Illusive Asymmetry in Stock Price Reactions to Monetary Policy Shocks*

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Abstract

Stock price data and high-frequency identification techniques are commonly used to assess the impact of monetary policy shocks on firms. This study cautions against this approach, showing that challenges in identifying monetary policy shocks due to information effects create endogeneity problems, particularly for larger firms' stock prices. We empirically demonstrate this issue and present a nominal asset pricing model incorporating granular origins of aggregate fluctuations and investors' imperfect knowledge of monetary policy rule parameters. It reveals that changes in investors' beliefs following FOMC announcements lead to monetary policy surprises and stock price changes due to shifts in stochastic discount factors.

Key words: Monetary policy shock, Stock returns, High-frequency identification, Information effect, Learning, Stochastic discount factors

JEL Classification: E43, E44, E52, E58

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1 Introduction

The influence of monetary policy on firms' performance and behavior is a critical channel for its transmission. Extensive empirical research has examined how monetary policy shocks differently affect large and small firms, with recent studies presenting conflicting evidence on which firms experience more pronounced impacts. Specifically, there is substantial evidence that monetary policy shocks have a greater effect on the production and investment activities of smaller firms, supporting the notion that these firms face tighter financial constraints and frictions, making them more sensitive to monetary policy shocks (e.g., Gertler and Gilchrist, 1994; Thorbecke, 1997; Ehrmann and Fratzscher, 2004; Maio, 2014; Ottonello and Winberry, 2020; Durante, Ferrando and Vermeulen, 2022). In contrast, several recent studies using high-frequency financial data and high-frequency identification (HFI) techniques indicate that larger firms' stock prices are more responsive to these shocks (e.g., Ozdagli, 2018; Chava and Hsu, 2020; Morlacco and Zeke, 2021; Döttling and Ratnovski, 2023).

This study reexamines stock price responses to monetary policy shocks, focusing on the identification challenges of these shocks inherent in the HFI approach. The HFI approach, which examines interest rate changes within a narrow window around Federal Open Market Committee (FOMC) announcements, referred to as monetary policy surprises, has gained traction for its potential to address endogeneity issues in empirical monetary policy analysis. However, recent studies have revealed significant methodological challenges, showing that high-frequency monetary policy surprises can be predicted using publicly available macroeconomic or financial market data before FOMC announcements (e.g., Cieslak, 2018; Miranda-Agrippino and Ricco, 2021; Bauer and Swanson, 2023a,b). Given this, Bauer and Swanson (2023a) highlight an endogeneity issue arising from information frictions, termed the Fed's response to the news channel, which questions the traditional view of monetary policy surprises as purely exogenous shocks. This effect suggests that monetary policy surprises might not only reflect exogenous policy shocks but also the disparity between the Fed's actual policy response function (f) and the private sector's ex-ante belief of that function ($\hat{f}$). Leveraging these insights, our emprical analysis examines how this identification issue concerning monetary policy shocks affects the estimation of stock price reactions to these shocks.

Section 2 unveils our principal empirical findings. First, we corroborate the observations from previous studies by Ozdagli (2018) and Chava and Hsu (2020), employing the conventional HFI method to quantify monetary policy surprises. Our results confirm that larger firms exhibit a stronger reaction to monetary policy surprises compared to their smaller counterparts.[1] Next, we demonstrate that these high-frequency monetary policy surprises can be predicted using publicly available macroeconomic data, indicating the presence of the Fed's response to the news channel, as suggested by Bauer and Swanson (2023a,b). Building on their insights, we compute a refined estimate of monetary policy shocks by filtering out the predictable component of the monetary policy surprises.

Our analysis reveals that using this refined measure of monetary policy surprises as an instrument for monetary policy shocks significantly reduces the excess stock return response of large firms. This implies that the excess stock return response of large firms is primarily driven by predictable monetary policy surprises, rather than unpredictable ones. Given that unpredictable monetary policy surprises are better indicators of monetary policy shocks, our empirical findings suggest that the greater stock price reactions of large firms to conventional monetary policy surprises do not reflect heterogeneity in the impact of monetary policy shocks on firm profits. Instead, these reactions result from investors revising their beliefs about the Fed's monetary policy rule, which affects stock prices differently across firms.

To clarify our interpretation of the empirical findings, Section 3 introduces a monetary asset pricing model that incorporates granular sources of aggregate fluctuations, drawing on Gabaix (2011). This model's representation of stock prices aligns with the Lucas (1978) tree economy framework. It includes a continuum of "small" firms and a finite number of "large" firms, where idiosyncratic shocks to these large firms generate granular-origin aggregate fluctuations. Consequently, large firms' output and profits exhibit a stronger correlation with aggregate fluctuations than those of smaller firms.

Households in this model are characterized by a money-in-the-utility function as described by Galí (2015), with the stochastic discount factor (SDF) influenced by nominal interest rates. The model incorporates a central bank's policy rule that links the nominal interest rate to aggregate measures, such as the GDP gap. The dynamic interaction between granular-

[1] Our analysis includes all publicly traded U.S. firms listed in Compustat, with stock returns calculated from daily returns on FOMC announcement days.

origin aggregate fluctuations and the SDF, influenced by nominal interest rates, elucidates how central bank responses to aggregate measures affect the covariance between the SDF and large firms' profit fluctuations.

The model highlights the presence of information frictions. Despite private sector agents being aware of the central bank's commitment to its policy rule, they possess imperfect knowledge about the specific parameters of the monetary policy rule. This setup results in (measured) monetary policy surprises stemming from the disparity between the Fed's actual policy response function and investors' ex-ante beliefs about that function, as well as from exogenous policy shocks.

The model incorporates a learning mechanism for private sector agents, allowing them to decipher the central bank's policy rule through FOMC announcements. Consequently, monetary policy surprises prompt investors to reassess the central bank's policy activeness, leading them to update their SDF. This update affects firms' stock prices heterogeneously as it impacts the covariance between investors' SDF and firms' dividend growth differently across small and large firms.

Leveraging this theoretical model, we illustrate that investors' updating process of their SDF upon FOMC announcements induces deceptive stock price reactions to monetary policy shocks. Specifically, even when monetary policy shocks have no impact on firms' profits, a distinct correlation emerges between monetary policy surprises and stock price changes following monetary policy announcements, with this correlation exhibiting significant variation between smaller and larger firms. Therefore, combined with the empirical findings noted earlier, we infer that the differences in the correlation between monetary policy surprises and stock price reactions to monetary policy announcements across firms do not mirror heterogeneity in the effects of monetary policy shocks on firm profitability. Instead, they primarily result from the heterogeneous effects that investors' learning about the monetary policy rule has on stock prices through changes in their SDF.

Finally, in Section 4, we provide further empirical evidence that supports the implications of our theoretical model. The model highlights that investors' learning about the policy rule parameter in response to monetary policy surprises is a key driver of heterogeneous stock price reactions. This suggests that when uncertainty about the future monetary policy stance is high, making it difficult for investors to learn, the effect of learning is small, and the heterogeneity in stock price reactions to monetary policy surprises is expected to be reduced. To empirically test this implication, we use the monetary policy uncertainty index constructed by Bauer, Lakdawala and Mueller (2022a) and extend the regression analysis in Section 2 to examine how the degree of monetary policy uncertainty affects the heterogeneity in stock price reactions to monetary policy surprises. The extended empirical analysis reveals that heterogeneous stock price reactions to monetary policy surprises are observed only when monetary policy uncertainty is low and investors can easily infer the monetary policy stance from FOMC announcements.

Related Literature This study contributes to the empirical literature on the effects of monetary policy on firms. Numerous studies have investigated how the impact of monetary policy on firm behavior varies between large and small firms. Pioneering work by Gertler and Gilchrist (1994) reveals that smaller firms exhibit a more pronounced investment response to monetary policy shocks. Subsequent studies, such as those by Ottonello and Winberry (2020) and Durante et al. (2022) validate this pattern using the HFI approach to further explore how investment reactions to monetary policy shocks differ across firm sizes. The accumulated evidence supports the financial constraint hypothesis, indicating that expansionary monetary policy alleviates financial restrictions for smaller firms, thereby eliciting a stronger investment response.[2]

Grounded in Tobin's Q theory, which shows a parallel between stock price responses and investment reactions, several studies have examined the sensitivity of stock returns to monetary policy shocks. The results, however, are mixed: while Ozdagli (2018), Morlacco and Zeke (2021), and Döttling and Ratnovski (2023) find that larger firms' stocks are more reactive to monetary policy shocks, studies by Thorbecke (1997), Ehrmann and Fratzscher (2004), and Maio (2014) report greater sensitivity among smaller firms' stocks.[3] Our study

[2] According to this hypothesis, a contractionary monetary shock increases the agency costs associated with external financing, reducing firms' access to bank loans. Consequently, these firms reduce their investment levels, leading to lower cash flows and returns.

[3] Thorbecke (1997) and Maio (2014) examine the impact of monetary policy on monthly returns, focusing on portfolio returns rather than individual-level responses. The monetary policy shocks in these studies are typically associated with changes in the federal funds rate, rather than futures contracts. In contrast, Ehrmann and Fratzscher (2004) analyzes the response of S&P 500 firms over the sample period 1994-

estimates firms' stock price reactions to monetary policy shocks using a refined approach and offers a theoretical rationale, grounded in asset pricing theory, for why the heterogeneity in stock price responses observed in earlier studies is substantially reduced in the refined estimates. The innovative aspect of our work lies in examining investors' learning about the monetary policy rule and the resulting impact of changes in the SDF on stock prices.

In addition, this study enriches the literature on the HFI of monetary policy shocks. Assessing the impact of changes in monetary policy is a crucial aspect of macroeconomics, yet encounters empirical hurdles due to endogeneity issues. To overcome these challenges, an increasing number of empirical studies have turned to the HFI approach. This method involves using high-frequency monetary policy surprises to assess the effects of monetary policy on various macroeconomic outcomes, as explored by Cochrane and Piazzesi (2002), Faust, Swanson and Wright (2004), Gertler and Karadi (2015), and Ramey (2016); on firms' investment decisions, as investigated by Jordà (2005), Ottonello and Winberry (2020) and Durante et al. (2022); and on stock prices, as demonstrated by Kuttner (2001), Gürkaynak, Sack and Swanson (2005), Bernanke and Kuttner (2005), Ozdagli (2018), and Döttling and Ratnovski (2023). While the HFI approach has been applied to explore the effects of monetary policy changes on various metrics, some studies such as those by Recent studies provide evidence suggesting that high-frequency changes in the federal funds rate may not exclusively represent exogenous policy shocks. Nakamura and Steinsson (2018) and Jarociński and Karadi (2020) contend that monetary policy announcements simultaneously reveal information about policy changes and provide insights into the central bank's assessment of the economic outlook. Bauer and Swanson (2023a,b) present a different interpretation by showing evidence that indicate that a measured monetary policy surprise is a mixture of a pure exogenous monetary policy shock and a discrepancy between the Fed's actual policy response function and the private sector's ex ante estimate of that function.[4] This paper adds further evidence to support the hypothesis put forward in Bauer and Swanson (2023b). In our study, we show that investors update their beliefs about the Taylor coefficients, which subsequently affects the investor's SDF. The different correlation between the SDF and dividends leads

2004, defining the policy shock as the difference between the FOMC decision announcement and market expectations.

[4]See also Miranda-Agrippino and Ricco (2021).

to different return responses for large and small firms.

Fourth, this paper contributes to the literature on the evolution of U.S. monetary policy behavior. Previous studies such as Clarida, Galí and Gertler (2000) and Coibion and Gorodnichenko (2011) have estimated time-varying Taylor coefficients, with a particular focus on the regime change before and after Volcker. Similarly, Boivin (2006) has estimated Taylor rules with drifting coefficients, using real-time data and accounting for heteroskedasticity in the policy shock. In addition, Bauer, Pflueger and Sunderam (2022b) has estimated time-varying perceptions of the Fed's policy rule from cross-sectional survey data, revealing systematic shifts in the perceived rule. This paper offer evidence suggesting changes in policy-rule parameters from an asset price perspective. It is the first study to demonstrate the existence of changes in the Taylor rule based on the price equation and the investor perspective.

Fifth, this paper is relevant to the literature that emphasizes the importance of idiosyncratic shocks to large firms. Gabaix (2011) presents a theoretical framework that suggests that when the distribution of firm sizes has fat tails, idiosyncratic shocks can account for a substantial fraction of the variation in output growth. Similarly, Carvalho and Grassi (2019) proposes a theory of aggregate fluctuations caused by firm-level disturbances that places more emphasis on the firm dynamics setup. One the empirical side, Di Giovanni, Levchenko and Mejean (2014) demonstrates that firm-specific components contribute to aggregate sales volatility using French data, , while Foerster, Sarte and Watson (2011) find that the importance of idiosyncratic shocks increased after the 1980s through factor methods to decompose aggregate and sector-specific shocks. However, Stella (2015) presents counterevidence to the granular hypothesis, showing a negative result when estimating a dynamic factor model with firm-level data. While the existing literature investigates the impact of these idiosyncratic shocks on aggregate fluctuations, this paper focuses specifically on understanding the granular origin of the price equation.

