0$ and $\mu_B = 0$:

$$\begin{aligned} d + b\lambda - P(1+r) &> 0 \\ d - P(1-c)(1+r) &< 0 \\ d - b\lambda - P(1+r) &< 0 \end{aligned}$$

Since $b\lambda > 0$, third condition would be satisfied when the second is satisfied, so the former is redundant. Plugging the expression for price in the first condition:

$$\lambda > \frac{dc(1-\alpha) - \frac{1}{\gamma}b^2\sigma_z^2}{b(1-c)(1-\alpha)} = \frac{dc}{b(1-c)} - \frac{b\sigma_z^2}{\gamma(1-c)(1-\alpha)}$$

And in the second condition:

$$\lambda > \frac{dc}{b(1-c)} + \frac{2b\sigma_z^2}{\gamma\alpha}$$

The second inequality is a more strict condition for λ, so it defines the condition for the equilibrium.

Proof of Corollary 1

Using the first order Taylor series expansion on the fractional term:

$$\begin{aligned} \frac{1}{\left(1-\frac{\alpha}{2}\right) - c(1-\alpha)} &= \frac{1}{1-\frac{\alpha}{2}} \times \frac{1}{1 - c\frac{1-\alpha}{1-\frac{\alpha}{2}}} \\ &= \frac{1}{1-\frac{\alpha}{2}} \times \left(1 + c\frac{1-\alpha}{1-\frac{\alpha}{2}} + \dots\right) \\ &\approx \frac{1}{1-\frac{\alpha}{2}} \times \left(1 + c\frac{1-\alpha}{1-\frac{\alpha}{2}}\right) \end{aligned}$$

Plugging this into the solution for the price, yields the desired result.

Appendix B

Appendix to Chapter 2

Additional Tables

Table B1: Controls for the regressions reported in Table 2.2, specifications (4), (5) and (6).

	(4)	(5)	(6)
MP1 * ME [USD Mil]	-0.000164***	-0.000166***	-0.000170***
	(-4.035)	(-4.299)	(-4.463)
MP1 * BM	0.00458	0.00708	0.00611
	(0.597)	(1.185)	(1.029)
MP1 * LOANS (%)	-0.00417	-0.00485	-0.00591
	(-0.284)	(-0.311)	(-0.361)
MP1 * IGAP (%)	-0.00572	-0.00385	-0.00368
	(-0.622)	(-0.417)	(-0.408)
MP1 * ROE (%)	0.0170	0.0170	0.0143
	(0.427)	(0.399)	(0.333)
MP1 * SDEP (%)	0.00942	0.0117	0.0105
	(0.395)	(0.492)	(0.436)
MP1 * DDEP (%)	0.115***	0.118***	0.116***
	(4.941)	(5.199)	(5.110)
R-squared	0.054	0.058	0.063
Observations	37378	37378	37378
Bank-Fixed Effects	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B2: Controls for the regressions reported in Table 2.2, specifications (7), (8) and (9).

	(7)	(8)	(9)
MP1 * SWAPS	-2.188**	-1.983**	-1.859**
	(-2.319)	(-2.189)	(-2.156)
MP1 * FUT	0.864	0.521	0.625
	(0.518)	(0.319)	(0.395)
MP1 * FOR	6.869***	7.470***	7.666***
	(2.636)	(2.885)	(2.962)
MP1 * ET OPT (w)	-5.532	-6.334	-7.356
	(-1.193)	(-1.354)	(-1.598)
MP1 * ET OPT (p)	6.546	7.225	7.974*
	(1.457)	(1.585)	(1.756)
MP1 * OTC OPT (w)	1.596	2.016	2.039
	(0.490)	(0.603)	(0.605)
MP1 * OTC OPT (p)	-2.117	-2.859	-3.231
	(-0.509)	(-0.650)	(-0.697)
R-squared	0.056	0.060	0.065
Observations	36232	36232	36232
Bank-Fixed Effects	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B3: Controls for the regressions reported in Table 2.3, specifications (4), (5) and (6).

	(4)	(5)	(6)
$MP1^2$ * ME [USD Mil]	0.00212***	0.00228***	0.00235***
	(5.889)	(6.040)	(5.355)
$MP1^2$ * BM	-0.170***	-0.0238	0.0478
	(-2.927)	(-0.487)	(0.537)
$MP1^2$ * LOANS (%)	-0.00682	-0.0527	-0.0657
	(-0.029)	(-0.224)	(-0.267)
$MP1^2$ * IGAP (%)	0.240**	0.249**	0.252**
	(2.232)	(2.221)	(2.164)
$MP1^2$ * ROE (%)	-0.152	0.252	0.181
	(-0.278)	(0.377)	(0.280)
$MP1^2$ * SDEP (%)	-0.245	-0.211	-0.191
	(-1.139)	(-0.944)	(-0.840)
$MP1^2$ * DDEP (%)	0.264	0.278	0.120
	(1.267)	(1.214)	(0.750)
R-squared	0.091	0.096	0.102
Observations	37671	37671	37671
Bank-Fixed Effects	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B4: Controls for the regressions reported in Table 2.3, specifications (7), (8) and (9).

	(7)	(8)	(9)
$MP1^2$ * SWAPS	23.08**	19.18*	21.92**
	(2.178)	(1.798)	(2.089)
$MP1^2$ * FUT	-21.07*	-19.16	-19.76
	(-1.695)	(-1.513)	(-1.298)
$MP1^2$ * FOR	-125.2***	-130.8***	-142.9***
	(-3.289)	(-4.074)	(-4.463)
$MP1^2$ * ET OPT (w)	224.9**	252.9**	280.6**
	(2.003)	(2.223)	(2.001)
$MP1^2$ * ET OPT (p)	-111.5	-140.6	-180.9
	(-0.701)	(-0.857)	(-1.075)
$MP1^2$ * OTC OPT (w)	-28.57	-29.49	-39.73
	(-0.964)	(-1.141)	(-1.651)
$MP1^2$ * OTC OPT (p)	25.19	31.30	61.46
	(0.381)	(0.473)	(0.900)
R-squared	0.095	0.100	0.106
Observations	36522	36522	36522
Bank-Fixed Effects	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$