Large Firms and Monetary Policy Surprises: Unraveling Excessive Stock Price Sensitivity*

Masayuki Okada† Kazuhiro Teramoto‡

February 8, 2026

Abstract

This paper proposes a novel mechanism explaining why large firms exhibit stronger stock price responses to monetary policy surprises. Empirically, we show that endogeneity arising from the ex-post predictability of these surprises disproportionately affects large firms, leading to overestimated stock return responses. We develop an asset pricing model with granular-origin aggregate fluctuations and investors' imperfect knowledge of monetary policy rule parameters. Belief revisions about the policy stance drive both monetary policy surprises and stronger stock price responses for large firms through changes in the risk premium—even without investor heterogeneity or differential effects of policy shocks on firm fundamentals.

Keywords: monetary policy surprises, stock returns, high-frequency identification, partial information, learning, granular-origin aggregate fluctuations

JEL Classification: E43, E44, E52, E58, G12

*First version: July 2024. A previous version has been circulated under the title "Illusive Asymmetry in Stock Price Reactions to Monetary Policy Shocks." The authors extend their gratitude to Jess Benhabib, Mark Gertler, Daisuke Ikeda, Hiroyuki Kubota, Sydney Ludvigson, Mototsugu Shintani, Koji Takahashi, Takayuki Tsuruga, Kozo Ueda, Kenji Wada, Shingo Watanabe, Masayuki Yagasaki, and the participants of the advanced macroeconomics workshop, the 2024 Asia Meeting of the Econometric Society, East & Southeast Asia, and a seminar at the Bank of Japan for their valuable comments and suggestions. Teramoto gratefully acknowledges the financial support of the JSPS Grant-in-Aid for Scientific Research (24K16356). The views expressed here are those of the authors and not necessarily those of the Bank of Japan.

†Bank of Japan. 2-1-1 Nihonbashi-Hongokucho, Chuo-ku, Tokyo, Japan. 103-0021. Email: masayuki.okada@boj.or.jp

‡Graduate School of Economics, Hitotsubashi University, 2-1 Naka, Kunitachi, Tokyo, Japan. 186-8603. Email: k.teramoto@r.hit-u.ac.jp

1 Introduction

Monetary policy affects firms differently depending on their characteristics, with firm size—typically measured by market capitalization, sales, or employment—widely viewed as a key dimension (Gertler and Gilchrist, 1994). A substantial empirical literature has explored how the transmission of monetary policy varies with firm characteristics, using diverse identification strategies. In recent years, high-frequency identification (HFI) methods have gained traction, employing changes in interest rates within narrow windows around Federal Open Market Committee (FOMC) announcements—so-called monetary policy surprises—as instruments for policy shocks. Applying this approach, recent studies (e.g., Ozdagli, 2018; Chava and Hsu, 2020; Morlacco and Zeke, 2021; Döttling and Ratnovski, 2023) consistently find that stock prices of larger firms respond more strongly to monetary policy *surprises*. Under the full-information rational expectations (FIRE) assumption, which ensures the validity of using these surprises as instruments, these findings are interpreted as evidence that large firms are more sensitive to monetary policy shocks.

Against this background, this study pursues two main objectives. First, we study whether and how the predictability of monetary policy surprises using information available prior to policy announcements (Cieslak, 2018; Miranda-Agrippino and Ricco, 2021; Karnaukh and Vokata, 2022; Bauer and Swanson, 2023a,b) can bias the estimation of firm-level stock price responses to monetary policy shocks. Importantly, our econometric framework allows for heterogeneity in the confounding effect across firms, and we find that large firms are disproportionately affected by overestimation bias. This finding suggests that the stronger stock price reactions of large firms reported in earlier studies may, at least in part, reflect endogeneity-driven overestimation rather than genuine differences in exposure to monetary policy shocks. Second, we provide a theoretical explanation for these empirical patterns, focusing on why large firms' stock prices react excessively to monetary policy surprises and why this excess sensitivity is specific to large firms.

We begin by empirically investigating the estimation bias resulting from the *ex post* predictability of monetary policy surprises, which suggests that markets have an imperfect understanding of the Federal Reserve's policy rule (Bauer and Swanson, 2023a,b; Sastry, forthcoming). With such incomplete knowledge, observed surprises include not only monetary policy shocks but also the gap between the Fed's actual policy rule and the private sector's prior belief, leading investors to revise their beliefs about the Fed's reaction function in response to those surprises.[1] Because such belief revisions can affect stock returns

[1] Using panel data on professional forecasts, Bauer, Pflueger, and Sunderam (2024) find that roughly half of the variation in monetary policy surprises can be attributed to forecasters' misperceptions of the policy rule.

contemporaneously, in our empirical analysis we focus on a confounding effect arising from this belief-revision channel, which generates spurious comovement between monetary policy surprises and stock returns and thereby biases shock-response estimates.

To detect this confounding effect, we conduct a simple endogeneity test. Our findings indicate that endogeneity leads to a downward bias in estimated stock return responses, overstating the negative impact of interest rate hikes on stock returns. Importantly, this bias is not uniform across firms: it is particularly pronounced among large firms, while smaller firms are largely unaffected. In other words, monetary policy surprises reflecting investors' misperceptions about the Fed's policy rule disproportionately inflate the estimated stock return sensitivity of large firms. We also demonstrate that, once this endogeneity is properly addressed, estimated responses appear far more uniform across firm sizes than previously reported. Taken together, these results suggest that the stronger stock price reactions of large firms to monetary policy surprises are largely attributable to belief-driven movements rather than greater fundamental exposure to monetary policy shocks.

A natural question is why we focus on firm size as the key dimension of heterogeneity. Firm size is associated with many firm characteristics often discussed in the context of monetary policy transmission—such as liability structure—implying that any size-related bias can contaminate a broad range of firm-level estimates. At the same time, one might suspect that the observed size-related heterogeneity in overestimation bias simply reflects variation along alternative dimensions of firm heterogeneity. Our empirical results provide little support for this interpretation: even after controlling for a rich set of firm characteristics related to firms' financial structures, large firms remain more prone to overestimation in their stock return responses to monetary policy surprises.

These empirical results point to a systematic pattern in which belief-driven revisions about monetary policy have a larger effect on the stock prices of large firms. To uncover a potential mechanism behind this pattern, we develop a nominal asset pricing model. The framework builds on the Lucas (1978) tree economy and incorporates granular-origin aggregate fluctuations à la Gabaix (2011). The economy features a continuum of small firms and a finite number of large firms. Idiosyncratic shocks to large firms contribute to aggregate fluctuations via the granular channel, whereas shocks to small firms are orthogonal to the aggregate economy. As a result, the output and profits of large firms are more strongly correlated with aggregate conditions than those of smaller firms.

Households exhibit money-in-the-utility preferences, so that the marginal utility of consumption depends on real money balances. This feature endogenously links the stochastic discount factor (SDF) to nominal interest rates. The central bank follows a data-dependent monetary policy rule, adjusting the nominal interest rate in response to aggregate indicators such as the output gap. Because large firms disproportionately shape aggregate outcomes, interest rate changes end up being more strongly correlated with large firms' fundamentals than with those of smaller firms. Importantly, the model does *not* assume that large firms' fundamentals, such as output, profits, or dividends, are inherently more exposed to monetary policy shocks. Rather, monetary policy, albeit unintentionally, is more responsive to large firms simply due to their outsized role in shaping macroeconomic aggregates.

This asymmetry affects stock prices through the risk premium component, which is governed by the covariance between the SDF and firm-level profit growth. The more responsive the central bank is to aggregate conditions, the more closely fluctuations in the SDF are tied to the performance of large firms, whose profits are more correlated with the aggregate economy. In contrast, the SDF-profit covariance for smaller firms remains small and largely irrelevant to monetary policy responsiveness. Consequently, monetary policy responsiveness disproportionately affects the risk premium embedded in large firms' stock prices.

Informational frictions play a central role in asset pricing. Specifically, we assume that investors do not perfectly perceive the parameters of the monetary policy rule—particularly those governing how interest rates respond to macroeconomic data—and instead form expectations about yields based on their forecasts of these parameters. As a result, measured monetary policy surprises reflect not only exogenous policy shocks but also the discrepancy between the Fed's actual policy function and the private sector's prior estimate. We further assume that investors update their beliefs about these parameters sequentially using real-time data in a Bayesian manner. This implies that monetary policy surprises prompt investors to revise their forecasts of the policy rule.[2] Since the SDF depends on nominal interest rates, these belief revisions directly affect the SDF and, in turn, asset prices.

In the presence of granular-origin aggregate fluctuations, these belief-driven changes in the SDF generate heterogeneous effects on stock returns. This heterogeneity arises not from differences in investor behavior, but from variation in the sensitivity of the risk premium, i.e., the covariance between the SDF and firm profits, which is more pronounced for larger firms. Consequently, monetary policy surprises, by triggering revisions in investors' expectations about the degree of policy responsiveness, produce systematically stronger stock price reactions for large firms than for smaller ones.

Related Literature This study contributes to two strands of empirical literature on monetary policy. First, it relates to research on heterogeneous firm-level responses to monetary policy shocks (e.g., Gertler and Gilchrist, 1994; Ippolito, Ozdagli, and Perez-Orive, 2018;

[2]See Bauer, Pflueger, and Sunderam (2024) for empirical evidence that monetary policy surprises prompt revisions in professional forecasters' beliefs about the Fed's policy rule parameters, particularly its responsiveness to GDP.

Ottonello and Winberry, 2020), which highlights the importance of identifying cross-firm variation to understand transmission mechanisms. For instance, the credit channel (Kiyotaki and Moore, 1997) suggests that financially constrained firms are more sensitive to policy changes. However, as mentioned, we show that conventional strategies may overstate heterogeneity, particularly by inflating the estimated sensitivity of large firms, due to confounding effects arising from investor belief revisions.

Second, this study relates to the growing literature on HFI of monetary policy shocks. While HFI methods, pioneered by Bernanke and Kuttner (2005) and Gürkaynak, Sack, and Swanson (2005), have become standard in empirical macroeconomics, recent work has raised concerns about their validity. In particular, high-frequency monetary policy surprises may embed endogenous components arising from informational frictions. One such channel, the Fed information effect, suggests that surprises reveal the central bank's private assessment of the economy and thus shift market expectations (e.g., Nakamura and Steinsson, 2018; Jarociński and Karadi, 2020). In contrast, Bauer and Swanson (2023a,b) and Bauer, Pflueger, and Sunderam (2024) emphasize the role of market misperceptions about the Fed's policy rule, consistent with evidence that surprises are predictable using public macro-financial news. Most recently, Sastry (forthcoming) offers a unified framework evaluating the relative importance of these channels and finds that the Fed information effect plays only a negligible quantitative role.