2 Empirical Analysis

Monetary policy impacts stock prices, with varying effects across different firms. This section empirically investigates how firm stock prices respond to monetary policy shocks, emphasizing the role of firm size.

2.1 Monetary Policy Surprise

We employ the high-frequency identification approach to estimate monetary policy shocks. Initially, we detail the conventional estimation of high-frequency monetary policy surprises and subsequently compute the refined estimates.

Conventional monetary policy surprise We adopt the high-frequency identification method, which uses changes in federal funds futures and three-month Eurodollar futures closely aligned with Federal Open Market Committee (FOMC) announcements (Bernanke and Kuttner, 2005; Gürkaynak et al., 2005; Nakamura and Steinsson, 2018; Bauer and Swanson, 2023b). Specifically, we quantify the monetary policy surprise by observing changes in federal funds and Eurodollar futures contracts within a 30-minute window— beginning 10 minutes before and concluding 20 minutes after each FOMC press release—using intraday tick data. Additionally, we use the first principal component of the changes in the first four quarterly Eurodollar futures contracts, ED1 through ED4, around the FOMC press releases. The sample period spans from 1990 to 2019.[5]

Predicatability of monetary policy surprise The use of high-frequency monetary policy surprises as instruments for monetary policy shocks is prevalent in empirical research. However, recent studies (e.g., Cieslak, 2018; Nakamura and Steinsson, 2018; Miranda-Agrippino and Ricco, 2021; Karnaukh and Vokata, 2022; Bauer and Swanson, 2023a,b) provide evidence suggesting that high-frequency monetary policy surprises comprise both exogenous monetary policy shocks and economic fundamentals that policymakers respond to endogenously. In particular, Bauer and Swanson (2023a,b) demonstrate that high-frequency

[5]Data is available from Michael Bauer's website: `https://www.michaeldbauer.com/publication/fed-info/`

monetary policy surprises are predictable using information available to private agents prior to FOMC announcements. Specifically, they present evidence rejecting the null hypothesis of $\beta = 0$ in the regression model below:

$$MPS_t = \alpha + \beta^{'} X_{t^-} + \varepsilon_t; \qquad \mathbb{E}\left[\varepsilon_t | X_{t^-}\right] = 0, \tag{1}$$

where MPS_t is the high-frequency measure of monetary policy surprise observed at the time of the FOMC announcement, and X_{t^-} includes information available to private sector agents before the announcement ($t^- \equiv \lim_{s \to t} s$).

In Table 1, we present the regression results for (1) in our sample, demonstrating that employment growth and commodity price changes are robust predictors of monetary policy surprises. Moreover, in Appendix C.2, we show that high-frequency monetary policy surprises exhibit procyclical behavior, as they are positively correlated with employment growth, payroll changes, and changes in the stock price index. Our theoretical analyses in the following sections highlight that this procyclicality of high-frequency monetary policy surprises plays a central role in explaining the empirical findings discussed below.

Bauer and Swanson (2023a,b) offer a theoretical explanation as to why predictable monetary policy surprises are not effective instruments for analyzing monetary policy shocks. They argue that predictable monetary policy surprises include both monetary policy shocks that are orthogonal to the economic fundamentals and shifts in private sector agents' expectations about the central bank's policy rule. To illustrate, consider the central bank's policy rule as follows:

$$i_t = f(X_{t^-}) + \varepsilon_{mp,t},$$

where i_t is the policy rate at time t, X_{t^-} contains the macroeconomic states, f denotes the Fed's policy function, and $\varepsilon_{mp,t}$ is a monetary policy shock with $\mathbb{E}[\varepsilon_{mp,t} \mid X_{t^-}] = 0$. Assume that X_t is known to both private agents and the central bank prior to the FOMC meeting, but that private agents have an imperfect information about f. Under these circumstances, the monetary policy surprise $MPS_t \equiv i_t - \mathbb{E}_{t^-}[i_t]$ consists of $\varepsilon_{mp,t} + [f(X_{t^-}) - \tilde{f}(X_{t^-})]$, where

Table 1: Monetary Policy Surprise and Predicatability

Dependent Variable:	Conventional Monetary Policy Surprise
Nonfarm Payrolls	0.0001^{*}
	(0.00003)
Empl. Growth	0.004^{**}
	(0.002)
S&P 500 Change	0.089^{*}
	(0.048)
Slope Change	-0.006
	(0.007)
Commodity Price Change	0.112^{***}
	(0.042)
Treasury Skewness	0.025^{**}
	(0.011)
Observations	240
R^2	0.137

Notes: The dependent variable is the first principal component of the changes in the first four quarterly Eurodollar futures contracts, ED1 through ED4, around the FOMC press releases. The independent variables are information about macroeconomic conditions available to private sector agents prior to FOMC announcements. Nonfarm Payrolls are the surprise component of the most recent Nonfarm Payrolls release. Empl. Growth is the log change in nonfarm payrolls over the past 12 months. S&P500 Change is the log change in the S&P 500 from 13 weeks prior to the announcement to the day before the announcement. Slope Change is the change in the yield curve slope. Commodity Price Change is the log change in the Bloomberg BCOM commodity price index from 13 weeks before the FOMC announcement to the day before the FOMC announcement. Treasury Skewness is the implied skewness of the 10-year Treasury yield from Bauer and Chernov (2024). We estimate the following regression equations:

$$MPS_t = \alpha + \beta^{'} X_{t^-} + \varepsilon_t$$

The sample period is 1990-2019. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2: Monetary Policy Surprise Sample Statistics

	Counts	Mean (bps)	SD (bps)	Counts positive	Counts negative
Conventional MPS	240	0.25	26.2	152	88
Refined MPS	240	0.35	22.8	128	112

Notes: This table presents the summary statistics for conventional and refined Monetary Policy Surprises (MPS) over the sample period from 1990 to 2019. "Counts positive (negative)" indicates the number of positive (negative) observations for each variable. All values are reported in basis points.

$\tilde{f}$ represents the private sector agents' ex-ante estimate of f. Since X_{t^-} is known to private sector agents prior to the FOMC announcement, the MPS_t includes the predictable components derived above, and the MPS_t is no longer orthogonal to the economic fundamentals X_{t^-} as MPS_t includes $f(X_{t^-}) - \tilde{f}(X_{t^-})$.

Refined monetary policy surprise To filter out predictable components resulting from imperfect information about the central bank's policy rule, we derive a refined measure of monetary policy surprise:

$$\widehat{MPS}_t = MPS_t - \hat{\alpha} - \hat{\beta}' X_{t^-},$$

where X_{t^-} includes the controls used in Table 1 (Nonfarm payrolls surprise, Employment growth, SP500, Yield curve slope, commodity price, and Treasury skewness, as suggested by Bauer and Swanson (2023b)), and $\hat{\alpha}$ and $\hat{\beta}$ are the OLS estimates of α and β from the regression model (1). In our analysis, we refer to $\widehat{MPS}_t$ as the "refined monetary policy surprise." By construction, the refined monetary policy surprise is not predictable from pre-announcement macroeconomic states. Table 2 presents the summary statistics for both conventional and refined monetary policy surprises.[6]

2.2 Firms' Data

Our main sample covers U.S. public firms from 1990 to 2019. We compile quarterly balance sheet information for each firm from the Compustat database and daily stock price data from the Center for Research in Security Prices (CRSP) U.S. Stock Database. The CRSP

[6] Data are available from Michael Bauer's website. https://www.michaeldbauer.com/publication/fed-info/

dataset provides daily stock prices for all publicly traded firms, which we merge with the Compustat fundamental data using a unique identifier. We exclude firms in the financial sector from the sample, as their asset size and leverage are regulated. Additionally, we omit firms with negative assets, negative sales, and negative long- and short-term debt. Firms are also excluded if they meet any of the following criteria: less than 10 quarters in the sample, sales growth greater than 100% or less than -100%, or leverage greater than 10.

Using the CRSP dataset, we calculate the daily excess return of the stock of firm i as follows:

$$\Delta y_{j,t} \equiv \left(\frac{q_{j,t} - q_{j,t-1}}{q_{j,t-1}} - \frac{p_t - p_{t-1}}{p_{t-1}} \right) \times 100,$$

where t is the FOMC day, $t-1$ is the day before the FOMC day, $q_{j,t}$ is the closing price of stock j, and p_t is the closing price of a one-month Treasury bill. This $\Delta y_{j,t}$ represents the change in stock price relative to bond price in response to the FOMC announcement.

2.3 Econometric Results

We estimate a regression of the form

$$\Delta y_{i,t}^{(k)} = \beta^{(k)} MPshock_t + \epsilon_{i,t}, \quad k \in \{1, \cdots, 10\}, \tag{2}$$

where t denotes the date of the FOMC press release, $MPshock_t$ represents the monetary policy shock occurring on date t, and $\epsilon_{i,t}$ is the error term. Here, $\Delta y_{i,t}^{(k)}$ denotes the stock price reaction of firm i within the k-th decile of firm size in the sample at time t. Firms are sorted based on their assets into ten groups, ranging from the smallest to the largest. For each $k \in \{1, \cdots, 10\}$, we estimate the coefficient $\beta^{(k)}$ using the firms within the kth portfolio.[7]

In the regression model, econometricians cannot directly observe $MPshock_t$. Therefore, to estimate $\beta^{(k)}$, we need to employ instruments. For this purpose, we use the conventional measure of MPS_t and the refined measure of $\widehat{MPS}_t$ as outlined in Section 2.1. We then compare the estimation results using these different instruments for $MPshock_t$.

[7] The portfolio is rebalanced every quarter.

Figure 1 presents the results of the estimation (2), with each point representing the point estimate $\beta^{(k)}$ for $k = 1, \ldots, 10$, along with 95% confidence intervals. The blue bars use the conventional policy shock as $MPshock_t$, while the red bars use the refined policy shock. When the conventional monetary policy shock is employed, there is notable heterogeneity in the stock return responses across firm sizes. An unexpected 1 percentage point change in the federal funds rate results in a 3.5 percent change in the stock price for the smallest firm portfolio, compared to a 5.5 percent change for the largest firm portfolio. In contrast, when the refined shock is used, the heterogeneity is significantly reduced. Although the smallest and largest portfolios still exhibit some differences, the coefficient for the smallest portfolio is -3.5, while for the second largest portfolio, it is -4.2.

Our estimation results indicate that the stock prices of larger firms are more responsive to the conventional monetary policy surprise. These findings contrast sharply with evidence suggesting that monetary policy has a greater impact on the investment of smaller firms (Gertler and Gilchrist, 1994; Ottonello and Winberry, 2020). According to Tobin's q theory, the responses of stock prices and investment should be aligned: an unexpected decline in the nominal policy rate should increase stock prices relative to replacement costs, leading to higher investment as the cost of equity financing falls. Our results, however, highlight discrepancies between the heterogeneous responses of investment and stock prices to monetary policy.

Table 3 and 4 report the estimated β_k in regressions of the form

$$\Delta y_{i,t} = \sum_{k=2}^{10} \left[\alpha_k + \beta_k \cdot MPshock_t\right] \times \mathbb{1}\left\{size_{i,t} \in [d_{k-1}, d_k)\right\} + \gamma MPshock_t + \Gamma X_{i,t} + FE_i + \epsilon_{i,t},$$

where k represents the firm size portfolio. The firms are sorted into ten groups based on their size and indexed as $k \in \{1, \cdots, 10\}$ from small to large. The coefficient γ measures the average impact of the monetary policy shock on the smallest group of firms denoted as group 1. The coefficients β_k measure the difference between the average impact on group k and that on group 1. The control variables $X_{i,t}$ include profitability, market-to-book ratio, leverage, and firm fixed effects FE_i. Table 3 uses the observed monetary policy shock as $MPshock_t$, while table 4 uses the refined monetary policy shock. Both tables report the

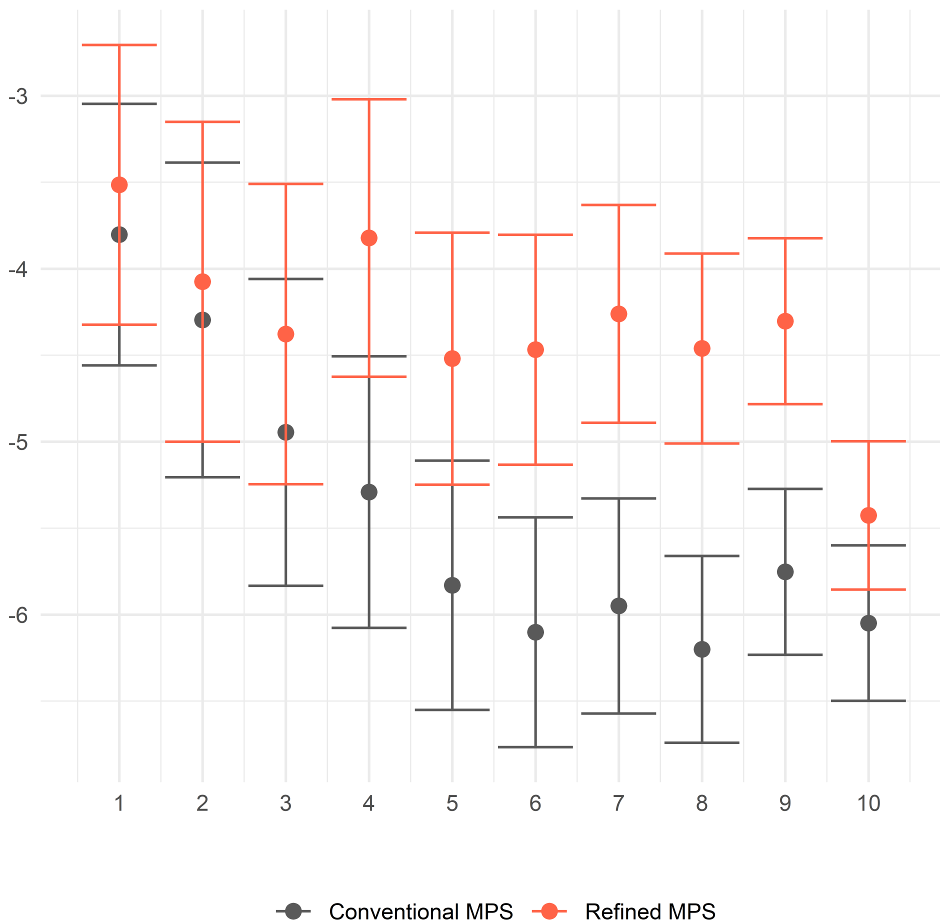


Figure 1: Elasticity of return to refined MP shock across the size.

Note: This figure shows the estimates of β^k for the separate regression of the form

$$\Delta y^k_{i,t} = \beta^k MPshock_t + \epsilon_{i,t}, \quad k \in \{1, \cdots, 10\},$$

where k denotes the portfolio sorted by the size of firms. Dots represent the point estimates of β^k. The bars represent the 95% confidence intervals. The vertical line represents the portfolio, k. The red color uses the conventional monetary policy shock as $MPshock_t$. The blue color uses the refined monetary policy shock as $MPshock_t$.

estimated β_k.

In Table 3, the estimated coefficients β_k using the observed monetary policy shock are statistically significant across five portfolios. For example, the stock prices of the largest firms react more by 2.3 percentage points compared to those of the smallest firms. Conversely, in Table 4, where the refined policy shock is used as the independent variable, the coefficients β_k do not show statistical significance across nine groups. When the refined monetary policy shock is employed, the heterogeneous response of stock price across different firm sizes is not observed.

3 Theoretical Explanation

In Section 2, we demonstrated that using the refined measure of monetary policy surprises as the instrument for monetary policy shocks significantly reduces the variation in stock price responses across firms of different sizes. This contrasts with the substantial differences observed when using the conventional high-frequency measure of monetary policy surprises. Drawing on insights from Bauer and Swanson (2023a,b), our empirical findings indicate that information effects arising from discrepancies between the Fed's actual policy response and the private sector's ex-ante beliefs about the policy function play an essential role in explaining the heterogeneity in stock price reactions observed in previous studies. In this section, we introduce a theoretical framework to elaborate on this perspective.

3.1 Model

We consider a three-period model ($t = 0, 1, 2$) with the following essential elements: (i) the central bank follows a specific monetary policy rule that links the nominal interest rate to aggregate indices, such as the GDP gap; and (ii) the private sector is aware that the central bank obeys this policy rule but has imperfect knowledge of the parameters of the policy rule.

The model economy consists of a representative household, final good-producing firms, fund management firms, and the central bank. The representative household supplies labor to the final good-producing firms, holds ownership of the fund management firms, consumes final goods, and saves in the form of money and short-term risk-free nominal bonds. The

Table 3: Return Sensitivity to Conventional Monetary Policy Shock and Firm Size

Dependent Variable:	Excess Return	
Model:	(1)	(2)
Group2*Conventional Shock	-0.6324	-0.6047
	(0.9471)	(0.9893)
Group3*Conventional Shock	-1.250	-1.172
	(0.9377)	(0.9991)
Group4*Conventional Shock	-1.531*	-1.495
	(0.9264)	(0.9945)
Group5*Conventional Shock	-1.775*	-2.058**
	(0.9121)	(0.9740)
Group6*Conventional Shock	-2.282**	-2.236**
	(0.8969)	(0.9603)
Group7*Conventional Shock	-2.335***	-2.148**
	(0.8923)	(0.9568)
Group8*Conventional Shock	-2.483***	-2.409**
	(0.8790)	(0.9395)
Group9*Conventional Shock	-2.069**	-1.974**
	(0.8750)	(0.9370)
Group10*Conventional Shock	-2.329***	-2.290**
	(0.8695)	(0.9301)
Firms Fixed-effects	No	Yes
Controls	No	Yes
Observations	739,669	664,398
R^2	0.00294	0.01851

Notes: The dependent variable is the change in the excess return of publicly traded firms on FOMC announcement dates. The conventional shock is the first principal component of changes in the federal funds rate and Eurodollar futures. Both are in percentage points. Groups 2 through 10 represent the deciles of firm size from smaller to larger. We estimate the following regression equations:

$$\Delta y_{i,t} = \sum_{k=2}^{10} [\alpha_k + \beta_k \cdot MPshock_t] \times \mathbb{1}\{size_{i,t} \in [d_{k-1}, d_k)\} + \gamma MPshock_t + \Gamma X_{i,t} + FE_i + \epsilon_{i,t},$$

and the table reports β_k for $k \in \{1, \cdots, 10\}$. The coefficients represent the difference from Group 1, which is the smallest firm. Column (1) does not include firm effects and control variables. Column (2) has the control variables, $X_{i,t}$, including the profitability, market-book ratio, and leverage and firm fixed effect. Errors in parentheses are clustered at the firm level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Return Sensitivity to Refined Monetary Policy Shock and Firm Size

Dependent Variable:	Excess Return	
Model:	(1)	(2)
Group2*Refined Shock	-0.5659	-0.5044
	(0.8291)	(0.9082)
Group3*Refined Shock	-0.8056	-0.8305
	(0.8107)	(0.8983)
Group4*Refined Shock	-0.3833	-0.2677
	(0.7947)	(0.8904)
Group5*Refined Shock	-0.7833	-1.066
	(0.7812)	(0.8727)
Group6*Refined Shock	-0.9016	-0.8993
	(0.7600)	(0.8514)
Group7*Refined Shock	-0.9652	-0.7354
	(0.7567)	(0.8492)
Group8*Refined Shock	-1.075	-0.9313
	(0.7418)	(0.8316)
Group9*Refined Shock	-0.8830	-0.7655
	(0.7305)	(0.8222)
Group10*Refined Shock	-1.942***	-1.860**
	(0.7269)	(0.8184)
Firms Fixed-effects	No	Yes
Controls	No	Yes
Observations	739,669	664,398
R^2	0.00172	0.01732

Notes: The dependent variable is the change in the excess return of publicly traded firms on FOMC announcement dates. The refined shock is obtained by regressing the conventional shock on macroeconomic conditions available at the time of the announcement. The details can be found in Bauer and Swanson (2023b). Both are in percentage points. Groups 2 through 10 represent the deciles of firm size from smaller to larger. We estimate the following regression equations:

$$\Delta y_{i,t} = \sum_{k=2}^{10} [\alpha_k + \beta_k \cdot MPshock_t] \times \mathbb{1}\{size_{i,t} \in [d_{k-1}, d_k)\} + \gamma MPshock_t + \Gamma X_{i,t} + FE_i + \epsilon_{i,t},$$

and the table reports β_k for $k \in \{2, \cdots, 10\}$. The coefficients represent the difference from Group 1, which is the smallest firm. Column (1) does not include firm effects and control variables. Column (2) has the control variables, $X_{i,t}$, including the profitability, market-book ratio, and leverage and firm fixed effect. Errors in parentheses are clustered at the firm level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

final good-producing firms employ labor as their sole input for producing a homogeneous final good, distributing their profits entirely to shareholders as dividends. Shares of final good-producing firms are publicly traded and purchased by fund management firms, who are entrusted by households. The central bank sets the short-term nominal interest rate and supplies money to meet the private sector's demand.

Final good-producing firms are ex-ante heterogeneous in their size. The small firm group comprises a continuum of "small" final good-producing firms with a measure $n_S > 0$, while the large firm group includes finitely many $N_L > 0$ "large" final good-producing firms, with N_L being a positive integer. In what follows, let J_S and J_L denote the set of small and large final good-producing firms, respectively, where $|J_S| = n_S$ and $|J_L| = N_L$.

In the initial period $t = 0$, the economy is assumed to be in a steady state where all final good-producing firms have identical labor productivity levels and output quantities. In periods $t = 1$ and $t = 2$, these firms exhibit ex-post heterogeneity due to idiosyncratic labor productivity shocks that occur at the beginning of each period. Final goods are considered perishable so that goods produced must be consumed within the same period.

We outline the sequence of events within periods $t = 1$ and $t = 2$. Each period begins with the realization of labor productivity for each final good-producing firm. After these firms decide on their hiring, the central bank holds a scheduled FOMC meeting to set the short-term nominal bond interest rate i_t for the ongoing period. Subsequently, dividends are distributed to shareholders, and households consume final goods and make savings. For clarity, we denote the start of period t (when labor productivity is realized) as t_o, and the midpoint of period t (the time of the FOMC meeting) as t_m. Therefore, the sequence follows $0 < 1_o < 1_m < 2_o < 2_m$, as depicted in Figure 2.

The following outlines our informational assumptions. By the time of the FOMC meeting, both the central bank and private sector agents (including households, final good-producing firms, and fund management firms) are informed about the labor productivity and output of all firms. At t_m, the central bank publicly announces its policy interest rate, making i_t known to private sector agents. Let $\mathcal{F}_s$ represent the information set available to private sector agents at time s. Given the timing and informational assumptions made above, $i_t \notin \mathcal{F}_{t_m^-}$ but $i_t \in \mathcal{F}_{t_m}$, where $t_m^- = \lim_{t \to t_m} t$ denotes the moment immediately before t_m.

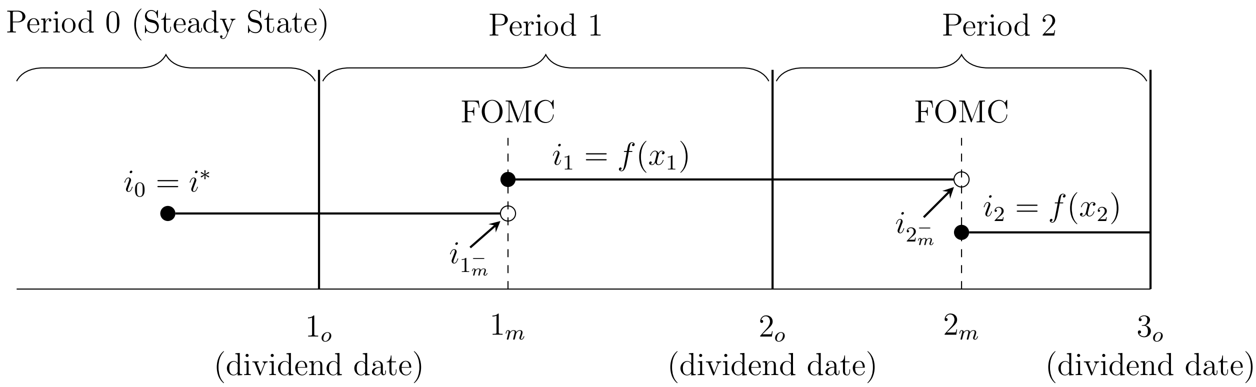


Figure 2: Timeline of the model

Household The representative household supplies labor ℓ_t to the final good-producing firms and owns the fund management firms. For simplicity, we assume that the real wage is fixed at a certain level, $\bar{w} > 0$, and that the household's labor supply is infinitely elastic at this wage rate. Households can save in money M_t and one-period risk-free nominal bonds B_t, aiming to maximize the expected present value of lifetime utility:

$$u(c_0, m_0) + \beta \mathbb{E} u(c_1, m_1) + \beta^2 \mathbb{E} u(c_2, m_2),$$

where $\beta \in (0, 1)$ is the subjective discount factor, c_t is consumption, $m_t = M_t/P_t$ is the real money balance at period t, and P_t denotes the nominal price level of the final good in period t. Following Galí (2015), we consider the non-separable money-in-utility preference:[8]

$$u(c_t, m_t) = \frac{\left(c_t^{1-\theta} m_t^{\theta}\right)^{1-\sigma}}{1-\sigma}; \qquad \theta \in (0,1), \quad \sigma > 0, \quad \sigma \neq 1. \tag{3}$$

The household's budget constraint is given by

$$c_t + \frac{M_{t+1}}{P_t} + \frac{1}{1+i_t}\frac{B_{t+1}}{P_t} = \frac{M_t}{P_t} + \frac{B_t}{P_t} + \bar{w}\ell_t + \Pi_t,$$

where i_t denotes the nominal interest rate on bonds payable at period $t+1$, and Π_t represents the real profits earned by the fund management firms during time t.