Yet despite growing attention to these endogeneity concerns, the implications of such endogeneity for firm-level heterogeneity remains underexplored. Existing studies have largely focused on aggregate outcomes, including the price level (Miranda-Agrippino and Ricco, 2021), exchange rates (Camara, 2025), bond prices and equity indices (Nakamura and Steinsson, 2018; Jarociński and Karadi, 2020; Bauer and Swanson, 2023b), and labor supply (Graves, Huckfeldt, and Swanson, 2023). Several studies using conventional monetary policy surprises report that large firms' stock prices respond more strongly to policy announcements (e.g., Ozdagli, 2018; Chava and Hsu, 2020; Morlacco and Zeke, 2021; Döttling and Ratnovski, 2023). This paper examines how identification issues inherent in HFI methods contribute to this pattern. We show that endogeneity-induced estimation bias, as mentioned, is not uniform across firms but disproportionately affects the stock prices of large firms, overstating their sensitivity to monetary policy shocks. This suggests a novel interpretation, namely, that the stronger response of the stock prices of large firms reflects greater sensitivity to revisions in market perceptions about the policy stance rather than fundamentally greater exposure to policy shocks. Using residualized instruments that remove the influence of public news, we find that the observed cross-sectional differences in stock price reactions across firm sizes diminish substantially.

Structure of the Study The remainder of the study is organized as follows. Section 2 proposes an endogeneity test and presents empirical evidence of the estimation bias. Section 3 develops a theoretical model to explain the bias. Section 4 discusses other potential sources of endogeneity, while Section 5 offers concluding remarks.

2 Empirical Analysis

In this section, we empirically investigate the effects of monetary policy on firms' stock prices, with particular attention to how these effects vary by firm size. We begin by revisiting established empirical findings based on high-frequency data, and then delve deeper into these results by highlighting potential endogeneity issues that may bias conventional interpretations.

2.1 Large Firms' Excessive Stock Price Sensitivity to Surprises

High-frequency monetary policy surprises—measured by changes in interest rate futures around FOMC announcements—have become a standard instrument for identifying monetary policy shocks in empirical macroeconomics. This identification strategy is particularly appealing because, under the FIRE assumption, these surprises provide valid instruments for discretionary policy shocks, provided there is sufficient variation.

A large empirical literature employs this HFI approach to examine the transmission of monetary policy to firm outcomes, paying particular attention to heterogeneity across firm characteristics. A consistent finding is that the stock prices of larger firms respond more strongly to monetary policy surprises (e.g., Ozdagli, 2018; Chava and Hsu, 2020; Morlacco and Zeke, 2021; Döttling and Ratnovski, 2023). In this subsection, we begin by documenting this pattern using our dataset.

Monetary Policy Surprise Throughout this paper, we denote the monetary policy surprise observed around the FOMC announcement in period t as MPS_t, defined by

$$MPS_t \equiv i_t - i_{t^-},$$

where i_t is the interest rate futures rate immediately after the FOMC announcement, and i_{t^-} is the rate just before the announcement ($t^- \equiv \lim_{s \to t} s$).

Following standard practice in the HFI literature, we measure monetary policy surprises using changes in federal funds futures and Eurodollar (ED) futures around FOMC announcements. Specifically, we compute the changes in these futures over a 30-minute window—beginning 10 minutes before and ending 20 minutes after each FOMC press release—using intraday tick data. For our baseline measure of MPS_t, we follow Nakamura and Steinsson (2018) and extract the first principal component of the changes in current- and next-month federal funds futures, as well as ED futures contracts spanning from the current quarter to four quarters ahead. The baseline analysis focuses on scheduled FOMC meetings only. Robustness analyses using alternative measures and including unscheduled meetings are provided in Section 2.4.

Data on Stock Prices We use daily stock prices for publicly traded U.S. firms obtained from the Center for Research in Security Prices (CRSP) U.S. Stock Database. The dataset includes firms incorporated in the United States and listed on the NYSE, Amex, or Nasdaq, excluding financial firms. The observation period spans from 1990 to 2019.

We compute the daily excess return of firm i's stock on FOMC announcement days as

$$\Delta y_{i,t} \equiv \frac{q_{i,t} - q_{i,t-1}}{q_{i,t-1}} - \frac{p_t - p_{t-1}}{p_{t-1}},$$

where t denotes the FOMC announcement day, $t-1$ is the previous trading day, $q_{i,t}$ is the closing price of stock i on day t, and p_t represents the closing price of one-month Treasury bills. This measure, $\Delta y_{i,t}$, captures the stock price change relative to the bond price movement in response to the FOMC announcement.

Data on Firm Characteristics We merge daily stock price data from CRSP with quarterly balance sheet information from Compustat using a consistent firm identifier. Following standard practice in the literature, we exclude firms in the financial sector from the analysis.[3]

In this study, we employ four commonly used measures of firm size: total assets, sales, book value of equity, and market value of equity. As shown in Table A.1 in Appendix A, these variables are strongly positively correlated, indicating that they capture closely related aspects of firm size.

In Table A.1, we also report correlations between firm size measures and commonly used firm characteristics, such as leverage, cash ratio, and short-term debt ratio. Given

[3] We further restrict the sample by removing firms reporting negative values for total assets, sales, or capital. To reduce the influence of outliers, we apply additional filters to exclude firms exhibiting implausible financial characteristics, such as a current cash outflow ratio exceeding 10% of total assets, a leverage ratio below zero or above ten, or quarterly sales growth exceeding ±100%, as well as firms with fewer than five years of non-missing data.

their systematic correlation with firm size, we control for these financial characteristics—in addition to standard firm fixed effects—when estimating size-related effects. Additional details on the construction of our firm-level data are provided in Supplementary Appendix F.

Econometric Model Let $\mathcal{F}_t$ denote the information set available to private sector agents at time t. We model monetary policy surprises using the following specification:

$$MPS_t = \beta^{'} X_{t-1} + \varepsilon_{mp,t}; \qquad \mathbb{E}\left[\varepsilon_{mp,t}|\mathcal{F}_{t^-}\right] = 0 \text{ and } \mathbb{E}\left[\varepsilon_{mp,t}^2|\mathcal{F}_{t^-}\right] = \sigma_{mp}^2 > 0, \tag{1}$$

where $X_{t-1} = (x_{1,t-1}, \ldots, x_{\ell,t-1})'$ is a vector of macroeconomic and financial variables observed by both the Fed and private sector agents up to the day before the FOMC meeting, $\beta = (\beta_1, \ldots, \beta_\ell)'$ is the coefficient vector, and $\varepsilon_{mp,t}$ represents the component of the surprise that is unpredictable even ex post from the perspective of private agents. This residual includes genuinely exogenous policy shocks and, potentially, the effects of the Fed's private information about macroeconomic conditions (e.g., Romer and Romer, 2000; Nakamura and Steinsson, 2018)—though the empirical literature suggests that the quantitative importance of the latter is negligibly small (Sastry, forthcoming).

The FIRE assumption requires $\beta = \mathbf{0}$; in other words, $\text{Cov}(MPS_t, X_{t-1}) = 0$ is a *necessary* condition for FIRE. Thus, finding $\beta \neq \mathbf{0}$, or equivalently, $\text{Cov}(MPS_t, X_{t-1}) \neq 0$ implies, at a minimum, a violation of the FIRE assumption. Moreover, $\beta \neq \mathbf{0}$ challenges the view that the discrepancy between monetary policy surprises and exogenous shocks is solely due to the Fed's private information about macroeconomic conditions (see Sastry, forthcoming).

To assess the effects of monetary policy shocks on stock prices across different firm sizes, we consider the following stochastic process for firm-level stock returns:

$$\Delta y_{i,t} = fe_i + \xi w_{i,t} + \sum_{k=1}^{10} \gamma_k \varepsilon_{mp,t} D_{\{size_{i,t}=k\}} + \delta_k' X_{t-1} D_{\{size_{i,t}=k\}} + e_{i,t}, \tag{2}$$

where fe_i captures unobserved firm fixed effects, $w_{i,t}$ is a vector of time-varying firm characteristics (described below), and $e_{i,t}$ is an error term satisfying $\mathbb{E}[e_{i,t} \mid \mathcal{F}_{t^-}] = 0$ for all i and is orthogonal to monetary policy shocks. The dummy variable $D_{\{size_{i,t}=k\}}$ equals one if firm i's size falls between the $(k-1)$-th and k-th deciles, i.e., $D_{\{size_{i,t}=k\}} = \mathbb{1}\left\{size_{i,t} \in [\bar{d}_{k-1}, \bar{d}_k)\right\}$. The coefficients of interest, γ_k, measure the impact of monetary policy shocks on the stock returns of firms in each size group $k = 1, \ldots, 10$. A further important aspect is that the inclusion of $\delta_k' X_{t-1}$ allows the effects of pre-announcement macro-financial variables to vary across firm sizes.

For time-varying firm characteristics $w_{i,t}$, we include a set of controls capturing the main channels through which monetary policy is commonly understood to affect asset prices in the literature. Specifically, to capture firms' exposure to changes in interest rates, we include the cash ratio, leverage, short-term debt share, and interest burden.[4] The cash ratio is defined as cash and short-term investments divided by total assets and proxies for liquidity. Leverage is defined as total debt divided by total assets, where total debt is the sum of short- and long-term debt. The short-term debt share is defined as short-term debt divided by total debt and captures debt maturity. Interest burden is measured as interest expense relative to total assets and reflects debt servicing costs. While the baseline specification includes these controls linearly, Section 2.4 presents robustness checks in which we additionally allow these firm characteristics to interact with monetary policy shocks, thereby allowing for a more flexible characterization of heterogeneity along these channels.

Estimation Results under the Conventional Assumption We begin by presenting estimates under the conventional assumption that monetary policy surprises are unpredictable ($\beta = \mathbf{0}$). Under this assumption, MPS_t serves as a valid instrument for $\varepsilon_{mp,t}$, and a fixed effects regression of (2) using only MPS_t—*without controlling for* X_{t-1}—yields consistent estimates of γ_k for $k = 1, \ldots, 10$. Specifically, $\mathbb{E}[\varepsilon_{mp,t}(\delta_k' X_{t-1} + e_{i,t})] = 0$ holds, implying that omitting X_{t-1} does not introduce omitted variable bias in estimating γ_k, even when $\delta_k \neq \mathbf{0}$.

Let $\hat{\gamma}_k^{mps}$ denote the conventional estimate of γ_k obtained using MPS_t as the instrument. Figure 1 presents these estimates, along with their 95% confidence intervals, using firm size measures based on total assets (Panel (a)) and sales (Panel (b)).[5]

The figure reveals pronounced heterogeneity in stock return responses across firm sizes: larger firms exhibit stronger reactions to monetary policy surprises. For instance, an unexpected 1 percentage point increase in the federal funds rate leads to an estimated 6.0% decline in stock prices for firms in the top 10% of the asset size distribution, compared to a 3.9% decline for those in the bottom 10% (see Panel (a)). This stronger sensitivity among larger firms is consistent with the findings of prior studies (e.g., Ozdagli, 2018; Chava and Hsu, 2020; Morlacco and Zeke, 2021; Döttling and Ratnovski, 2023).

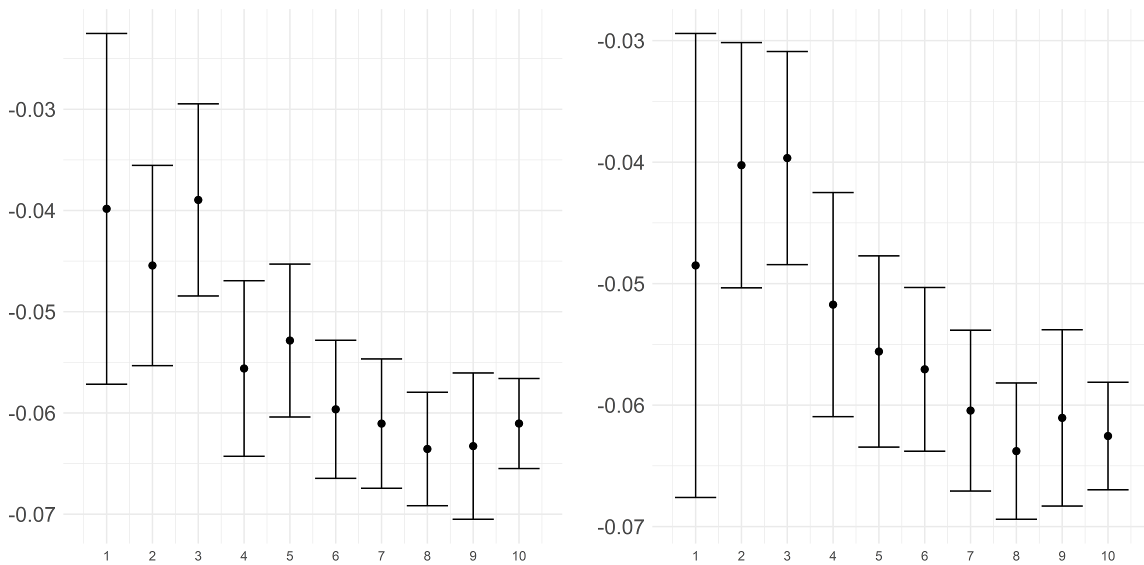
It has to be stressed that these estimates are obtained under the conventional assumption that MPS_t is unpredictable. In the next subsection, we critically assess the validity of this assumption and investigate how its potential violation may bias the estimation results.

[4]These controls are relevant for estimating firm size effects because these financial structure variables are systematically related to firm size measures. See Table A.1 in Appendix A for further details.

[5]Firm size classifications are rebalanced at the start of each quarter. Supplementary Appendix C.1 examines alternative rebalancing schemes.

Figure 1: Estimates of γ_k ($k = 1, \ldots, 10$) under the FIRE Assumption: $\hat{\gamma}_k^{mps}$

(a) Assets (b) Sales



Note: This figure presents $\hat{\gamma}_k^{mps}$, the estimates of γ_k ($k = 1, \ldots, 10$) from (2) under the FIRE assumption, where MPS_t, a widely used high-frequency indicator of monetary policy surprises, is used as an instrument for monetary policy shocks. The index k represents the firm size group, with firms in group k falling between the $(k-1)$-th and k-th deciles in terms of size. The firms size classification uses information from the previous quarter's balance sheet and is based on total assets in Panel (a) and sales in Panel (b). The composition of firm size groups is rebalanced for every quarter. Dots represent the point estimates of γ_k, while bars indicate the 95% confidence intervals. Standard errors are clustered at the firm level.

2.2 Predictability of Monetary Policy Surprise

In their empirical analysis, Bauer and Swanson (2023a) present evidence challenging both the FIRE assumption and the interpretation that policy surprises reveal Fed private information.[6] Estimating regression model (1), they show that macroeconomic news released prior to FOMC meetings significantly predicts subsequent monetary policy surprises. Table A.2 in Appendix A reports the corresponding estimates using our sample. Consistent with Bauer and Swanson (2023a), we find that publicly available information—such as employment growth, commodity price changes, and 10-year Treasury yield skewness—explains a nontrivial fraction of the variation in MPS_t, accounting for approximately 14%.[7] In addition, the

[6] See also Sastry (forthcoming).

[7] Section 2.4 provides sensitivity analyses using alternative measures of macroeconomic news. See also Cieslak (2018); Jarociński and Karadi (2020); Miranda-Agrippino and Ricco (2021); Karnaukh and Vokata (2022); Sastry (forthcoming) for additional evidence.

table confirms the presence of predictable components across horizons.[8]

Our results further indicate that monetary policy surprises are *procyclical*, exhibiting positive associations with employment growth, nonfarm payroll changes, and stock market performance. To illustrate this pattern, Figure 2 decomposes the original monetary policy surprise measure MPS_t into a predictable component, $\hat{\beta}'X_{t-1}$, and a residual component, $\widehat{MPS}_t = MPS_t - \hat{\beta}'X_{t-1}$, using the estimated coefficients $\hat{\beta}$. The figure shows that the predictable component captures much of the procyclical variation in MPS_t, while the residualized series appears considerably more acyclical. Notably, sharp negative surprises (greater than -10 basis points) predominantly occurred during or near recessions, with the exception of the July 1995 rate cut, whereas all large positive surprises (above 10 basis points) took place during expansions. Our estimates suggest that these large negative surprises observed during the 2001 recession and the Great Recession of 2008–09 are largely explained by the predictable component.

Plausible Underlying Mechanism Before turning to the implications for potential biases in estimating stock return responses, we briefly outline a widely accepted mechanism that can account for the observed predictability of monetary policy surprises. This mechanism reflects a specific form of informational friction between the central bank and financial markets, but it differs from the Fed information effect, which attributes policy surprises to the Fed's informational superiority regarding macroeconomic fundamentals. Instead, it emphasizes the market's imperfect understanding of the Fed's policy rule.

Consider the Fed's policy rule,

$$i_t = f(X_{t-1}) + \varepsilon_{mp,t},$$

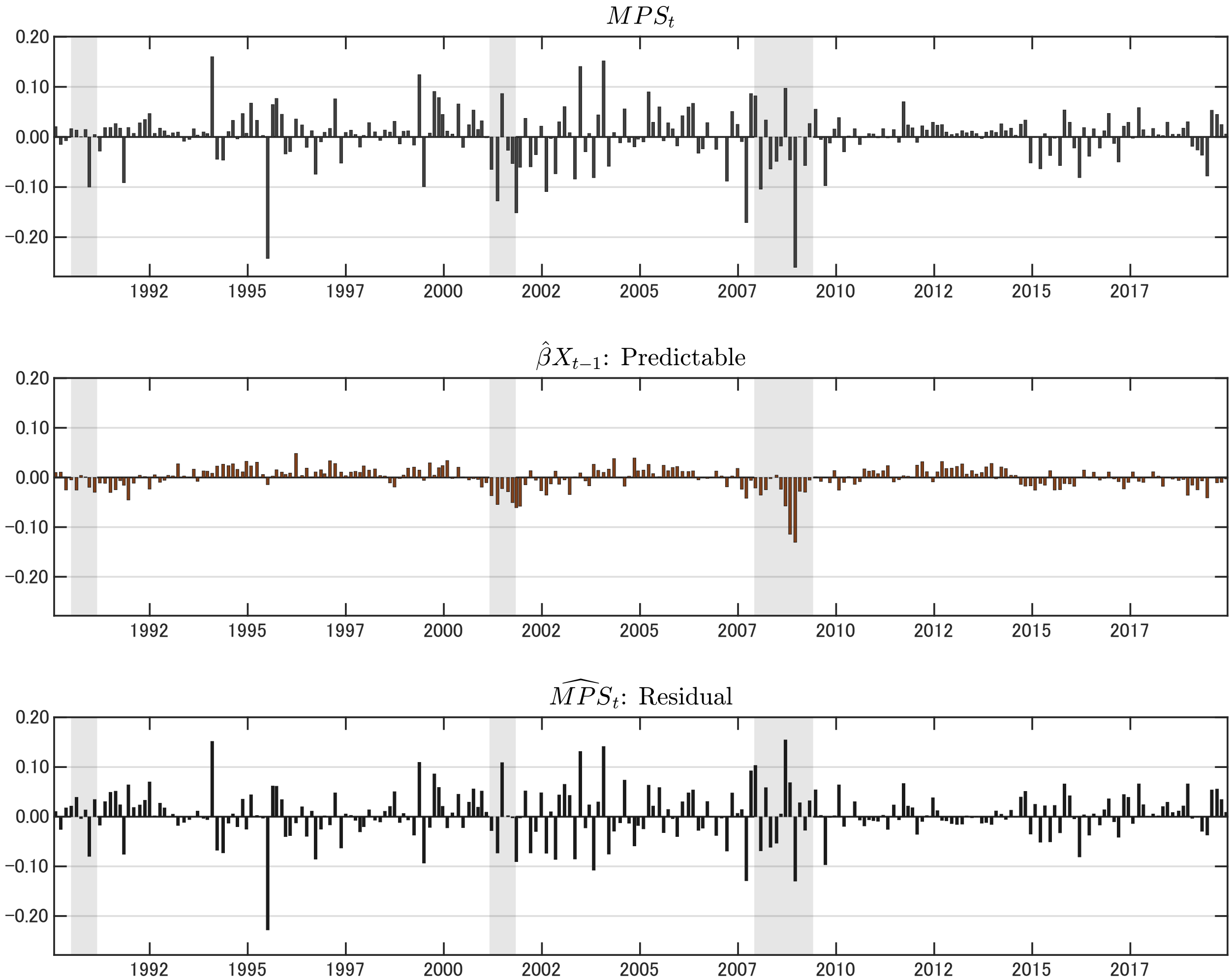
where i_t is the federal funds rate, f is the true policy function in response to a vector of macro-financial indicators X_{t-1}, and $\varepsilon_{mp,t}$ is an exogenous shock. While X_{t-1} is public and observed by both the Fed and private agents, only the Fed knows f; private agents form expectations based on an imperfect estimate $\tilde{f}$. Monetary policy surprises thus take the form:

$$i_t - \mathbb{E}[i_t \mid \mathcal{F}_{t^-}] = \varepsilon_{mp,t} + [f(X_{t-1}) - \tilde{f}(X_{t-1})],$$

where $\mathcal{F}_{t^-}$ denotes the information set available to private agents immediately prior to the policy announcement. Hence, measured policy surprises incorporate not only exogenous

[8] Specifically, we construct MPS_t using Eurodollar futures at different horizons—ED1 (current quarter), ED2 (two quarters ahead), ED3 (three quarters ahead), and ED4 (four quarters ahead)—and estimate predictability regressions based on (1) for each alternative measure.

Figure 2: Monetary Policy Surprise and Its Decomposition



Note: This figure plots the baseline high-frequency monetary policy surprise measure, MPS_t and its decomposition, $MPS_t = \hat{\beta}' X_{t-1} + \widehat{MPS}_t$, around scheduled FOMC meetings from 1990 to 2019. around scheduled FOMC meetings from 1990 to 2019. The upper, middle, and lower panels show the original series, the predictable component, and the residual component, respectively. Shaded areas represent recessions as determined by the National Bureau of Economic Research (NBER). Data source: Michael Bauer's website.

shocks but also systematic deviations between the Fed's true policy response and market perceptions of that response to publicly available macro-financial news.

From this perspective, the empirical finding that large negative monetary policy surprises occur disproportionately during deep recessions suggests that market misperceptions about the monetary policy rule tend to be more pronounced in recessions than in expansionary periods. Intuitively, periods of economic stress may be associated with greater uncertainty about the Fed's reaction function, leading markets to misinterpret the systematic component of policy decisions.