[8] In the limit $\sigma \to 1$, (3) reduces to the additive-separable money-in-utility form.

Given $M_0 \geq 0$ and $B_0 \geq 0$, the household chooses $\{c_t, M_{t+1}, B_{t+1}\}_{t=0}^2$. The optimality condition for the short-term nominal bond holding yields, for $t = 0, 1$,

$$1 = \mathbb{E}\left[\Lambda_{t,t+1}\left(\frac{1+i_t}{\pi_{t+1}}\right)\middle|\mathcal{F}_{t_m}\right],$$

where $\pi_{t+1} \equiv P_{t+1}/P_t$ denotes the gross rate of inflation between t and $t+1$. The stochastic discount factor (SDF) $\Lambda_{t,t+1}$ is given by

$$\Lambda_{t,t+1} = \beta\left(\frac{c_{t+1}}{c_t}\right)^{-\sigma}\left(\frac{m_{t+1}/c_{t+1}}{m_t/c_t}\right)^{\theta(1-\sigma)}. \tag{4}$$

The money demand function is given by

$$m_t = \iota(i_t)c_t; \qquad \iota(i_t) = \frac{\theta}{1-\theta}\left(\frac{i_t}{1+i_t}\right)^{-1}. \tag{5}$$

Since $i'(\cdot) < 0$, the demand for money is decreasing in nominal interest rate. Substituting (5) into (4) and using $\iota(i_t)^{-1} \approx \theta^{-1}(1-\theta)i_t$, we obtain

$$\Lambda_{t,t+1} = \beta\left(\frac{c_{t+1}}{c_t}\right)^{-\sigma}\left(\frac{\iota(i_{t+1})}{\iota(i_t)}\right)^{\theta(1-\sigma)} \approx \beta\left(\frac{c_{t+1}}{c_t}\right)^{-\sigma}\left(\frac{i_{t+1}}{i_t}\right)^{\theta(\sigma-1)}. \tag{6}$$

We note that (6) implies that, holding the consumption growth rate constant, an increase in the growth rate of the nominal interest rate, i_{t+1}/i_t, increases (decreases) the stochastic discount factor if $\sigma > (<)1$. Furthermore, (6) implies $\Lambda_{0,2} = \Lambda_{0,1}\Lambda_{1,2}$.

Final good-producing firms Each final good-producing firm has a diminishing returns-to-scale production function:

$$y_{j,t} = Az_{j,t}^{1-\alpha}\ell_{j,t}^{\alpha}; \qquad A > 0,\ \alpha \in (0,1)$$

where $y_{j,t}$, $\ell_{j,t}$, and $z_{j,t}$ represent the firm's output, labor input, and labor productivity, respectively. The final goods are sold in a perfectly competitive market.

These firms issue equity and distribute their profits entirely as dividends to shareholders.

Given this production function, the dividends of firm j at time t are given by

$$d_{j,t} = \max_{\ell} \quad A z_{j,t}^{1-\alpha} \ell^{\alpha} - \bar{w}\ell.$$

Initially ($t = 0$), all firms have a labor productivity of unity ($z_{j,0} = 1$ for every j). Subsequently, labor productivity experiences random growth, in line with the key stylized features of the firm-dynamics literature (See e.g., Gabaix, 2011). Hence, it must be held that

$$\frac{\Delta z_{j,t+1}}{z_{j,t}} = \sigma_g \varepsilon_{j,t+1},$$

where $\Delta z_{j,t+1} = z_{j,t+1} - z_{j,t}$, $\sigma_g > 0$ is the standard deviation of the productivity growth, and $\varepsilon_{j,t+1}$ is an independently and identically distributed standard Gaussian variable, leading to $z_{j,t}$ following a martingale process. In our analysis, we assume that σ_g is sufficiently small, such that $\sigma_g^k \approx 0$ for $k \geq 3$.

Solving the profit maximization problem results in the optimal labor input $\ell_{j,t} = z_{j,t}(A\alpha/\bar{w})^{\frac{1}{1-\alpha}}$. Assuming $A^{\frac{1}{1-\alpha}}(\alpha/\bar{w})^{\frac{\alpha}{1-\alpha}} = 1$ without loss of generality, output is

$$y_{j,t} = z_{j,t} A^{\frac{1}{1-\alpha}} \left(\frac{\alpha}{\bar{w}}\right)^{\frac{\alpha}{1-\alpha}} = z_{j,t}.$$

Therefore, profits, or dividends, are

$$d_{j,t} = \alpha^{-\frac{1}{1-\alpha}} z_{j,t}.$$

In the initial period ($t = 0$), with $z_{j,t} = 1$ for all j, $y_{j,t} = 1$ and $d_{j,t} = \alpha^{-\frac{1}{1-\alpha}} \equiv d_0$ for all firms. In periods $t = 1$ and $t = 2$, the growth rates of a firm's output and dividends are

$$\frac{\Delta y_{j,t+1}}{y_{j,t}} = \frac{\Delta d_{j,t+1}}{d_{j,t}} = \frac{\Delta z_{j,t+1}}{z_{j,t}} = \sigma_g \varepsilon_{j,t+1}, \qquad \forall j \in J_S \cup J_L$$

Given that idiosyncratic productivity growth shocks occur at the beginning of each period, all private sector agents and the central bank are informed about each firm's output before the FOMC meeting. Hence, $\{z_{j,t}, \ell_{j,t}, y_{j,t}, d_{j,t}\} \in \mathcal{F}_{t_m^-}$ for all j.

Aggregate Output Let y_t denote aggregate output, i.e., GDP, at time t. By the random growth assumption and the law of large number, it holds that

$$y_t \equiv \int_{j \in J_S} y_{j,t} dj + \sum_{j \in J_L} y_{j,t} = n_S + \sum_{j \in J_L} y_{j,t}. \tag{7}$$

Furthermore, let $g_{Y,t+1} = \Delta y_{t+1}/y_t$ denote the growth rate of GDP. The following proposition derives the growth rate of aggregate output $g_{Y,t+1} = \Delta y_{t+1}/y_t$ and the covariance of the growth rate of aggregate output and that of individual firms' output:

Proposition 1. *The growth rate of aggregate output is given by*

$$g_{Y,t+1} \equiv \frac{\Delta y_{t+1}}{y_t} = \sigma_g \sum_{j \in J_L} \frac{y_{j,t}}{y_t} \varepsilon_{j,t+1},$$

with $\mathbb{E}[g_{Y,t+1}] = 0$ *and* $\sigma_{g_Y,t} = \sqrt{Var_t(g_{Y,t+1})} = \sigma_g \sqrt{\sum_{j \in J_L} (y_{j,t}/y_t)^2}$*. The covariance of the growth rate of aggregate output and that of individual firms' output is given by*

$$Cov_t\left(g_{Y,t+1}, \frac{\Delta y_{j,t+1}}{y_{j,t}}\right) = \begin{cases} 0 & \textit{for } j \in J_S \\ \frac{y_{j,t}}{y_t}\sigma_g^2 & \textit{for } j \in J_L \end{cases}. \tag{8}$$

Proof of Proposition 1. See Appendix A. □

Proposition 1 demonstrates that productivity shocks to small firms do not influence GDP fluctuations, indicating that all variations in GDP and GDP growth stem from shocks to large firms. Regarding (8), two key points emerge. Firstly, for small firms, there is no correlation between the growth rate of their own output ($\Delta y_{j,t+1}/y_{j,t}$) and the growth rate of aggregate output ($g_{Y,t+1}$). Secondly, for large firms, a higher share of output ($y_{j,t}/y_t$) correlates with a stronger connection between the growth rate of their own output ($\Delta y_{j,t+1}/y_{j,t}$) and the growth rate of aggregate output ($g_{Y,t+1}$).

Moreover, (7) implies that in the initial period ($t = 0$) where $z_{j,t} = 1$ for all j, $y_0 = n_S + N_L$, indicating that the share of final good output produced by small firms is $n_S/(n_S + N_L)$, while the share produced by a large firm is $1/(n_S + N_L)$.

Fund Management Firms There exists a continuum of competitive fund management firms with measure one. These firms are risk-neutral and use the household's stochastic discount factor (6) to discount future payoffs, reflecting their ownership by households. In the initial period ($t = 0$), each fund management firm holds an equal stake in all final goods-producing firms and can adjust its asset portfolio at any time. Additionally, these fund management firms have the ability to issue and acquire short-term real bonds that yield one unit of the final good at the end of the following period.

Let $q_{j,t}$ denote the stock price of final good-producing firm j in time t. Those before the dividend date in the initial period are given by

$$q_{j,0} = d_0 + \mathbb{E}\left[\Lambda_{0,1} d_{j,1} | \mathcal{F}_0\right] + \mathbb{E}\left[\Lambda_{0,2} d_{j,2} | \mathcal{F}_0\right], \qquad \forall j \in J_S \cup J_L,$$

where $\mathbb{E}\left[\cdot | \mathcal{F}\right]$ represents the expectation conditional on the information set $\mathcal{F}$. In period $t = 1$, they are given by, for all $j \in J_S \cup J_L$,

$$q_{j,\tau} = d_{j,1} + \mathbb{E}\left[\Lambda_{1,2} d_{j,2} | \mathcal{F}_\tau\right] \qquad \text{for} \quad \tau \in [1_o, 2_o).$$

In period $t = 2$,

$$q_{j,\tau} = d_{j,2} \qquad \text{for} \quad \tau \in [2_o, 3_o).$$

Central Bank In period $t = 0$, when the economy is in a steady state, the central bank sets the initial interest rate at $i_0 = i^* > 0$. In subsequent periods, $t = 1$ and $t = 2$, the central bank adjusts the nominal interest rate according to the following policy rule:

$$\frac{i_t - i_{t-1}}{i_{t-1}} = \alpha_{mp} \left(\frac{\Delta y_t}{y_{t-1}} \right) + \epsilon_{i,t}; \qquad \epsilon_{i,t} \overset{\text{IID}}{\sim} N(0, \sigma_i^2).$$

Here, α_{mp} denotes the policy parameter that dictates the adjustment of the policy rate in response to the GDP growth rate. For example, if $i_{t-1} = 0.01$, the left-hand side represents the percentage point change in the policy rate, and thus, the central bank increases the policy rate by α_{mp} basis points when the GDP growth rate is 1 percent. A normally distributed IID random variable $\epsilon_{i,t}$ represents the exogenous monetary policy shock. In our analysis, we assume that σ_i is sufficiently small, such that $\sigma_i^k \approx 0$ for $k \geq 3$.

Informational Frictions, Monetary Policy Surprise, and Learning Following Bauer and Swanson (2023a,b), we suppose that while private sector agents understand that the central bank adopts the policy rule indicated in our model, they lack precise knowledge of the policy parameter α_{mp} and the realized value of $\epsilon_{i,t}$. Therefore, before the period 1 FOMC meeting, their expected policy rate is $\mathbb{E}\left[i_1 \mid \mathcal{F}_{1_m^-}\right] = i^* + i^*\tilde{\alpha}_{mp,0}g_{Y,1}$, where $\tilde{\alpha}_{mp,0}$ is the private sector agents' ex-ante estimate of the policy parameter α_{mp}. Consequently, the monetary policy surprise is given by

$$MPS_{1_m} = i_1 - \mathbb{E}\left[i_1 \mid \mathcal{F}_{1_m^-}\right] = i^*\left(\alpha_{mp} - \hat{\alpha}_{mp,0}\right) g_{Y,1} + \epsilon_{i,1}.$$

This implies that unless $\tilde{\alpha}_{mp,0} = \alpha_{mp}$ and $g_{Y,1} = 0$, private sector agents, even observing i_t, cannot discern whether the surprise arises from misinformation regarding the policy parameter or a discretionary policy shock.