This mechanism—originally termed the "Fed-response-to-news" channel by Bauer and Swanson (2023a)—has gained prominence in light of growing evidence of market misperceptions and learning (e.g., Bauer, Pflueger, and Sunderam, 2024; Sastry, forthcoming). Section 3 formalizes this friction and shows how belief updating about f generates heterogeneity in stock price responses across firm sizes.

2.3 Endogeneity Problem and Estimation Bias

The fact that $\beta \neq \mathbf{0}$ in (1) implies that MPS_t is correlated with certain pre-announcement public news. This correlation introduces a potential endogeneity problem when using MPS_t as an instrument to estimate the effect of monetary policy shocks: its predictable component may be correlated with variables that also affect stock returns $\Delta y_{i,t}$, thus acting as a confounder. In (2), we explicitly allow for heterogeneity in the influence of public macroeconomic and financial news X_{t-1} across firm size groups through the coefficients δ_k.

Specifically, estimating γ_k using MPS_t as an instrument yields:[9]

$$\frac{\mathbb{E}\left[MPS_t \Delta y_{i,t}\right]}{\mathbb{E}\left[MPS_t \varepsilon_{mp,t}\right]} = \gamma_k + \frac{\mathbb{E}\left[X'_{t-1}\Lambda_k X_{t-1}\right]}{\sigma^2_{mp}}, \qquad \text{where} \quad \Lambda_k \equiv \beta\delta'_k.$$

This expression makes it clear that when $\beta \neq \mathbf{0}$, using MPS_t as an instrument generally does *not* yield a consistent estimate of γ_k unless $\delta_k = \mathbf{0}$.[10] In particular, if $\mathbb{E}\left[X'_{t-1}\Lambda_k X_{t-1}\right]$ is positive, the estimator is biased upward, and vice versa. Accordingly, our estimation allows the severity of endogeneity bias to vary across firms of different sizes.

Consequently, the key results are summarized in the following proposition:

Proposition 1. *When $\beta \neq \mathbf{0}$, estimation using MPS_t as an instrument for monetary policy shocks yields:*

(i) A consistent estimate of γ_k if $\delta_k = \mathbf{0}$.

(ii) A potentially inconsistent estimate otherwise:

(ii-1) An upward bias if $\mathbb{E}\left[X'_{t-1}\Lambda_k X_{t-1}\right] > 0$.

(ii-2) A downward bias if $\mathbb{E}\left[X'_{t-1}\Lambda_k X_{t-1}\right] < 0$.

[9]In the special case where X_{t-1} is a scalar (i.e., $\ell = 1$), $\frac{\mathbb{E}[MPS_t \Delta y_{i,t}]}{\mathbb{E}[MPS_t \varepsilon_{mp,t}]} = \gamma_k + \beta\delta_k \frac{\mathbb{E}\left[X^2_{t-1}\right]}{\sigma^2_{mp}}$.

[10]If $\delta_k = \mathbf{0}$, public news has no direct effect on stock returns for firms in size group k, and there are no endogeneity concerns with regard to the stock returns of those firms.

Endogeneity Test Proposition 1 shows that the presence and direction of estimation bias in γ_k depend on the parameters δ_k for $k = 1, \ldots, 10$. Endogeneity arises when $\delta_k \neq \mathbf{0}$, and the sign of the bias is governed by the sign of $\mathbb{E}\left[X'_{t-1}\Lambda_k X_{t-1}\right]$. Below, we outline a procedure to test the null hypothesis of no endogeneity, $\delta_k = \mathbf{0}$, and to assess the potential direction of bias.

(i) **Residualize** MPS_t: Regress MPS_t on X_{t-1} using ordinary least squares and compute the residual $\widehat{MPS}_t$.

(ii) **Estimate the augmented model**: Estimate the fixed-effects regression of $\Delta y_{i,t}$ on $\widehat{MPS}_t$ and X_{t-1} to obtain estimates of δ_k. Specifically,

$$\Delta y_{i,t} = fe_i + \sum_{k=1}^{10} \gamma_k \widehat{MPS}_t D_{\{size_{i,t}=k\}} + \delta'_k X_{t-1} D_{\{size_{i,t}=k\}} + e_{i,t},$$

where $e_{i,t}$ denotes the error term.

(iii) **Test for endogeneity**: Conduct an F-test for the joint null hypothesis $\delta_k = \mathbf{0}$.

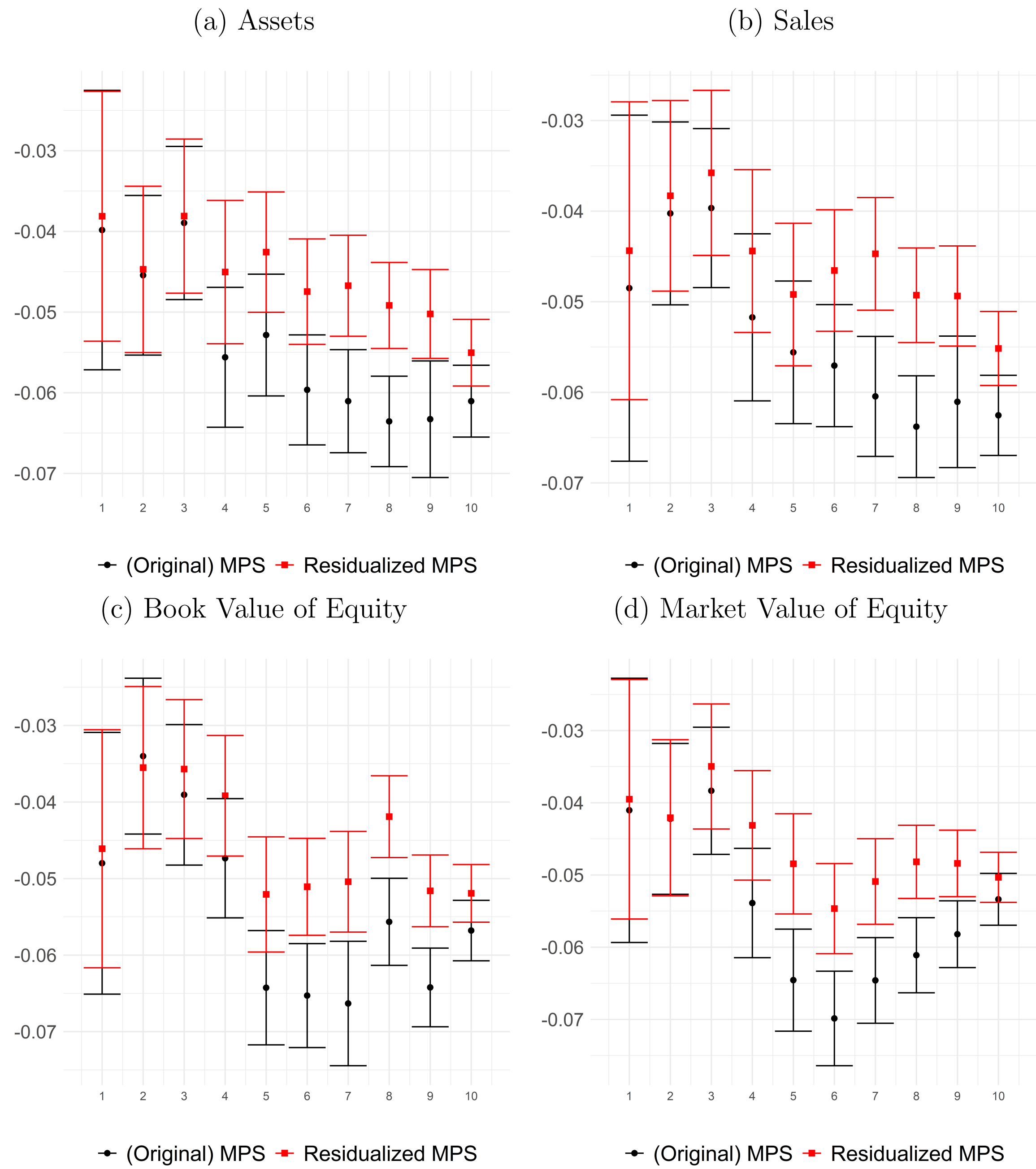
(iv) **Assess direction of bias**: If the null is rejected, evaluate the sign of $\frac{1}{T}\sum_t X'_{t-1}\beta\delta'_k X_{t-1}$, which is the sample analogue of $\mathbb{E}\left[X'_{t-1}\Lambda_k X_{t-1}\right]$, to determine whether the bias in $\hat{\gamma}_k^{mps}$ is upward or downward.

In what follows, let $\hat{\gamma}_k^{rmps}$ denote the estimate of γ_k obtained using the residualized monetary policy surprise $\widehat{MPS}_t$ as an instrument for monetary policy shocks.[11]

Results Figure 3 compares the original estimates $\hat{\gamma}_k^{mps}$ (circular markers) and estimates using the residualized monetary policy surprise $\hat{\gamma}_k^{rmps}$ (square markers). Across all firm size definitions—total assets in Panel (a), sales in Panel (b), book equity in Panel (c), and market equity in Panel (d)—the residualized instrument yields systematically smaller stock return responses, particularly for firms in the upper size deciles. Although some heterogeneity remains, the cross-sectional dispersion in estimated responses is substantially smaller than that implied by the conventional FIRE-based specification. This pattern suggests that the stronger stock price responses of large firms reported in earlier studies may, at least in part, reflect endogeneity rather than genuine differences in sensitivity to monetary policy shocks.

[11] An alternative but equivalent procedure for implementing the endogeneity test replaces step (ii) by estimating the fixed effects model using $\Delta y_{i,t}$ as the dependent variable and MPS_t and X_{t-1} as independent variables. The only difference is that the original monetary policy surprises MPS_t, rather than the residualized ones $\widehat{MPS}_t$, are included as independent variables. By the Frisch-Waugh-Lovell theorem, both approaches yield identical estimation outcomes.

Figure 3: Estimates of γ_k $(k = 1, \ldots, 10)$: Conventional versus Residualized Instrument



Note: This figure compares two estimates of γ_k $(k = 1, \ldots, 10)$: $\hat{\gamma}_k^{mps}$, obtained from (2) using the original monetary policy surprise measure MPS_t, and $\hat{\gamma}_k^{rmps}$, based on the residualized measure $\widehat{MPS}_t$. The $\hat{\gamma}_k^{mps}$ estimates are shown with circle markers, while the $\hat{\gamma}_k^{rmps}$ estimates are shown with square markers. The residualized monetary policy surprise is obtained by regressing MPS_t on a set of macroeconomic and financial market news variables, X_{t-1} (see Table A.2). The firms size classification uses information from the previous quarter's balance sheet and is based on total assets in Panel (a), sales in Panel (b), book value of equity in Panel (c), and market value of equity in Panel (d). The composition of firm size groups is rebalanced for every quarter. The bars indicate 95% confidence intervals, and standard errors are clustered at the firm level.

Indeed, the overestimation of stock return responses documented above appears to stem from endogeneity bias, as evidenced by the endogeneity tests discussed earlier. Table 1 reports the results. The second and third columns present the F-statistics and corresponding p-values for the joint hypothesis test $\delta_{k,1} = \cdots = \delta_{k,\ell} = 0$ for each $k = 1, \ldots, 10$. The null is strongly rejected at the 1% level across all deciles, indicating that the conventional estimates $\hat{\gamma}_k^{mps}$, obtained using the raw high-frequency monetary policy surprise measure as instrument, are likely subject to endogeneity bias.[12]

The fourth column of Table 1 reports the estimates of $\mathbb{E}\left[X'_{t-1}\Lambda_k X_{t-1}\right]$, scaled by 10,000 for readability. As discussed earlier, this statistic informs the direction and magnitude of the endogeneity bias: a negative value indicates that the magnitude of the estimated stock return response is overstated (corresponding to an overstatement of the negative effect of monetary policy shocks). The results show that, for firms in the upper portion of the size distribution ($k \geq 4$), the estimates of $\mathbb{E}\left[X'_{t-1}\Lambda_k X_{t-1}\right]$ are consistently negative and statistically significantly different from zero, indicating that the magnitude of the estimated stock return using MPS_t is overstated for these firms. This pattern suggests that stock returns of larger firms are more heavily influenced by macroeconomic and financial news that simultaneously affect monetary policy surprises, resulting in more severe endogeneity bias.

2.4 Robustness Analysis

This subsection presents a series of robustness checks assessing the sensitivity of our findings. In particular, we consider (i) additional firm-level controls; (ii) alternative constructions of monetary policy surprises; (iii) monetary policy surprises associated with unscheduled FOMC meetings; and (iv) alternative public news measures as predictors of policy surprises.

Revisiting Firm Characteristic Controls In the baseline specification in (2), we include firm characteristic controls—namely, the cash ratio, leverage, short-term debt share, and interest burden—to account for variation in stock returns associated with firms' financial structures. While this specification absorbs stock price variation attributable to these characteristics in a linear and additive manner, it does not allow for the possibility that monetary policy shocks interact with firm characteristics in shaping stock return responses.

To address this concern, we augment the baseline specification by allowing monetary policy shocks to interact directly with firm characteristics. Specifically, we estimate the

[12] The full set of estimated coefficients δ_k is reported in Table D.1 in Appendix D.

Table 1: Endogeneity Test

Firm Size	F-Statistic	$\Pr(F_{null} \geq F \mid \delta_k = \mathbf{0})$	$\frac{1}{T}\sum_t X'_{t-1}\beta\delta'_k X_{t-1}$
$k=1$	7.4	$< 10^{-6}$	-0.39 (0.94)
$k=2$	13.1	$< 10^{-6}$	1.08 (0.35)
$k=3$	16.2	$< 10^{-6}$	0.31 (0.30)
$k=4$	33.0	$< 10^{-6}$	-1.57 (0.29)
$k=5$	46.3	$< 10^{-6}$	-3.03 (0.27)
$k=6$	55.4	$< 10^{-6}$	-2.93 (0.26)
$k=7$	63.7	$< 10^{-6}$	-4.02 (0.24)
$k=8$	86.9	$< 10^{-6}$	3.17 (0.22)
$k=9$	78.0	$< 10^{-6}$	-3.12 (0.38)
$k=10$	72.5	$< 10^{-6}$	-1.59 (0.19)

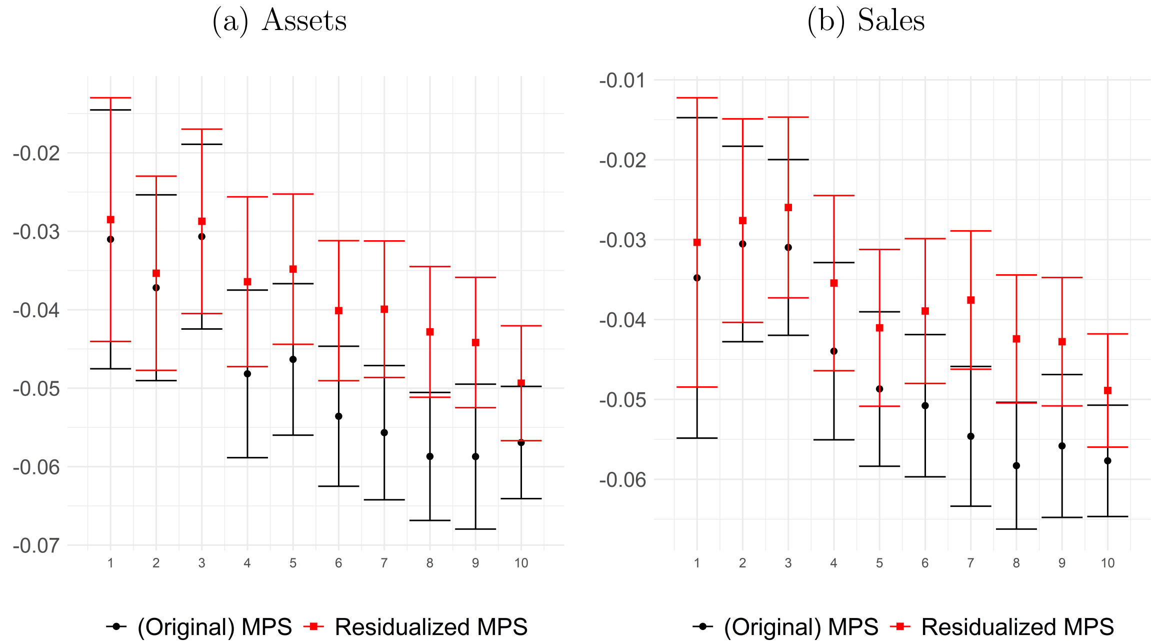
Note: This table reports the results of the endogeneity test. The column labeled "F-Statistic" presents the F-statistic for the joint hypothesis test $\delta_1 = \cdots = \delta_\ell = 0$, while the column labeled "$\Pr(F_{\text{null}} \geq F \mid \delta_k = \mathbf{0})$" shows the corresponding p-value. The column "$\frac{1}{T}\sum_t X'_{t-1}\beta\delta'_k X_{t-1}$" reports the estimate of $\mathbb{E}\left[X'_{t-1}\Lambda_k X_{t-1}\right]$, scaled by 10,000 for readability. Bootstrapped standard errors are reported in parentheses; see Appendix G for details. Firms are grouped by size based on total assets.

following specification:

$$\Delta y_{i,t} = fe_i + \xi w_{i,t} + \varphi w_{i,t}\varepsilon_{mp,t} + \sum_{k=1}^{10} \gamma_k \varepsilon_{mp,t} D_{\{size_{i,t}=k\}} + \delta'_k X_{t-1} D_{\{size_{i,t}=k\}} + e_{i,t},$$

These interaction controls capture standard channels of monetary policy transmission emphasized in the literature. Specifically, the cash ratio reflects liquidity buffers (Chava and Hsu, 2020; Jeenas, 2023), leverage proxies for dependence on external finance (Ozdagli, 2018; Chava and Hsu, 2020), the short-term debt share captures maturity and interest rate reset exposure (Ippolito, Ozdagli, and Perez-Orive, 2018; Gürkaynak, Karasoy-Can, and Lee, 2022), and interest burden reflects cash-flow sensitivity to changes in debt servicing costs (Döttling and Ratnovski, 2023; Ippolito, Ozdagli, and Perez-Orive, 2018; Gürkaynak, Karasoy-Can, and Lee, 2022).

Figure 4: Estimates of γ_k ($k = 1, \ldots, 10$): With Additional Firm Characteristics Controls



Note: This figure presents the estimates of γ_k ($k = 1, \ldots, 10$) from the augmented specification that incorporates firms' profitability, price-to-book ratio, book leverage, and sales growth as time-varying firm-specific characteristics. Estimates based on the original monetary policy surprise measure (MPS_t) are denoted by $\hat{\gamma}_k^{mps}$ and shown with circular markers, while those based on the residualized surprises ($\widehat{MPS}_t$) are denoted by $\hat{\gamma}_k^{rmps}$ and displayed with square markers. The residualized monetary policy surprise is obtained by regressing MPS_t on a set of macroeconomic and financial market news variables, X_{t-1} (see Table A.2). Firm size is measured using total assets in Panel (a) and sales in Panel (b). The composition of firm size groups is rebalanced for every quarter. The bars indicate 95% confidence intervals, and standard errors are clustered at the firm level.

Figure 4 reports the estimates of γ_k obtained from the specification with interaction controls, comparing those based on the original monetary policy surprise measure $\hat{\gamma}_k^{mps}$ (circles), with those based on residualized surprises $\hat{\gamma}_k^{rmps}$ (squares). Although the inclusion of interaction controls affects the magnitudes of the estimates, the main pattern remains: conventional estimates continue to overestimate the sensitivity of stock return responses for large firms, whereas residualized surprises yield more uniform responses across firm sizes.

Alternative Measures of Monetary Policy Surprises The baseline analysis measures monetary policy surprises using the first principal component of changes in federal funds and ED futures. However, a potential concern is that the results may be sensitive to which future contracts are chosen for the analysis (Brennan, Jacobson, Matthes, and Walker, 2024). To address this concern, we also construct MPS_t separately using Eurodollar futures at horizons ranging from the current quarter to four quarters ahead (ED1–ED4). Table A.2 reports the corresponding predictability regressions, confirming that public macro-financial variables significantly predict MPS_t across all horizons, as discussed above. Figure D.1 presents estimated stock return responses using these alternative measures and their residualized surprises, $\widehat{MPS}_t$. The responses based on the residualized surprises are consistently smaller in magnitude, particularly for large firms, in line with the baseline findings and highlighting that the predictability of measured monetary policy surprises leads to overestimation of stock return sensitivity for large firms.[13]

Unscheduled FOMC Meetings As an additional robustness check, we incorporate monetary policy surprises associated with unscheduled FOMC meetings. Although such meetings are relatively infrequent, they offer valuable variation for identification purposes, particularly because they tend to occur during periods of heightened economic and financial uncertainty. Including these events increases the total number of monetary policy announcements in our sample to 273.[14] We construct monetary policy surprise measures for these events using the same principal component approach as in the baseline specification. Figure D.2 in Supplementary Appendix D shows that, although incorporating unscheduled meetings somewhat attenuates the estimated overestimation bias, the qualitative pattern of disproportionate sensitivity among large firms remains intact.

Alternative Publicly Available News The baseline analysis follows Bauer and Swanson (2023b) and constructs the vector of pre-announcement macro-financial variables, X_{t-1}, to include payroll surprises, changes in nonfarm payrolls, S&P 500 returns, changes in the term spread, commodity price changes, and Treasury yield skewness. To assess the robustness of our findings, we re-estimate the model using several alternative specifications of X_{t-1}.

We conduct two sets of robustness analyses. First, we consider a more parsimonious specification of X_{t-1} that includes only variables closely associated with large firm performance: payroll surprises, payroll growth, and S&P 500 returns.[15] Second, we expand the baseline information set to include broader measures of macroeconomic conditions. Specifically, we augment X_{t-1} with lagged values of the Aruoba-Diebold-Scotti (ADS) Business Conditions Index (Aruoba, Diebold, and Scotti, 2009), the Brave-Butters-Kelley (BBK) Business Cycle Index (Brave, Butters, and Kelley, 2019), and consumer unemployment sentiment from the University of Michigan Survey of Consumers, following Bu, Rogers, and Wu (2021) and

[13] Differences in the response are most pronounced for ED3 and ED4, suggesting that longer-horizon futures account for much of the predictability-driven bias in the baseline principal component.