We also consider that private sector agents update their belief about the policy parameter in response to monetary policy announcements using the Kalman filter. Starting from the initial belief $\alpha_{mp} \sim N(\tilde{\alpha}_{mp,0}, \tilde{\sigma}^2_{mp,0})$, the announcement at $t = 1_m$ leads to an updated belief as follows:

$$\tilde{\alpha}_{mp,1} = \tilde{\alpha}_{mp,0} + \kappa_1\left(i_1 - \mathbb{E}\left[i_1 \mid \mathcal{F}_{1_m^-}\right]\right) = \tilde{\alpha}_{mp,0} + \kappa_1 MPS_{1m}, \tag{9}$$

and the updated prediction error is:

$$\hat{\sigma}^2_{mp,1} = \hat{\sigma}^2_{mp,0}\left(1 - g_{Y,1}\kappa_1\right),$$

where the Kalman gain κ_1 being:

$$\kappa_1 = \frac{1}{i^* g_{Y,1}}\left(\frac{g_{Y,1}^2\tilde{\sigma}^2_{mp,0}}{g_{Y,1}^2\tilde{\sigma}^2_{mp,0} + (\sigma_i/i^*)^2}\right).$$

In particular, (9) induces the following feature of how investors update their expectation:

Proposition 2. *The Kalman filter scheme implies that $\tilde{\alpha}_{mp,1} > \tilde{\alpha}_{mp,0}$ when $g_{Y,1} > 0$ and $MPS_{1m} > 0$, or $g_{Y,1} < 0$ and $MPS_{1m} < 0$, and $\tilde{\alpha}_{mp,1} < \tilde{\alpha}_{mp,0}$ when $g_{Y,1} > 0$ and $MPS_{1m} < 0$, or $g_{Y,1} < 0$ and $MPS_{1m} > 0$.*

Equilibrium Conditions The clearing condition for the final good market is given by $c_t = y_t$. The net supply of risk-free bond is assumed to be zero $B_t = 0$. Money is supplied by the central bank to meet demand.

3.2 Equilibrium Stock Prices

The equilibrium stock prices are expressed as follows.

$$q_{j,\tau} = \begin{cases} d_0 \mathbb{E}\left[1 + \Lambda_{0,1}\left(\frac{y_{j,1}}{y_0}\right)\left(1 + \Lambda_{1,2}\left(\frac{y_{j,2}}{y_{j,1}}\right)\right)\middle|\mathcal{F}_0\right] & \text{for} \quad \tau = 0 \\ d_{j,1}\mathbb{E}\left[1 + \Lambda_{1,2}\left(\frac{y_{j,2}}{y_{j,1}}\right)\middle|\mathcal{F}_\tau\right] & \text{for} \quad \tau \in [1_o, 2_o) \\ d_{j,2} & \text{for} \quad \tau \in [2_o, 3_o) \end{cases} .$$

Combined with the market-clearing conditions and the monetary policy rule, we obtain the expression for the SDF as follows:

Lemma 1. *The equilibrium SDF is given by*

$$\Lambda_{t,t+1} \approx \beta \exp(-\left(\sigma + \theta(1-\sigma)\alpha_{mp}\right) g_{Y,t+1} - \theta(1-\sigma)\epsilon_{i,t+1}),$$

as long as $g_{Y,t+1}$ and i_t are sufficiently small.

Proof of Lemma 1. See Supplementary Appendix A. □

We highlight that under the non-separable money-in-utility preference (3), the investor's SDF is shaped by their perceptions of the monetary policy parameter, α_{mp}. Consequently, the FOMC announcement at time 1_m, which updates the private sector agents' information set $\mathcal{F}$, leads to adjustments in the investors' SDF and thus in stock prices. For ease of explanation, let us denote $\tilde{\Lambda}^{(0)}_{t,t+1} = \Lambda_{t,t+1} \mid \mathcal{F}_{1_m^-}$ as the investors' SDF prior to the FOMC announcement at time 1_m, and $\tilde{\Lambda}^{(1)}_{t,t+1} = \Lambda_{t,t+1} \mid \mathcal{F}_{1_m}$ as the SDF following the announcement.

Using the notations introduced above, the stock prices in period 1 can be written as

$$q_{j,\tau} = \begin{cases} d_{j,1}\left[1 + \mathbb{E}[\tilde{\Lambda}^{(0)}_{1,2}] + \mathrm{Cov}\left(\tilde{\Lambda}^{(0)}_{1,2}, \frac{y_{j,2}}{y_{j,1}}\right)\right] & \text{for} \quad \tau \in [1_o, 1_m) \\ d_{j,1}\left[1 + \mathbb{E}\left[\tilde{\Lambda}^{(1)}_{1,2}\right] + \mathrm{Cov}\left(\tilde{\Lambda}^{(1)}_{1,2}, \frac{y_{j,2}}{y_{j,1}}\right)\right] & \text{for} \quad \tau \in [1_m, 2_o) \end{cases}. \tag{10}$$

It further should be noted that the risk premium component, as indicated by the covariance term in (10), differs between large and small firms. Specifically, the proposition below reveals that for small firms, the risk premium component is, irrespective of the degree of monetary policy activity α_{mp}:

Proposition 3. *For small firms $j \in J_S$, their output growth and the equilibrium SDF are uncorrelated regardless of $\alpha_{mp} > 0$, i.e., $\forall j \in J_S$*

$$\mathrm{Cov}\left(\Lambda_{1,2}, \frac{y_{j,2}}{y_{j,1}}\right) = 0.$$

On the other hand, for large firms $j \in J_L$,

$$\mathrm{Cov}\left(\Lambda_{1,2}, \frac{y_{j,2}}{y_{j,1}}\right) \approx -C\frac{y_{j,1}}{y_1}\sigma_g^2\left[\sigma + \theta(1-\sigma)\alpha_{mp}\right]; \qquad C = \beta\left(1 + \frac{(\theta(1-\sigma)\sigma_i)^2}{2}\right) > 0.$$

Hence, for large firms, the correlation depends on the monetary policy parameter as $\sigma \neq 1$.

Proof of Proposition 3. See Supplementary Appendix A. □

Stock Price Reactions around FOMC Announcements We analyze the reactions of stock prices to the FOMC announcements, with a particular focus on the announcement at time 1_m. We examine the correlation between stock price reactions and the monetary policy surprises.

We define the the stock price reaction at time 1_m as $\Delta q_{j,1_m}/q_{j,1_m^-}$ where $\Delta q_{j,1_m} = q_{j,1_m} -$

$q_{j,1_m^-}$. Using (10), the stock price reaction is given by

$$\frac{\Delta q_{j,1_m}}{q_{j,1_m^-}} = \frac{d_{j,1}}{q_{j,1_m^-}} \left[\mathbb{E}\left[\tilde{\Lambda}_{1,2}^{(1)}\right] - \mathbb{E}\left[\tilde{\Lambda}_{1,2}^{(0)}\right] + \operatorname{Cov}\left(\tilde{\Lambda}_{1,2}^{(1)}, \frac{y_{j,2}}{y_{j,1}}\right) - \operatorname{Cov}\left(\tilde{\Lambda}_{1,2}^{(0)}, \frac{y_{j,2}}{y_{j,1}}\right)\right]. \tag{11}$$

This implies that even if the divide process $y_{j,2}/y_{j,1}$ is unchanged, stock prices may change in response to monetary policy announcements due to shifts in investors' expectations regarding monetary policy and the associated changes in the stochastic discount factor (from $\tilde{\Lambda}_{1,2}^{(1)}$ to $\tilde{\Lambda}_{1,2}^{(0)}$). Further insights are provided below:

Lemma 2. *The difference in expected values of the SDF before and after the FOMC announcement at time 1_m, $\mathbb{E}\left[\tilde{\Lambda}_{1,2}^{(1)}\right] - \mathbb{E}\left[\tilde{\Lambda}_{1,2}^{(0)}\right]$, and the difference in their covariance with the firm's output growth, $\operatorname{Cov}\left(\tilde{\Lambda}_{1,2}^{(1)}, y_{j,2}/y_{j,1}\right) - \operatorname{Cov}\left(\tilde{\Lambda}_{1,2}^{(0)}, y_{j,2}/y_{j,1}\right)$, are respectively given by:*

$$\mathbb{E}\left[\tilde{\Lambda}_{1,2}^{(1)}\right] - \mathbb{E}\left[\tilde{\Lambda}_{1,2}^{(0)}\right] = \theta(1-\sigma)\left[\sigma(\tilde{\alpha}_{mp,1} - \tilde{\alpha}_{mp,0}) + \frac{\theta(1-\sigma)}{2}\left(\tilde{\sigma}_{mp,1}^2 - \tilde{\sigma}_{mp,0}^2\right)\right]\sigma_{g_Y,1}^2,$$

and

$$\operatorname{Cov}\left(\tilde{\Lambda}_{1,2}^{(1)}, \frac{y_{j,2}}{y_{j,1}}\right) - \operatorname{Cov}\left(\tilde{\Lambda}_{1,2}^{(0)}, \frac{y_{j,2}}{y_{j,1}}\right) = \begin{cases} 0, & j \in J_S \\ \frac{y_{j,1}}{y_1}\sigma_g^2\theta(\sigma-1)\left(\tilde{\alpha}_{mp,1} - \tilde{\alpha}_{mp,0}\right), & j \in J_L \end{cases}.$$

Proof of Lemma 2. See Supplementary Appendix A. □

This lemma demonstrates that while the change in investors' expected SDF value is uniform across firms, the change in their assessment of the covariance between SDF and firms' output growth differs between small and large firms, highlighting heterogeneity. Hence, combined with (11), this lemma suggests that stock price reactions to policy announcements may occur and differ among firms, even without direct impacts of monetary policy on firms' profitability.

3.3 Monetary Policy Surprises and Stock Price Reactions

Building upon the preceding analysis, we derive the association between the rate of stock price changes $\Delta q_{j,t_m}/q_{j,t_m^-}$ and the monetary policy surprise MPS_{t_m} as follows:

$$\begin{aligned}\beta_j \mid \mathbb{Z}_{j,t} \equiv & \frac{\operatorname{Cov}\left(\frac{\Delta q_{j,t_m}}{q_{j,t_m^-}}, MPS_{t_m} \mid \mathbb{Z}_{j,t}\right)}{\operatorname{Var}(MPS_{t_m})} \\ = & \frac{\frac{d_{j,t}}{q_{j,t_m^-}}\left(\operatorname{Cov}\left(\Delta p_{t_m}, MPS_{t_m}\right) + \mathbb{1}_{\{j\in J_L\}}\left(\frac{y_{j,t}}{y_t}\sigma_g^2\right)\theta(\sigma-1)\operatorname{Cov}\left(\Delta\tilde{\alpha}_{mp,t}, MPS_{t_m}\right)\right)}{\operatorname{Var}(MPS_{t_m})},\end{aligned} \tag{12}$$

where $\mathbb{Z}_{j,t}$ represents the firm-specific information available before the FOMC announcement, including the ratios $(d_{j,t}/q_{j,t_m^-}, y_{j,t}/y_t) \in \mathbb{Z}_{j,t}$. Here, $\Delta p_{t_m} = p_{t_m} - p_{t_m^-}$ represents the price change of the short-term discount bond around the FOMC announcement, and $\Delta\tilde{\alpha}_{mp,t} = \tilde{\alpha}_{mp,t} - \tilde{\alpha}_{mp,t-1}$ denotes the adjustment in investors' expectation of the policy parameter around the announcement. According to (12), the covariance $\operatorname{Cov}(\Delta\tilde{\alpha}_{mp,t}, MPS_{t_m})$, which reflects how investors' belief revisions regarding the policy parameter correlate with monetary policy surprises, plays a pivotal role in explaining the heterogeneity in stock price reactions to these surprises between small and large firms. Specifically, if $\sigma > 1$, stock price reactions tend to be more pronounced for large firms when $\operatorname{Cov}(\Delta\tilde{\alpha}_{mp,t}, MPS_{t_m}) > 0$.

4 Additional Evidence

The above model emphasizes that investors' learning about the policy rule parameter in response to monetary policy surprises is a key driver of heterogeneous stock price reactions. In this section, we empirically test this implication by extending the regression analysis presented in Section 2. Specifically, the model suggests that when uncertainty about the future monetary policy stance is high, making it difficult for investors to learn, the effect of learning on stock prices is small. Based on this insight, our extended empirical analysis examines how the degree of monetary policy uncertainty affects the heterogeneity in stock price reactions to monetary policy surprises.

Specifically, we estimate

$$\Delta y_{i,t}^{k,u} = \beta^{k,u} MPshock_t^u + \epsilon_{i,t}, \quad k \in \{1, \cdots, 10\}, \quad u \in \{h, m, l\}, \tag{13}$$

where t denotes the date of the FOMC meeting, $MPshock_t$ is the conventional monetary policy surprise on date t, and $\epsilon_{i,t}$ is the error term. Additionally, $\Delta y_{i,t}^{k,u}$ represents the stock price reaction of firm i in the k-th decile of firm size at time t. The superscript u denotes the index of monetary policy uncertainty. We divide the sample period into three categories based on the level of uncertainty: high, middle, and low uncertainty periods (h, m, l). [9] The uncertainty measure is based on the prices of Eurodollar futures and options, reflecting the market-based conditional volatility of the future short-term interest rate (Bauer et al., 2022a).

We separately estimate the regression (13) for each $k \in \{1, \cdots, 10\}$ and $u \in \{h, m, l\}$. Figure 3 presents the results of point estimate, $\beta^{k,u}$ for $(k, u) = \{(1, h), (1, l), \cdots, (10, h), (10, l)\}$, along with 95% confidence intervals. The blue line represents the results for low uncertainty $(u = l)$, while the red line represents high uncertainty $(u = h)$. The results indicate that the heterogeneous response of stock prices to monetary policy surprises is more pronounced when monetary policy uncertainty is low. In contrast, when monetary policy uncertainty is high, the heterogeneity in stock price responses is significantly reduced.