[14] Over our sample period, 33 announcements were made in conjunction with unscheduled FOMC meetings. Among these, eight meetings on the following dates involved emergency policy rate changes: October 15, 1998; January 3, 2001; April 18, 2001; September 17, 2001; August 10, 2007; January 22, 2008; March 16, 2008; and October 8, 2008.

[15] This narrower set excludes bond market and commodity price indicators.

Sastry (forthcoming). Table D.2 (in Supplementary Appendix D) shows that these indices possess predictive power for monetary policy surprises. Figures D.3 and D.4 present the results based on the narrower and expanded sets of public information variables, respectively. Across both exercises, our main results remain robust to the alternative composition of public information. Notably, the reduction in the estimated stock price responses, particularly for larger firms, is more pronounced when the broader macroeconomic controls are included. This is consistent with the view that controlling for aggregate business cycle conditions, which are more strongly influenced by large firms, helps mitigate the downward bias in the estimated effect of monetary policy shocks on their stock prices.

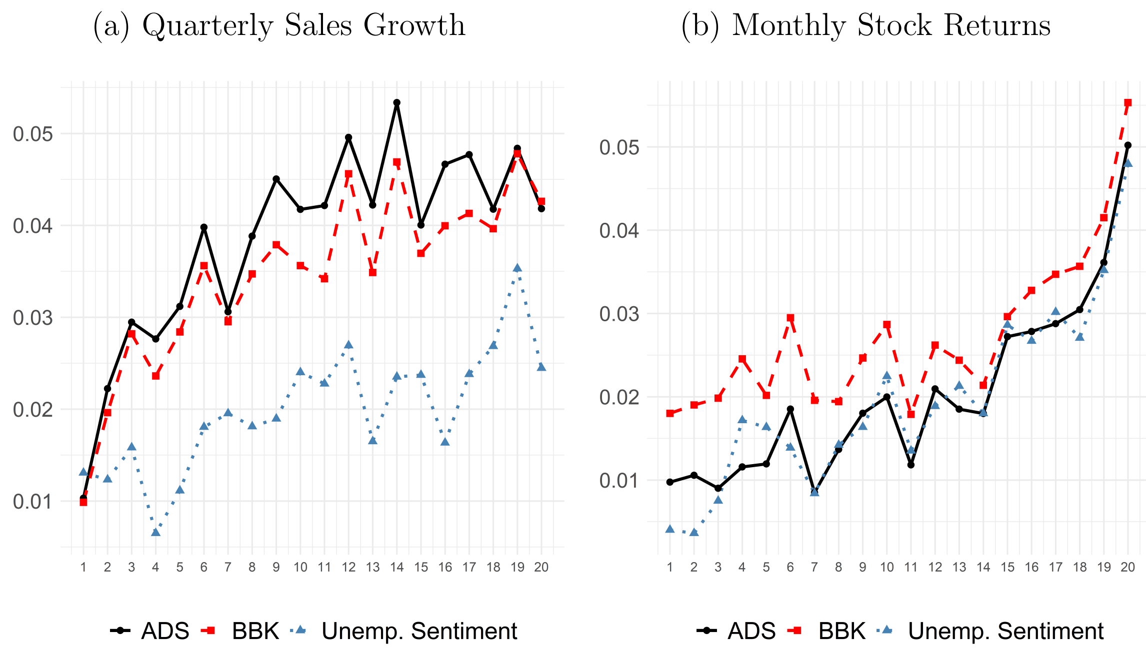
2.5 Firm Performance and Aggregate Fluctuations

The preceding analysis shows that the predictability of monetary policy surprises—which suggests the presence of informational frictions, particularly investors' imperfect knowledge of the central bank's policy rule—potentially introduces bias into estimates of the effects of monetary policy shocks on firm-level stock prices. A novel aspect of our empirical findings is that this bias is not uniform across firms: it disproportionately affects large firms. While the next section formally develops the mechanism behind this asymmetry, the remainder of this section presents evidence on a key underlying source of heterogeneity, namely, the fact that large firms' fundamentals (e.g., their output, profits, and dividends) are more strongly correlated with aggregate economic conditions than those of smaller firms. As the theoretical framework will show, this implies that a data-dependent monetary policy—where the central bank adjusts interest rates in response to aggregate indicators—responds more strongly (albeit unintentionally) to the performance of large firms, simply because they exert greater influence on those indicators. This asymmetry plays a central role in generating the differential bias in stock return responses across firms.

Figure 5 reports the correlation between firm performance, measured by quarterly sales growth (Panel (a)) and monthly stock returns (Panel (b)), and aggregate economic indices across twenty firm size groups sorted by asset size. As aggregate indicators, we use the ADS and BBK Business Conditions Indices and the Michigan Survey's unemployment sentiment index, all of which significantly predict monetary policy surprises (see Table D.2).[16] The figure reveals a clear upward trend: the correlation with macroeconomic conditions increases with firm size. For example, in Panel (a), the correlation between sales growth and the ADS index is around 0.01-0.02 for the smallest firms and rises to 0.04-0.05 for the largest. Similar

[16] In Panel (a), we compute the correlation between firm-level sales growth from the previous quarter and the level of each aggregate index. In Panel (b), the correlation is between firm-level stock returns from the previous month and the current level of each index.

Figure 5: Correlation of Firm Performance with Macroeconomic Indicators (ADS Index, BBK Index, Michigan Survey Unemployment Sentiment Index) by Firm Size Group



Note: This figure presents the correlation between firm performance and macro indices across firm size groups. Firms are sorted into 20 bins $k \in \{1, \ldots, 20\}$ by asset size. Panel (a) reports the correlation between quarterly sales growth and aggregate indicators, while Panel (b) displays the correlation using monthly stock returns. "ADS" denotes the ADS Business Conditions Index (Aruoba, Diebold, and Scotti, 2009) and "BBK" refers to the BBK Business Cycle Index (Brave, Butters, and Kelley, 2019). Meanwhile, "Unemp. Sentiment" refers to consumer sentiment about how unemployment will evolve in the next year, from the Michigan Survey of Consumers.

patterns are observed across other indicators and for stock return correlations, suggesting that larger firms are more closely tied to macroeconomic fluctuations.

3 Theoretical Explanation

The preceding section showed that publicly available macro-financial news before FOMC meetings acts as a confounding factor, jointly influencing both measured monetary policy surprises and firms' stock returns. This simultaneity introduces endogeneity bias, leading to an overestimation of the causal effects of policy shocks on asset prices. The bias is more pronounced for large firms, suggesting that the stronger responses of their stock returns to policy surprises—widely documented in prior studies—largely reflect the predictable component of those surprises, rather than heightened sensitivity of their fundamentals to monetary shocks.

In this section, we develop a theoretical framework to explain why public news serves as a confounder and why its influence is especially strong for larger firms. The model builds on the informational structure proposed by Bauer and Swanson (2023a,b), in which private sector agents possess an imperfect understanding of the central bank's policy rule and update their beliefs about the degree of policy responsiveness over time. These agents form expectations about interest rate decisions based on macro-financial news available prior to FOMC announcements, but due to incomplete knowledge of the reaction function, their expectations systematically diverge from actual policy decisions. As a result, measured monetary policy surprises partially reflect belief revisions as well as purely exogenous shocks.

To capture firm-level heterogeneity, the model incorporates the granular hypothesis of Gabaix (2011), which assumes that idiosyncratic shocks to a small number of large firms disproportionately drive aggregate fluctuations. This structure implies that large firms' fundamentals are more closely correlated with macroeconomic conditions than those of smaller firms.

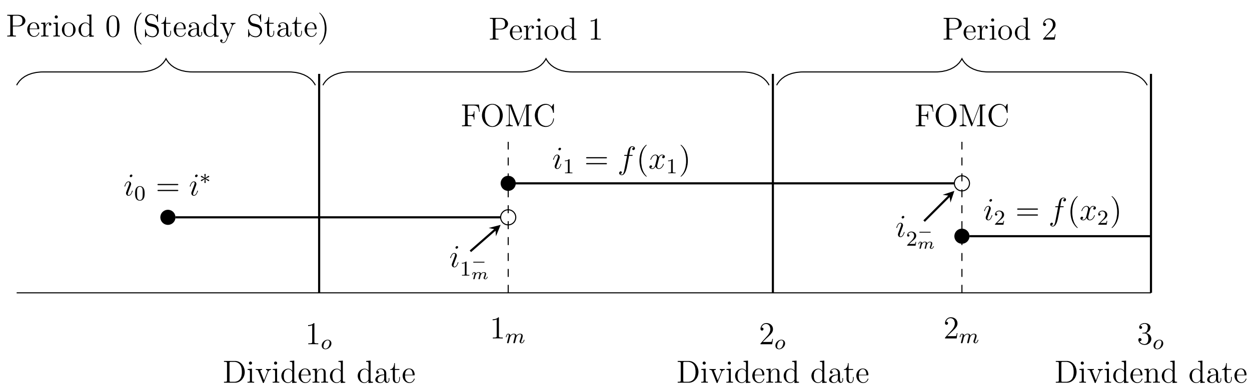
The central bank primarily follows a data-dependent policy rule, adjusting the nominal interest rate in response to aggregate indicators such as the output gap, but may occasionally deviate from this rule due to exogenous discretionary shocks. To clarify the role of belief revisions in driving stock price responses, we assume that these exogenous monetary policy shocks have the same effect on the fundamentals of all firms and normalize their impact to zero without loss of generality. However, because agents in the private sector lack full knowledge of the monetary policy function, monetary policy *surprises* reflect not only exogenous shocks but also belief-driven components—implying that their effects on stock prices are not necessarily uniform.

3.1 Model

We consider a three-period economy ($t = 0, 1, 2$) comprising a representative household, final good-producing firms, fund management firms, and the central bank. The representative household supplies labor to final good-producing firms, owns fund management firms, consumes final goods, and saves through money and short-term risk-free nominal bonds. Final good-producing firms employ labor as their sole input to produce a homogeneous final good and distribute all profits to shareholders as dividends. These firms' shares are publicly traded and acquired by fund management firms, which act on behalf of households. The central bank determines 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 size. The small firm sector consists of a continuum of small firms with measure $n_S > 0$, while the large firm sector

Figure 6: Timeline of the Model



comprises a finite number ($N_L > 0$) of large firms, where N_L is a positive integer. Let J_S and J_L denote the sets of small and large final good-producing firms, respectively, such that $|J_S| = n_S$ and $|J_L| = N_L$.

In the initial period ($t = 0$), the economy is in a steady state, with all final good-producing firms exhibiting identical labor productivity and output levels. In periods $t = 1$ and $t = 2$, firms display ex-post heterogeneity due to idiosyncratic labor productivity shocks that materialize at the beginning of each period. Since final goods are perishable, they must be produced and consumed within the same period.

The sequence of events in periods $t = 1$ and $t = 2$ unfolds as follows. Each period begins with the realization of labor productivity shocks for all final good-producing firms. After firms determine their hiring decisions, the central bank conducts a scheduled FOMC meeting to set the short-term nominal bond interest rate i_t for the current period. Following this, dividends are distributed to shareholders, and households allocate their consumption and savings decisions.

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. The sequence of events follows $0 < 1_o < 1_m < 2_o < 2_m$, as illustrated in Figure 6.

The informational assumptions are as follows. 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 $\mathcal{F}_t$ represent the information set available to private sector agents at time t. Given the timing and informational assumptions above, we have $i_t \notin \mathcal{F}_{t_m^-}$ but $i_t \in \mathcal{F}_{t_m}$, where $t_m^- = \lim_{t \to t_m} t$ denotes the moment immediately before t_m.

Household The representative household supplies labor ℓ_t to final good-producing firms and owns fund management firms. To simplify the analysis, we assume a fixed real wage $\bar{w} > 0$ and that the household's labor supply is infinitely elastic at this wage rate. The household allocates its savings between money balances M_t and one-period risk-free nominal bonds B_t, and maximizes 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 denotes consumption, $m_t = M_t/P_t$ represents the real money balance, and P_t is the nominal price level of the final good at time t. Preferences follow a generalized money-in-utility specification:

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

The commonly used log-separable utility function, $\theta \log(c_t) + (1-\theta)\log(m_t)$, arises in the limit as $\sigma \to 1$. The household faces the following period budget constraint:

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

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

Given initial money holdings $M_0 \geq 0$ and bonds $B_0 \geq 0$, the household chooses $\{c_t, M_{t+1}, B_{t+1}\}_{t=0}^{2}$. The household's demand for real money balances satisfies

$$m_t = \iota(i_t) c_t, \qquad \iota(i_t) = \frac{\theta}{1-\theta}\left(\frac{i_t}{1+i_t}\right)^{-1} \approx \frac{\theta}{1-\theta} i_t^{-1}. \tag{4}$$

Since $\iota'(i_t) < 0$, real money demand is decreasing in the nominal interest rate, consistent with standard monetary theory. Moreover, money demand is proportional to consumption expenditures, reflecting the transactions motive for holding money.

The non-separability of preferences in (3), that is, $\sigma \neq 1$, implies that the marginal utility of consumption depends on real money balances. This feature plays a central role in the nonneutrality of money, introducing a channel through which monetary policy has real effects (Fischer, 1979; Walsh, 2010; Galí, 2015). As a consequence, the intertemporal marginal rate of substitution—and thus the stochastic discount factor (SDF)—is given by:

$$\Lambda_{t,t+1} = \beta \left(\frac{c_{t+1}}{c_t}\right)^{-\sigma} \left(\frac{m_{t+1}/c_{t+1}}{m_t/c_t}\right)^{\theta(1-\sigma)}. \tag{5}$$

The household's optimality condition for nominal bond holdings yields the following Euler equation 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 inflation rate between periods t and $t+1$.

The SDF expression in (5) highlights how the effect of real money growth on the SDF depends critically on the value of σ. When $\sigma < 1$ (equivalently $1 - \sigma > 0$), consumption and real money balances are complements in utility; that is, the cross-partial derivative $u_{cm}(c_t, m_t) > 0$, implying that the marginal utility of consumption increases with higher real money balances. In contrast, when $\sigma > 1$ (i.e., $1-\sigma < 0$), consumption and real balances are substitutes, and the marginal utility of consumption decreases with an increase in real money holdings. This complementarity or substitutability shapes how monetary policy affects the SDF and, consequently, asset prices.

To analyze the role of monetary policy more directly, it is helpful to express the SDF in terms of nominal interest rates instead of real money balances. Substituting the money demand condition (4) into (5), we obtain:

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

This expression reveals that the SDF depends not only on consumption growth but also on the change in nominal interest rates. As in the case of standard asset pricing models, an increase in the consumption growth rate c_{t+1}/c_t lowers the SDF. Additionally, due to the complementarity or substitutability between consumption and money, an increase in the nominal interest rate lowers the SDF when $\sigma < 1$ (i.e., consumption and money are complements) but raises the SDF when $\sigma > 1$ (i.e., they are substitutes). As formally shown in Lemma 1, this relationship implies that a central bank policy rule that adjusts the nominal interest rate procyclically (Taylor, 1993) amplifies cyclical fluctuations in the SDF if $\sigma < 1$ and mitigates them if $\sigma > 1$. In this sense, the case of $\sigma > 1$ aligns with the standard New Keynesian paradigm, where active monetary policy helps stabilize consumption and the SDF over the business cycle.

Final Good-Producing Firms Each final good-producing firm operates under 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 $z_{j,t}$ denote the firm's output, labor input, and labor productivity, respectively. The final good is sold in a perfectly competitive market.

These firms issue equity and distribute their profits entirely as dividends to shareholders. Given the production function, firms' dividends at time t are given by:

$$d_{j,t} = \max_{\ell}\left[Az_{j,t}^{1-\alpha}\ell^{\alpha} - \bar{w}\ell\right].$$

In the initial period ($t = 0$), all firms have identical labor productivity, normalized to unity ($z_{j,0} = 1$ for all j). Subsequently, labor productivity evolves stochastically, following the key features of firm dynamics documented in the literature (see, e.g., Gabaix, 2011). Specifically, productivity growth follows:

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

where $\Delta z_{j,t+1} = z_{j,t+1} - z_{j,t}$, $\sigma_g > 0$ is the standard deviation of productivity growth, and $\varepsilon_{j,t+1}$ is an independent and identically distributed (i.i.d.) standard Gaussian variable. This implies that $z_{j,t}$ follows a martingale process. For analytical tractability, we assume that σ_g is sufficiently small, ensuring $\sigma_g^2 > 0$ but $\sigma_g^k \approx 0$ for all $k \geq 3$, thus restricting the higher-order moments of the shock distribution.

Solving firms' profit maximization problem yields the optimal labor input:

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

Without loss of generality, we normalize $A^{\frac{1}{1-\alpha}}(\alpha/\bar{w})^{\frac{\alpha}{1-\alpha}} = 1$, so that firm output simplifies to $y_{j,t} = z_{j,t}$. Consequently, firm profits (dividends) are given by

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

At $t = 0$, when $z_{j,0} = 1$ for all firms, output and dividends are given by $y_{j,0} = 1$ and

$d_{j,0} = \alpha^{-\frac{1}{1-\alpha}} \equiv d_0$. In periods $t = 1$ and $t = 2$, firm output and dividends grow at the same rate as productivity:

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

Since idiosyncratic productivity shocks occur at the beginning of each period, all private sector agents and the central bank observe firm-level output before the FOMC meeting. Thus, the information set satisfies: $\{z_{j,t}, \ell_{j,t}, y_{j,t}, d_{j,t}\} \in \mathcal{F}_{t_m^-}$ for all j.

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

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

This implies that in the initial period ($t = 0$), where $z_{j,0} = 1$ for all j, aggregate output is given by $y_0 = n_S + N_L$.[17]

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

Proposition 2. *The growth rate of aggregate output is given by*

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

where $\mathbb{E}[g_{Y,t+1}] = 0$ *and* $\sigma_{g_Y,t} \equiv \sqrt{Var_t(g_{Y,t+1})} = \sigma_g \sqrt{\sum_{j \in J_L} (y_{j,t}/y_t)^2}$.

The covariance between the growth rate of aggregate output and the growth rate of an individual firm's output is given by

$$Cov_t\left(g_{Y,t+1}, \frac{\Delta y_{j,t+1}}{y_{j,t}}\right) = \begin{cases} 0 & \text{for } j \in J_S, \\ \frac{y_{j,t}}{y_t}\sigma_g^2 & \text{for } j \in J_L. \end{cases} \tag{7}$$

[17] This result indicates that the share of total output produced by small firms is $n_S/(n_S + N_L)$, while the share produced by each large firm is $1/(n_S + N_L)$.

Proof of Proposition 2. See Appendix B. □

Proposition 2 establishes that productivity shocks to small firms do not contribute to GDP fluctuations, implying that all variations in GDP and GDP growth originate from shocks to large firms. Specifically, we highlight two key insights from (7). First, for small firms, there is no correlation between their individual output growth rate ($\Delta y_{j,t+1}/y_{j,t}$) and the aggregate output growth rate ($g_{Y,t+1}$). Second, for large firms, the correlation between their individual output growth rate and aggregate GDP growth increases with their relative output share ($y_{j,t}/y_t$), indicating that larger firms have a more pronounced impact on macroeconomic fluctuations. This is consistent with the evidence presented in Section 2.5.

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

Let $q_{j,t}$ denote the stock price of final good-producing firm j at time t. Prior to the dividend payout in the initial period ($t = 0$), the stock price is 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 $\mathbb{E}[\cdot \mid \mathcal{F}]$ denotes the expectation conditional on the information set $\mathcal{F}$.

In period $t = 1$, the stock price before the dividend payout is given by:

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

In period $t = 2$, the stock price before the final dividend payout simplifies to:

$$q_{j,\tau} = d_{j,2}, \qquad \forall j \in J_S \cup J_L,\ \tau \in [2_o, 3_o).$$

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

$$\frac{i_t - i_{t-1}}{i_{t-1}} = \alpha_{mp}\left(\frac{\Delta y_t}{y_{t-1}}\right) + \varepsilon_{mp,t}, \qquad \varepsilon_{mp,t} \overset{\text{IID}}{\sim} N(0, \sigma_{mp}^2). \tag{8}$$

Here, α_{mp} is the policy coefficient governing the response of the nominal interest rate to GDP growth. For example, if $i_{t-1} = 0.01$ (1%), then a 1% increase in GDP leads the central bank to raise the policy rate by α_{mp} basis points. The term $\varepsilon_{mp,t}$ represents an exogenous monetary policy shock, assumed to be independently and normally distributed with mean zero and variance σ_{mp}^2. We further assume that σ_{mp} is sufficiently small, so that higher-order terms $\sigma_{mp}^k \approx 0$ for all $k \geq 3$.

Informational Frictions, Monetary Policy Surprises, and Learning Following Bauer and Swanson (2023a,b), we assume that private-sector agents understand that the central bank follows the policy rule in (8) but lack precise knowledge of the policy parameter α_{mp} and the realized value of $\varepsilon_{mp,t}$. Consequently, before the period 1 FOMC meeting, their expected policy rate is:

$$\mathbb{E}\left[i_1 \mid \mathcal{F}_{1_m^-}\right] = i^* + i^*\tilde{\alpha}_0 g_{Y,1},$$

where $\tilde{\alpha}_0$ represents their ex-ante estimate of α_{mp}. Thus, the monetary policy surprise is given by:

$$MPS_{1_m} = i_1 - \mathbb{E}\left[i_1 \mid \mathcal{F}_{1_m^-}\right] = i^*\left(\alpha_{mp} - \tilde{\alpha}_0\right) g_{Y,1} + \varepsilon_{mp,1}.$$

This expression implies that unless $\tilde{\alpha}_0 = \alpha_{mp}$ or $g_{Y,1} = 0$, private-sector agents cannot fully distinguish whether monetary policy surprises arise from incorrect expectations about the policy parameter or from an exogenous discretionary shock, even after observing i_t.