5 Conclusion

This study has reevaluated stock price responses to monetary policy shocks, focusing on the identification challenges of these shocks within the high-frequency identification approach. We first present evidence indicating that the identification challenges posed by information effects cast doubt on existing findings suggesting that larger firms exhibit greater responsiveness to monetary policy shocks in their stock prices. Specifically, we demonstrate that while larger firms' stock prices show greater responsiveness to conventionally measured monetary policy surprises, the excess stock price reactions for large firms are minimal when using refined estimates of monetary policy shocks that filter out the predictable components from conventional surprises. This implies that the monetary policy surprises predictable by in-

[9] Given the time-series data on uncertainty measures, we first compute the 33rd percentile and the 66th percentile of the uncertainty measure. When the uncertainty measure at time t is below the 33rd percentile, u is grouped as low uncertainty (l). When the uncertainty measure at time t is between the 33rd and 66th percentiles, u is grouped as middle uncertainty (m). When the uncertainty measure at time t is above the 66th percentile, u is grouped as high uncertainty (h).

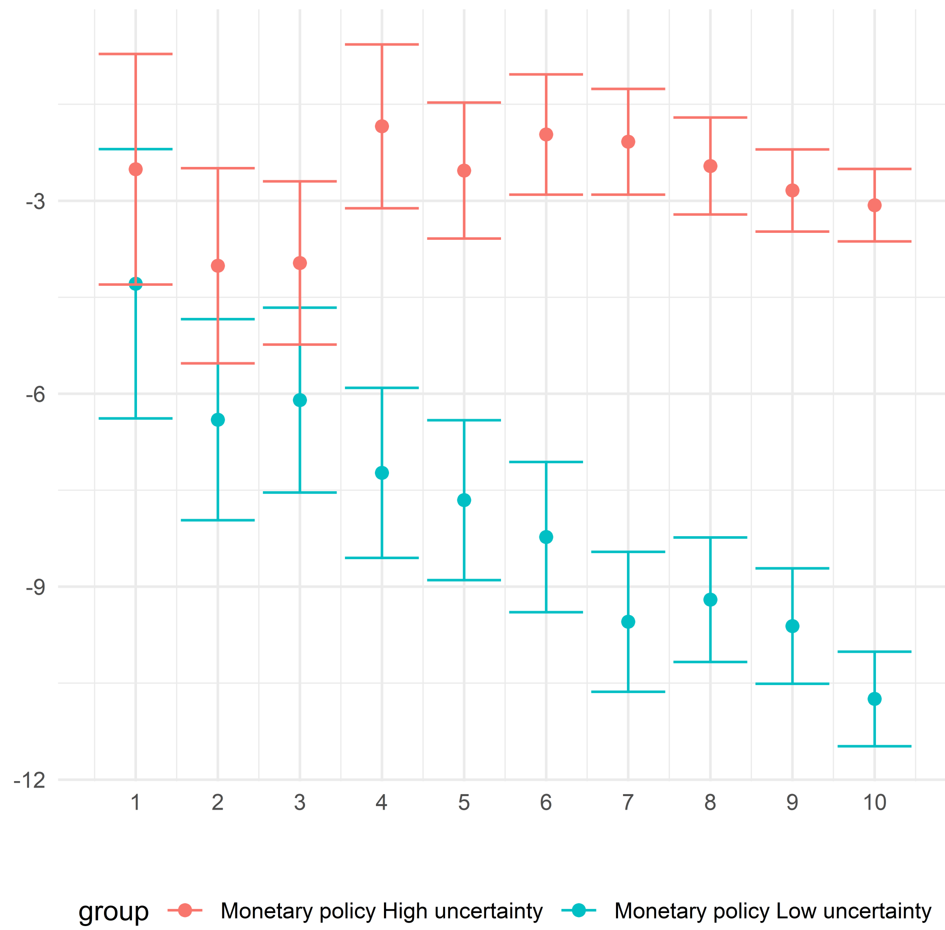


Figure 3: Elasticity of return to MP shock across firm size conditional on monetary policy uncertainty.

Note: This figure shows the estimates of β_m^u for the separate regression of the form

$$\Delta y_{i,t}^{k,u} = \beta^{k,u} MPshock_t^u + \epsilon_{i,t}, \quad k \in \{1, \cdots, 10\}, \quad u \in \{h, m, l\},$$

where t denotes the date of the FOMC, $MPshock_t$ is the conventional monetary policy surprise on date t, and $\epsilon_{i,t}$ is the error term. Also, $\Delta y_{i,t}^{k,u}$ is the stock price reaction of firm i that is the k-th decile of firm size in the sample at time t. Superscript u is the index of monetary policy uncertainty. The bars represent the 95% confidence intervals. The vertical line represents the portfolio, k. The blue line shows the results when u is low uncertainty measure, and the red line is the case when u is high uncertainty measure.

vestors, rather than unpredictable monetary policy shocks, cause the excess stock price reactions for large firms.

We then provided a theoretical analysis to explain why predictable monetary policy surprises produce asymmetric stock price reactions. To this end, we developed a monetary asset pricing model that incorporates granular sources of aggregate fluctuations, with the central bank following a policy rule that links the nominal interest rate to aggregate indices. The model includes investors' imperfect knowledge and learning about the central bank's policy rule parameter, as described in Bauer and Swanson (2023a,b). This setup results in monetary policy surprises stemming from the disparity between the Fed's actual policy response function and investors' ex-ante beliefs about that function, as well as from exogenous policy shocks. The theoretical model shows that investors' learning about the policy rule parameter upon monetary policy surprises leads to a heterogeneous impact on the covariance between investors' stochastic discount factor and firms' dividend growth across small and large firms. This results in heterogeneous stock price reactions to the monetary policy surprises, even though monetary policy shocks have no impact on firms' dividend growth. In summary, monetary policy surprises prompt investors to reassess the central bank's policy activeness, leading them to update their stochastic discount factors. This update affects firms' stock prices heterogeneously.

References

Bauer, Michael and Mikhail Chernov, "Interest Rate Skewness and Biased Beliefs," *Journal of Finance*, 2024, *79* (1), 173–217.

Bauer, Michael D., Aeimit Lakdawala, and Philippe Mueller, "Market-Based Monetary Policy Uncertainty," *Economic Journal*, 2022, *132* (644), 1290–1308.

_ **and Eric T. Swanson**, "An Alternative Explanation for the "Fed Information Effect"," *American Economic Review*, 2023, *113* (3), 664–700.

_ **and** _ , "A Reassessment of Monetary Policy Surprises and High-Frequency Identification," *NBER Macroeconomics Annual*, 2023, *37* (1), 87–155.

—, **Carolin Pflueger, and Adi Sunderam**, "Perceptions about Monetary Policy," Technical Report, National Bureau of Economic Research 2022.

Bernanke, Ben S. and Kenneth N. Kuttner, "What Explains the Stock Market's Reaction to Federal Reserve Policy?," *Journal of Finance*, 2005, *60* (3), 1221–1257.

Boivin, Jean, "Has U.S. Monetary Policy Changed? Evidence from Drifting Coefficients and Real-Time Data," *Journal of Money, Credit and Banking*, 2006, *38* (5), 1149–1173.

Carvalho, Vasco M. and Basile Grassi, "Large Firm Dynamics and the Business Cycle," *American Economic Review*, 2019, *109* (4), 1375–1425.

Chava, Sudheer and Alex Hsu, "Financial Constraints, Monetary Policy Shocks, and the Cross-Section of Equity Returns," *Review of Financial Studies*, 2020, *33* (9), 4367–4402.

Cieslak, Anna, "Short-Rate Expectations and Unexpected Returns in Treasury Bonds," *Review of Financial Studies*, 2018, *31* (9), 3265–3306.

Clarida, Richard, Jordi Galí, and Mark Gertler, "Monetary Policy Rules and Macroeconomic Stability: Evidence and Some Theory," *Quarterly Journal of Economics*, 2000, *115* (1), 147–180.

Cochrane, John H. and Monika Piazzesi, "The Fed and Interest Rates - A High-Frequency Identification," *American Economic Review*, May 2002, *92* (2), 90–95.

Coibion, Olivier and Yuriy Gorodnichenko, "Monetary Policy, Trend Inflation, and the Great Moderation: An Alternative Interpretation," *American Economic Review*, February 2011, *101* (1), 341–370.

Döttling, Robin and Lev Ratnovski, "Monetary Policy and Intangible Investment," *Journal of Monetary Economics*, 2023, *134*, 53–72.

Durante, Elena, Annalisa Ferrando, and Philip Vermeulen, "Monetary Policy, Investment and Firm Heterogeneity," *European Economic Review*, 2022, *148*, 104251.

Ehrmann, Michael and Marcel Fratzscher, "Taking Stock: Monetary Policy Transmission to Equity Markets," *Journal of Money, Credit and Banking*, 2004, *36* (4), 719–737.

Faust, Jon, Eric T. Swanson, and Jonathan H. Wright, "Identifying VARS Based on High Frequency Futures Data," *Journal of Monetary Economics*, 2004, *51* (6), 1107–1131.

Foerster, Andrew T., Pierre-Daniel G. Sarte, and Mark W. Watson, "Sectoral versus Aggregate Shocks: A Structural Factor Analysis of Industrial Production," *Journal of Political Economy*, 2011, *119* (1), 1–38.

Gabaix, Xavier, "The Granular Origins of Aggregate Fluctuations," *Econometrica*, 2011, *79* (3), 733–772.

Galí, Jordi, *Monetary Policy, Inflation, and the Business Cycle: An Introduction to the New Keynesian Framework and Its Applications*, Princeton University Press, 2015.

Gertler, Mark and Peter Karadi, "Monetary Policy Surprises, Credit Costs, and Economic Activity," *American Economic Journal: Macroeconomics*, 2015, *7* (1), 44–76.

_ **and Simon Gilchrist**, "Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms," *Quarterly Journal of Economics*, 1994, *109* (2), 309–340.

Giovanni, Julian Di, Andrei A. Levchenko, and Isabelle Mejean, "Firms, Destinations, and Aggregate Fluctuations," *Econometrica*, 2014, *82* (4), 1303–1340.

Gürkaynak, Refet S., Brian P. Sack, and Eric T. Swanson, "Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements," *International Journal of Central Banking*, May 2005, *1* (1).

Jarociński, Marek and Peter Karadi, "Deconstructing Monetary Policy Surprises—the Role of Information Shocks," *American Economic Journal: Macroeconomics*, 2020, *12* (2), 1–43.

Jordà, Òscar, "Estimation and Inference of Impulse Responses by Local Projections," *American Economic Review*, March 2005, *95* (1), 161–182.

Karnaukh, Nina and Petra Vokata, "Growth Forecasts and News About Monetary Policy," *Journal of Financial Economics*, 2022, *146* (1), 55–70.

Kuttner, Kenneth N., "Monetary Policy Surprises and Interest Rates: Evidence from the Fed Funds Futures Market," *Journal of Monetary Economics*, 2001, *47* (3), 523–544.

Lucas, Robert E., "Asset Prices in an Exchange Economy," *Econometrica*, 1978, *46* (6), 1429–1445.

Maio, Paulo, "Another Look at the Stock Return Response to Monetary Policy Actions," *Review of Finance*, 2014, *18* (1), 321–371.

Miranda-Agrippino, Silvia and Giovanni Ricco, "The Transmission of Monetary Policy Shocks," *American Economic Journal: Macroeconomics*, 2021, *13* (3), 74–107.

Morlacco, Monica and David Zeke, "Monetary Policy, Customer Capital, and Market Power," *Journal of Monetary Economics*, 2021, *121*, 116–134.

Nakamura, Emi and Jón Steinsson, "High-Frequency Identification of Monetary Non-Neutrality: The Information Effect," *Quarterly Journal of Economics*, 2018, *133* (3), 1283–1330.

Ottonello, Pablo and Thomas Winberry, "Financial Heterogeneity and the Investment Channel of Monetary Policy," *Econometrica*, 2020, *88* (6), 2473–2502.

Ozdagli, Ali K., "Financial Frictions and the Stock Price Reaction to Monetary Policy," *Review of Financial Studies*, 2018, *31* (10), 3895–3936.

Perez-Quiros, Gabriel and Allan Timmermann, "Firm Size and Cyclical Variations in Stock Returns," *Journal of Finance*, 2000, *55* (3), 1229–1262.

Ramey, Valerie A., "Macroeconomic Shocks and Their Propagation," in "Handbook of Macroeconomics," Vol. 2, Elsevier, 2016, chapter 2, pp. 71–162.

Stella, Andrea, "Firm Dynamics and the Origins of Aggregate Fluctuations," *Journal of Economic Dynamics and Control*, 2015, *55*, 71–88.

Thorbecke, Willem, "On Stock Market Returns and Monetary Policy," *Journal of Finance*, 1997, *52* (2), 635–654.

Appendices

APPENDIX A Proofs

This appendix presents the proofs of theorems, propositions, and lemmas.

Proof of Proposition 1. The growth rate of y_t is given

$$
\begin{aligned}
g_{Y,t+1} = \frac{\Delta y_{t+1}}{y_t} = \frac{1}{y_t}&\left(\underbrace{\int_{j\in J_S} \Delta y_{j,t+1} dj}_{=0} + \sum_{j\in J_L} \Delta y_{j,t+1}\right) \\
&= \frac{1}{y_t}\left(\sum_{j\in J_L} y_{j,t}\frac{\Delta y_{j,t+1}}{y_{j,t}}\right) \\
&= \sum_{j\in J_L} \frac{y_{j,t}}{y_t}\frac{\Delta z_{j,t+1}}{z_{j,t}} \\
&= \sigma_g \sum_{j\in J_L} \frac{y_{j,t}}{y_t}\varepsilon_{j,t+1}.
\end{aligned}
$$

□

Proof of Lemma 1.

$$
\begin{aligned}
\Lambda_{t,t+1} =& \beta \left(\frac{y_{t+1}}{y_t}\right)^{-\sigma} \left(\frac{\iota(i_{t+1})}{\iota(i_t)}\right)^{\theta(1-\sigma)} \\
\approx& \beta \left(1 + g_{Y,t+1}\right)^{-\sigma} \left(\frac{i_{t+1}}{i_t}\right)^{-\theta(1-\sigma)} \\
=& \beta \left(1 + g_{Y,t+1}\right)^{-\sigma} \left(1 + \alpha_{mp} g_{Y,t+1} + \epsilon_{i,t+1}\right)^{-\theta(1-\sigma)} \\
\approx& \beta \exp(-\sigma g_{Y,t+1}) \exp(-\theta(1-\sigma)(\alpha_{mp} g_{Y,t+1} + \epsilon_{i,t+1})) \\
=& \beta \exp(-\left(\sigma + \theta(1-\sigma)\alpha_{mp}\right) g_{Y,t+1} - \theta(1-\sigma)\epsilon_{i,t+1}).
\end{aligned}
$$

□

Proof of Proposition 3. Since $\mathbb{E}[\Delta y_{j,t+1}/y_{j,t}] = \sigma_g \mathbb{E}[\varepsilon_{j,t+1}] = 0$, we have

$$
\begin{aligned}
\mathrm{Cov}_1\left(\Lambda_{1,2}, \frac{y_{j,2}}{y_{j,1}}\right) =& \mathrm{Cov}_1\left(\Lambda_{1,2}, \frac{\Delta y_{j,2}}{y_{j,1}}\right) \\
=& \mathbb{E}_1\left[\Lambda_{1,2}\frac{\Delta y_{j,2}}{y_{j,1}}\right] \\
\approx& \mathbb{E}_1\left[\beta \exp(-\left(\sigma + \theta(1-\sigma)\alpha_{mp}\right) g_{Y,2} - \theta(1-\sigma)\epsilon_{i,2})\sigma_g \varepsilon_{j,2}\right] \\
=& \mathbb{E}_1\left[\beta \exp(-\left(\sigma + \theta(1-\sigma)\alpha_{mp}\right) g_{Y,2}) \exp(-\theta(1-\sigma)\epsilon_{i,2})\sigma_g \varepsilon_{j,2}\right] \\
=& \mathbb{E}_1\left[\beta \sigma_g \exp(-\left(\sigma + \theta(1-\sigma)\alpha_{mp}\right) g_{Y,2})\varepsilon_{j,2} \exp(-\theta(1-\sigma)\epsilon_{i,2})\right] \\
=& \mathbb{E}_1\left[\beta \sigma_g \mathbb{E}\left[\exp(-\left(\sigma + \theta(1-\sigma)\alpha_{mp}\right) g_{Y,2})\varepsilon_{j,2} \mid \epsilon_{i,2}\right] \exp(-\theta(1-\sigma)\epsilon_{i,2})\right] \\
=& \mathbb{E}_1\left[\beta \sigma_g \mathbb{E}\left[\exp(-\left(\sigma + \theta(1-\sigma)\alpha_{mp}\right) g_{Y,2})\varepsilon_{j,2}\right] \exp(-\theta(1-\sigma)\epsilon_{i,2})\right].
\end{aligned}
$$

Proposition 1 has shown that $g_{Y,t+1} = \sigma_g \sum_{j \in J_L} (y_{j,t}/y_t)\varepsilon_{j,t+1}$. Thus, for small firms $j \in J_S$,

$$
\mathbb{E}_1\left[\exp(-\left(\sigma + \theta(1-\sigma)\alpha_{mp}\right) g_{Y,2})\varepsilon_{j,2}\right] = 0.
$$

Hence,

$$
\mathrm{Cov}_1\left(\Lambda_{1,2}, \frac{y_{j,2}}{y_{j,1}}\right) = 0, \qquad \forall j \in J_S.
$$

For large firm $j \in J_L$,

$$
\begin{aligned}
&\mathbb{E}_1\left[\exp\left(-\left(\sigma + \theta(1-\sigma)\alpha_{mp}\right)\sigma_g \sum_{j \in J_L} \frac{y_{j,1}}{y_1}\varepsilon_{j,2}\right)\sigma_g \varepsilon_{j,2}\right] \\
&= \mathbb{E}_1\left[\exp\left(-\left(\sigma + \theta(1-\sigma)\alpha_{mp}\right)\sigma_g \frac{y_{j,1}}{y_1}\varepsilon_{j,2}\right)\sigma_g \varepsilon_{j,2}\right] \\
&\approx \mathbb{E}_1\left[\left(1 - \left(\sigma + \theta(1-\sigma)\alpha_{mp}\right)\sigma_g \frac{y_{j,1}}{y_1}\varepsilon_{j,2}\right)\sigma_g \varepsilon_{j,2}\right] \\
&= -\frac{y_{j,1}}{y_1}\mathbb{E}_1\left[\left(\sigma + \theta(1-\sigma)\alpha_{mp}\right)\sigma_g^2 \varepsilon_{j,2}^2\right] \\
&= -\frac{y_{j,1}}{y_1}\sigma_g^2\left[\sigma + \theta(1-\sigma)\alpha_{mp}\right].
\end{aligned}
$$

Hence,

$$
\begin{aligned}
\mathrm{Cov}_1\left(\Lambda_{1,2}, \frac{y_{j,2}}{y_{j,1}}\right) &\approx -\beta\frac{y_{j,1}}{y_1}\sigma_g^2\left[\sigma + \theta(1-\sigma)\alpha_{mp}\right]\mathbb{E}\left[\exp(-\theta(1-\sigma)\epsilon_{i,2})\right] \\
&\approx -\beta\frac{y_{j,1}}{y_1}\sigma_g^2\left[\sigma + \theta(1-\sigma)\alpha_{mp}\right]\left(1 + \frac{(\theta(1-\sigma)\sigma_i)^2}{2}\right).
\end{aligned}
$$

$\square$

Proof of Lemma 2. Approximating $\Lambda_{t,t+1}$ regarding $g_{Y,t+1}$ and $\epsilon_{i,t+1}$ up to the second order yields,

$$\Lambda_{t,t+1} \approx \beta \left(\begin{array}{l} 1-(\sigma+\theta(1-\sigma)\alpha_{mp})\, g_{Y,t+1} - \theta(1-\sigma)\epsilon_{i,t+1} \\ +\frac{1}{2}\left[\begin{array}{l} (\sigma+\theta(1-\sigma)\alpha_{mp})^2\, g_{Y,t+1}^2 + (\theta(1-\sigma))^2\, \epsilon_{i,t+1}^2 \\ +2\,(\sigma+\theta(1-\sigma)\alpha_{mp})\,\theta(1-\sigma) g_{Y,t+1}\epsilon_{i,t+1} \end{array} \right] \end{array} \right)$$

Thus, we have

$$\begin{aligned} \mathbb{E}\left[\tilde{\Lambda}_{1,2}^{(0)}\right] &= \mathbb{E}\left[\tilde{\Lambda}_{1,2}^{(0)} \mid \mathcal{F}_{1_m^-}\right] \\ &\approx \beta\left(1+\frac{1}{2}\left\{\left[\sigma^2+2\theta\sigma(1-\sigma)\tilde{\alpha}_{mp,0}+(\theta(1-\sigma))^2\,\tilde{\sigma}_{mp,0}^2\right]\sigma_{g_Y,1}^2+(\theta(1-\sigma))^2\,\sigma_i^2\right\}\right). \end{aligned}$$

Similarly, we have

$$\mathbb{E}\left[\tilde{\Lambda}_{1,2}^{(1)}\right] \approx \beta\left(1+\frac{1}{2}\left\{\left[\sigma^2+2\theta\sigma(1-\sigma)\tilde{\alpha}_{mp,1}+(\theta(1-\sigma))^2\,\tilde{\sigma}_{mp,1}^2\right]\sigma_{g_Y,1}^2+(\theta(1-\sigma))^2\,\sigma_i^2\right\}\right).$$

So, we have

$$\mathbb{E}\left[\tilde{\Lambda}_{1,2}^{(1)}\right]-\mathbb{E}\left[\tilde{\Lambda}_{1,2}^{(0)}\right] \approx \theta(1-\sigma)\left[\sigma(\tilde{\alpha}_{mp,1}-\tilde{\alpha}_{mp,0})+\frac{\theta(1-\sigma)}{2}\left(\tilde{\sigma}_{mp,1}^2-\tilde{\sigma}_{mp,0}^2\right)\right]\sigma_{g_Y,1}^2.$$

We turn to the covariance terms. For small firms $j \in J_S$, it is clear that $\mathrm{Cov}\left(\tilde{\Lambda}_{1,2}^{(0)}, \frac{y_{j,2}}{y_{j,1}}\right) = \mathrm{Cov}\left(\tilde{\Lambda}_{1,2}^{(1)}, \frac{y_{j,2}}{y_{j,1}}\right) = 0$. On the other hand, for large firms $j \in J_L$,

$$\begin{aligned} \mathrm{Cov}\left(\tilde{\Lambda}_{1,2}^{(0)}, \frac{y_{j,2}}{y_{j,1}}\right) =& \mathbb{E}\left[\exp\left(-(\sigma+\theta(1-\sigma)\alpha_{mp})\,\sigma_g\sum_{j\in J_L}\frac{y_{j,1}}{y_1}\varepsilon_{j,2}\right)\sigma_g\varepsilon_{j,2} \mid \mathcal{F}_{1_m^-}\right] \\ \approx& \mathbb{E}\left[\left(1-(\sigma+\theta(1-\sigma)\alpha_{mp})\,\sigma_g\frac{y_{j,1}}{y_1}\varepsilon_{j,2}\right)\sigma_g\varepsilon_{j,2} \mid \mathcal{F}_{1_m^-}\right] \\ =& -\frac{y_{j,1}}{y_1}\mathbb{E}\left[(\sigma+\theta(1-\sigma)\alpha_{mp})\,\sigma_g^2\varepsilon_{j,2}^2 \mid \mathcal{F}_{1_m^-}\right] \\ =& -\frac{y_{j,1}}{y_1}\sigma_g^2\left[\sigma+\theta(1-\sigma)\tilde{\alpha}_{mp,0}\right] \end{aligned}$$

Similarly, we have

$$\mathrm{Cov}\left(\tilde{\Lambda}_{1,2}^{(1)}, \frac{y_{j,2}}{y_{j,1}}\right) = -\frac{y_{j,1}}{y_1}\sigma_g^2\left[\sigma+\theta(1-\sigma)\tilde{\alpha}_{mp,1}\right].$$

So, we have

$$\text{Cov}\left(\tilde{\Lambda}_{1,2}^{(1)}, \frac{y_{j,2}}{y_{j,1}}\right) - \text{Cov}\left(\tilde{\Lambda}_{1,2}^{(0)}, \frac{y_{j,2}}{y_{j,1}}\right) = \frac{y_{j,1}}{y_1}\sigma_g^2\theta(\sigma-1)\left(\tilde{\alpha}_{mp,1} - \tilde{\alpha}_{mp,0}\right).$$

$\square$

Derivation of (12)

$$\begin{aligned}
&\text{Cov}\left(\frac{\Delta q_{j,t_m}}{q_{j,t_m^-}}, MPS_{t_m} \mid \mathbb{Z}_{j,t}\right) \\
&= \mathbb{E}\left[\frac{\Delta q_{j,t_m}}{q_{j,t_m^-}}, MPS_{t_m} \mid \mathbb{Z}_{j,t}\right] \\
&= \frac{d_{j,t}}{q_{j,t_m^-}}\left(\mathbb{E}\left[\left(p_{t_m} - p_{t_m^-}\right) MPS_{t_m}\right] + \theta(\sigma-1)\left(\frac{y_{j,t}}{y_t}\sigma_g^2\right)\mathbb{E}\left[\left(\tilde{\alpha}_{mp,t} - \tilde{\alpha}_{mp,t-1}\right) MPS_{t_m}\right]\right).
\end{aligned}$$

APPENDIX B Data

B.1 Definition of variables

- Asset is *atq*. This item represents the total value of assets reported on the Balance Sheet.
- Sales are *saleq*. Capital is *ppentq*. Size is $\log(asset)$.
- Book value of equity is the book value of preferred stock and equity (item *seq*).
- Market value of equity is from monthly CRSP. This is the product of the number of outstanding shares *shrout* and the last traded price in a month *altprc*. Then, the logged value is used.

APPENDIX C Robustness

C.1 Relation to the literature

Ehrmann and Fratzscher (2004), Maio (2014), and Perez-Quiros and Timmermann (2000) find that smaller firms' stocks are more responsive to the monetary policy shock. This section addresses why they have different conclusions.

Ehrmann and Fratzscher (2004) First, this research and Ehrmann and Fratzscher (2004) have three key differences 1. firms covered in the sample, 2. the sample period 3. monetary policy shock. While they use only S&P 500 firms, this research includes all firms that are included in CRSP, namely firms included in NYSE, AMEX, and NASDAQ. This subsection shows that when the sample is limited in a very specific way, we can replicate the result that the smaller firms are more responsive. Therefore, point 1 is critical, but we find that the sample selection in Ehrmann and Fratzscher (2004) is not robust to the assumptions.

As shown in the main text, when sample firms cover the all firms included in NYSE, AMEX, and NASDAQ, the larger firms are more responsive to the monetary policy shock. In this sense, the result in this research is a more general result than that in Ehrmann and Fratzscher (2004). However, to see how the sample selection matters, I limit the sample to only larger firms as Ehrmann and Fratzscher (2004) limits the sample to only S&P 500 firms.

The procedure is

1. Measure the market equity. When the FOMC is in month t, the measured market equity is in month t.
2. Pool the entire sample and sort the firms into 10 groups based on the market equity from smaller to larger.
3. Use the sample in groups 7-10.
4. Estimate the following regression:

$$\text{Return}_{i,t} = \beta_1 MPS_t + \beta_2 \text{market capital}_{it} + \beta_3 MPS_t * \text{market capital}_{it} + \epsilon_{it}$$

Table 5 shows the estimated result for that specification. The first column shows that the estimated β_3 is significantly positive, as consistent with Ehrmann and Fratzscher (2004).

However, these results are sensitive to procedures 1-3.

1. When the market equity is measured by lagged variable, the estimated β_3 is significantly negative. When the FOMC is in month t and the measure market equity is in month $t-3$, the coefficient is no longer positive.
2. If the firms are sorted every period, the estimated β_3 is significantly negative. In the previous procedure, the sample is pooled and rank firms. Here, the firms are ranked every period and sorted into 10 groups.
3. When the sample includes the group of 1-6, the coefficients are significantly negative.

The second column in table 5 shows the estimated result when the entire sample is used for the estimation. The estimated β_3 is significantly negative. The third column uses the same sample, namely only large market capital firms, but the heterogeneity is measured as asset. The estimated β_3 is significantly negative.

$$\text{Return}_{i,t} = \beta_1 MPS_t + \beta_2 \text{asset}_{it} + \beta_3 MPS_t * \text{asset}_{it} + \epsilon_{it}$$

Table 5: Return sensitivity to monetary policy shock

Dependent Variable:	excess return		
Model:	(1)	(2)	(3)
Variables			
Constant	0.6073***	0.0189	0.7459***
	(0.0315)	(0.0152)	(0.0267)
Market cap.	-0.0350***	0.0395***	
	(0.0040)	(0.0026)	
MP shock	-8.626***	-2.104***	-4.495***
	(0.6327)	(0.3040)	(0.5296)
Market cap. × MP shock	0.2736***	-0.5850***	
	(0.0812)	(0.0520)	
Asset			-0.0543***
			(0.0035)
Asset × MP shock			-0.2728***
			(0.0690)
Fit statistics			
Observations	289,819	739,569	289,612
R^2	0.01394	0.00326	0.01460
Adjusted R^2	0.01393	0.00326	0.01459

IID standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Maio (2014) Maio (2014) also find that the smaller firms' stocks are more responsive to monetary policy. There are two key differences between Maio (2014) and this paper. First, Maio (2014) uses monthly return data of the portfolio. Second, the monetary policy shock is not a high-frequency change in interest rates around FOMC announcements. It uses two proxies for monetary policy actions: (i) the monthly change in the Fed fund rate, $\Delta\text{FFR}_t = \text{FFR}_t - \text{FFR}_{t-1}$. (ii) the difference between Fed fund rate and the lagged 1-month Treasury bill rate: $\text{FFR}_t - R_{f,t-1}$. Monthly frequency makes the identification difficult because the monthly portfolio return is affected by many factors other than monetary policy announcements. Similarly, monthly the difference between Fed fund rate and the lagged 1-month Treasury bill rate can include both anticipated and unanticipated changes in monetary policy actions.

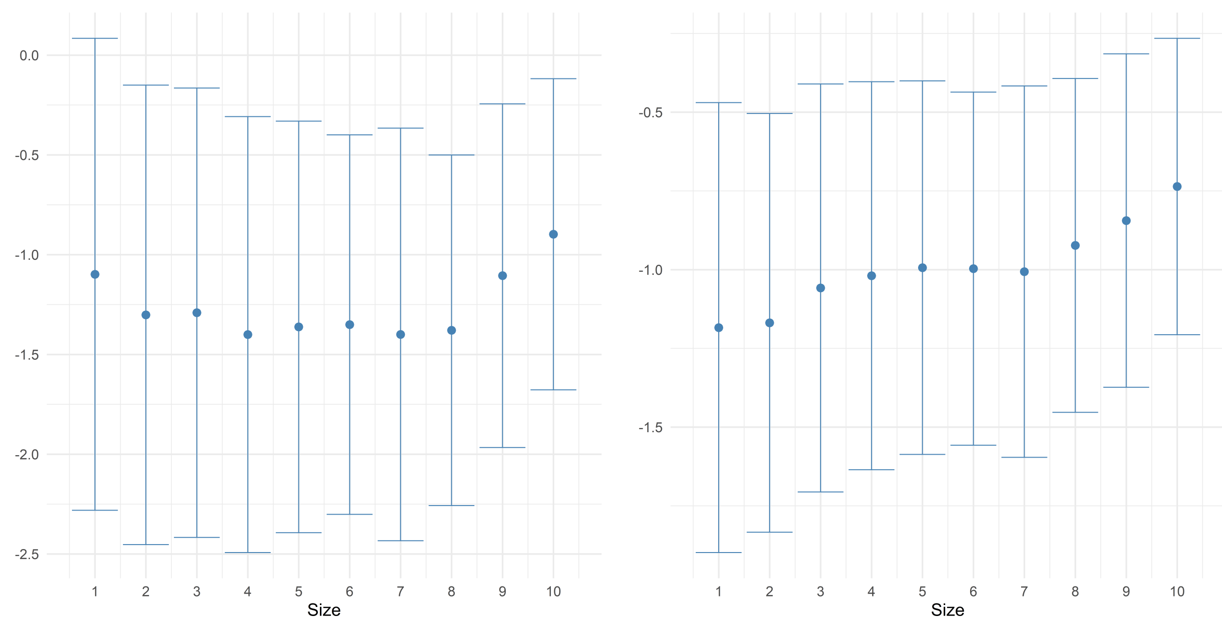
To replicate the results for Maio (2014), I estimate these regressions on a monthly basis:

$$r_{i,t} = a^i + b^i \Delta\text{FFR}_t + \epsilon_{i,t}$$

$$r_{i,t} = a^i + b^i (\text{FFR}_t - R_{f,t-1}) + \epsilon_{i,t}$$

where i is the index of the portfolio sorted by the size of firms, and $r_{i,t}$ is the monthly return of portfolio i. The return of the portfolio is obtained from French's website.

Figure C.1 shows the estimated results for b^i. Although the result using ΔFFR_t does not show the heterogeneity across firm size, the result using $\text{FFR}_t - R_{f,t-1}$ shows that the smaller firms portfolio shows larger elasticity.



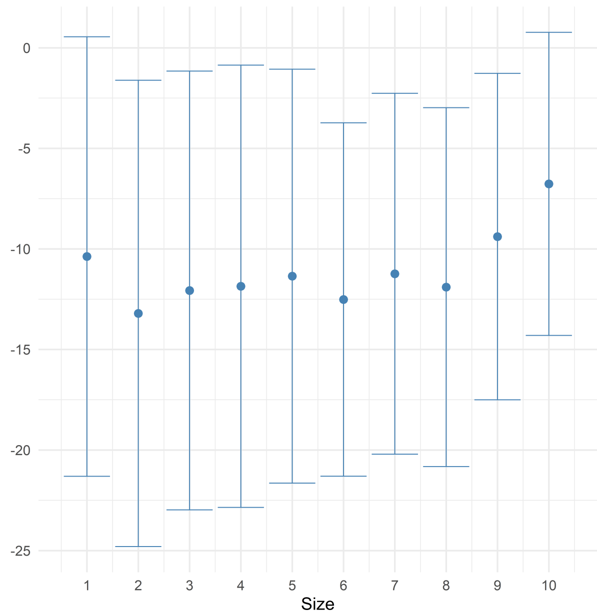
(a) ΔFFR_t **(b)** $\text{FFR}_t - R_{f,t-1}$

Figure C.1: Replicated Maio (2014)

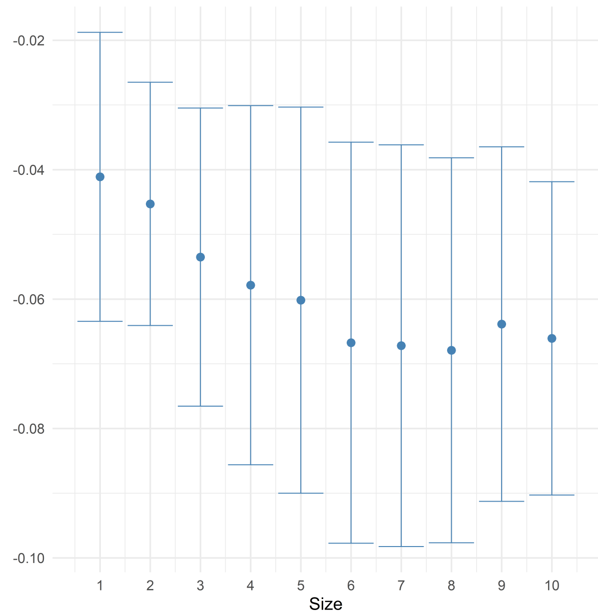
However, this result is not robust to the choice of frequency or the choice of monetary policy shock. I estimate this regression

$$r_{i,t} = a^i + b^i MPS_t + \epsilon_{i,t}.$$

for (a) monthly frequency of returns and (b) the sample is only daily returns on FOMC announcement days. (b) is an event-study approach. The proxy for monetary policy action is the intraday change in interest rates on FOMC announcement days. Figure C.2-(a) uses intraday change in interest rates as proxy and $r_{i,t}$ is monthly portfolio return. It does not show that the smaller firms portfolio shows larger elasticity. Figure C.2-(b) uses intraday change in interest rates as proxy and $r_{i,t}$ is daily return on announcement days. It shows that the larger firms' returns have larger elasticity.



(a) High-frequency change in FFR



(b) Daily portfolio return on FOMC days

Figure C.2: Different specification for Maio (2014).

C.2 predictability

Table 6: Monetary Policy Surprise and Predicatability

Dependent Variable:	Conventional Monetary Policy Surprise					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
GDP Growth Forecast	0.011***					0.007***
	(0.002)					(0.002)
SP500 Change		0.173***				0.111**
		(0.046)				(0.054)
Nonfarm Payroll Change			0.005***			0.001
			(0.002)			(0.003)
GDP Growth Revision				0.017***		0.007
				(0.005)		(0.005)
Nonfarm Payrolls Revision					0.0001***	0.00004
					(0.00003)	(0.00004)
Observations	176	240	240	176	240	176
R^2	0.120	0.057	0.027	0.066	0.026	0.168

Notes: The dependent variable is the first principal component of the changes in the first four quarterly Eurodollar futures contracts, ED1 through ED4, around the FOMC press releases. The independent variables are information about macroeconomic conditions available to private sector agents prior to FOMC announcements. GDP Growth Forecast is a Greenbook forecast for real GDP growth. SP500 Change is the log change in the S&P 500 from 13 weeks prior to the announcement to the day before the announcement. GDP Growth Revision is a revision of the Greenbook forecast for real GDP growth between consecutive meetings. Nonfarm Payroll Change is the log change in nonfarm payrolls over the past 12 months. Nonfarm Payrolls Revision is the surprise component of the most recent nonfarm payrolls. We estimate the following regression equations:

$$MPS_t = \alpha + \beta' X_{t^-} + \varepsilon_t$$

The sample period is 1990-2019 for columns (2), (3), and (5), and 1990-2011 for columns (1), (4), and (6). *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.