We also consider that private sector agents update their belief about the policy parameter using the Kalman filter. Starting from the initial belief $\alpha_{mp} \sim N(\tilde{\alpha}_0, \tilde{\sigma}_{\alpha,0}^2)$, the announcement at $t = 1_m$ leads to the following updated belief:

$$\tilde{\alpha}_1 = \tilde{\alpha}_0 + \kappa_1\left(i_1 - \mathbb{E}\left[i_1 \mid \mathcal{F}_{1_m^-}\right]\right) = \tilde{\alpha}_0 + \kappa_1 MPS_{1m}. \tag{9}$$

Moreover, the updated prediction error is:

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

where the Kalman gain κ_1 is:

$$\kappa_1 = \frac{1}{i^* g_{Y,1}} \left(\frac{g_{Y,1}^2 \tilde{\sigma}_{\alpha,0}^2}{g_{Y,1}^2 \tilde{\sigma}_{\alpha,0}^2 + (\sigma_{mp}/i^*)^2} \right). \tag{10}$$

In particular, (9) leads to the following prediction about how investors update their expectations:

Proposition 3. *The Kalman filter implies the following state-dependent updating behavior for beliefs about the monetary policy parameter:*

- *If $g_{Y,1} > 0$ (expansion), belief revisions move in the* same *direction as monetary policy surprises:*
$$\begin{cases} \tilde{\alpha}_1 > \tilde{\alpha}_0 \quad \textit{and} \quad MPS_{1m} > 0, \\ \tilde{\alpha}_1 < \tilde{\alpha}_0 \quad \textit{and} \quad MPS_{1m} < 0, \end{cases}$$

- *If $g_{Y,1} < 0$ (recession), belief revisions move in the* opposite *direction as monetary policy surprises:*
$$\begin{cases} \tilde{\alpha}_1 < \tilde{\alpha}_0 \quad \textit{and} \quad MPS_{1m} > 0, \\ \tilde{\alpha}_1 > \tilde{\alpha}_0 \quad \textit{and} \quad MPS_{1m} < 0, \end{cases}$$

Proof of Proposition 3. This result follows directly from (9) and (10). □

Proposition 3 implies that $\text{Cov}(\tilde{\alpha}_1 - \tilde{\alpha}_0, MPS_{1m})$ is likely to be positive during expansions and negative during recessions. This prediction is in line with empirical evidence from Bauer, Pflueger, and Sunderam (2024), who show that professional forecasters' assessments of the monetary policy rule vary systematically with monetary policy surprises depending on the state of the economy.

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

3.2 Equilibrium Stock Prices

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:*

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

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

Proof of Lemma 1. See Supplementary Appendix B. □

We emphasize that under the non-separable money-in-utility preferences specified in (3), with $\sigma \neq 1$, the investor's SDF depends on the monetary policy parameter α_{mp}, which governs the central bank's responsiveness to macroeconomic conditions.[18] Specifically, a higher value of α_{mp}, i.e., a more responsive monetary policy, amplifies cyclical fluctuations in the SDF when $\sigma < 1$, and vice versa. This implies that when investors are uncertain about the precise value of α_{mp}, belief revisions regarding monetary policy responsiveness can influence asset prices.

Our primary interest lies in the FOMC announcement at time 1_m. Upon the announcement, private agents observe the realized policy rate i_1 and revise their belief about α_{mp}, updating it from a prior $\tilde{\alpha}_0$ to a posterior $\tilde{\alpha}_1$, as described in (9). For notational clarity, let $\tilde{\Lambda}^{(0)}_{1,2} = \Lambda_{1,2} \mid \mathcal{F}_{1_m^-}$ denote the SDF prior to the announcement and $\tilde{\Lambda}^{(1)}_{1,2} = \Lambda_{1,2} \mid \mathcal{F}_{1_m}$ the SDF

[18] In the separable case where $\sigma \to 1$, the SDF simplifies to $\Lambda_{t,t+1} \approx \beta \exp(-g_{Y,t+1})$, as in log-utility preferences $\log(c_t)$. In this case, even with money-in-utility preferences, the SDF does not depend on the monetary policy parameter.

after the announcement. Using this notation, stock prices in period $t = 1$ are written as:

$$q_{j,\tau} = \begin{cases} d_{j,1}\left[1 + \mathbb{E}[\tilde{\Lambda}^{(0)}_{1,2}] + \mathrm{Cov}\left(\tilde{\Lambda}^{(0)}_{1,2}, \frac{y_{j,2}}{y_{j,1}}\right)\right] & \text{for } \tau \in [1_o, 1_m) \\ d_{j,1}\left[1 + \mathbb{E}[\tilde{\Lambda}^{(1)}_{1,2}] + \mathrm{Cov}\left(\tilde{\Lambda}^{(1)}_{1,2}, \frac{y_{j,2}}{y_{j,1}}\right)\right] & \text{for } \tau \in [1_m, 2_o) \end{cases}. \tag{11}$$

It is worth emphasizing that the risk premium component—captured by the covariance term in (11)—varies systematically with firm size. As the following proposition shows, this component is identically zero for small firms, regardless of the monetary policy parameter α_{mp}. In contrast, for large firms, the risk premium depends on α_{mp} whenever $\sigma \neq 1$:

Proposition 4. *For small firms $j \in J_S$, their output growth and the equilibrium SDF are uncorrelated for any $\alpha_{mp} > 0$, that is, $\forall j \in J_S$,*

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

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

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

Proof of Proposition 4. See Supplementary Appendix B. □

Stock Price Reactions around FOMC Announcements We analyze the reactions of stock prices to FOMC announcements, with a particular focus on the announcement at time 1_m. We define the stock return 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 (11), the stock return is given by:

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

This implies that even if the dividend process $y_{j,2}/y_{j,1}$ is unchanged, stock prices may respond to monetary policy announcements due to shifts in investors' expectations, which affect both the expected value of the SDF and the associated risk premium. The following are further insights:

Lemma 2. *The shift in the expected value of the SDF after the FOMC announcement at time 1_m is given by:*

$$\mathbb{E}\left[\tilde{\Lambda}_{1,2}^{(1)}\right] - \mathbb{E}\left[\tilde{\Lambda}_{1,2}^{(0)}\right] = \theta(1-\sigma)\left[\sigma(\tilde{\alpha}_1 - \tilde{\alpha}_0) + \frac{(\theta(1-\sigma))^2}{2}\left(\tilde{\sigma}_{\alpha,1}^2 - \tilde{\sigma}_{\alpha,0}^2\right)\right]\sigma_{g_Y,1}^2.$$

The shift in the risk premium is given by:

$$\mathrm{Cov}\left(\tilde{\Lambda}_{1,2}^{(1)}, \frac{y_{j,2}}{y_{j,1}}\right) - \mathrm{Cov}\left(\tilde{\Lambda}_{1,2}^{(0)}, \frac{y_{j,2}}{y_{j,1}}\right) = \begin{cases} 0, & j \in J_S \\ -\beta\frac{y_{j,1}}{y_1}\sigma_g^2\theta(1-\sigma)(\tilde{\alpha}_1 - \tilde{\alpha}_0), & j \in J_L \end{cases}.$$

Proof of Lemma 2. See Supplementary Appendix B. □

This lemma shows that, conditional on the ex-ante price-dividend ratio $d_{j,1}/q_{j,1_m^-}$, the stock return around FOMC announcements differs between large and small firms because shifts in investors' expectations about monetary policy heterogeneously affect the risk premium.

3.3 Stock Return and Policy Surprises: Model Prediction

We now examine the correlation between stock returns, measured by $\Delta q_{j,1_m}/q_{j,1_m^-}$, and monetary policy surprises, denoted MPS_{1m}. Building on the preceding theoretical framework, we derive the following expression for their conditional relationship:

$$\begin{aligned}\gamma_j \mid \mathbb{Z}_{j,1} \equiv & \frac{\mathrm{Cov}\left(\frac{\Delta q_{j,1_m}}{q_{j,1_m^-}}, MPS_{1_m} \mid \mathbb{Z}_{j,1}\right)}{\mathrm{Var}(MPS_{1_m})} \\ = & \frac{\frac{d_{j,1}}{q_{j,1_m^-}}\left[\mathrm{Cov}\left(\Delta p_{1_m}, MPS_{1_m}\right) + \mathbb{1}_{\{j\in J_L\}}\left(\frac{y_{j,1}}{y_1}\sigma_g^2\right)\theta(\sigma-1)\,\mathrm{Cov}\left(\Delta\tilde{\alpha}_1, MPS_{1_m}\right)\right]}{\mathrm{Var}(MPS_{1_m})},\end{aligned} \quad (12)$$

where $\mathbb{Z}_{j,1}$ denotes the firm-specific information available prior to the FOMC announcement, including the ratios $(d_{j,1}/q_{j,1_m^-}, y_{j,1}/y_1) \in \mathbb{Z}_{j,1}$. Here, $\Delta p_{1_m} = p_{1_m} - p_{1_m^-}$ captures the change in the short-term discount bond price around the FOMC announcement, and $\Delta\tilde{\alpha}_1 = \tilde{\alpha}_1 - \tilde{\alpha}_0$ denotes the revision in investors' expectations about the central bank's policy rule parameter.

Equation (12) highlights that, conditional on the price-dividend ratio, the covariance between stock returns and monetary policy surprises arises from two components (captured by the square brackets in the numerator). The first term, $\mathrm{Cov}\left(\Delta p_{1_m}, MPS_{1_m}\right)$, reflects the change in the expected SDF in response to monetary policy surprises, which affects all firms symmetrically regardless of size. By contrast, the second term, $\mathbb{1}_{\{j \in J_L\}}\left(\frac{y_{j,1}}{y_1}\sigma_g^2\right)\theta(\sigma - 1)\,\mathrm{Cov}\left(\Delta\tilde{\alpha}_1, MPS_{1_m}\right)$, is specific to large firms. This term captures the variation in the risk premium component arising from belief revisions about the central bank's policy stance.

Importantly, the sign of $(\sigma-1)\,\mathrm{Cov}\left(\Delta\tilde{\alpha}_1, MPS_{1_m}\right)$ determines the direction of this differential effect. The case $(\sigma-1)\,\mathrm{Cov}\left(\Delta\tilde{\alpha}_1, MPS_{1_m}\right) < 0$—implying that larger firms' stock returns respond more negatively to rate hike surprises—is consistent with the empirical findings in Section 2. This condition appears plausible in light of standard calibrations of σ in monetary economics and the supporting evidence discussed in Section 2.

The sign of this term depends on both $\sigma - 1$ and $\mathrm{Cov}(\Delta\tilde{\alpha}_1, MPS_{1_m})$. We argue that the conditions $\sigma - 1 > 0$ and $\mathrm{Cov}\left(\Delta\tilde{\alpha}_1, MPS_{1_m}\right) < 0$ are plausible based on both theoretical reasoning and empirical evidence. First, the parameter σ governs the substitutability ($\sigma > 1$) or complementarity ($\sigma < 1$) between consumption and real money balances. While direct empirical estimates of its value are limited, its role in asset pricing models is well established. In particular, as shown in Lemma 1, σ determines the relationship between the activeness of monetary policy and fluctuations in the SDF. In particular, $\sigma > 1$ aligns with the standard New Keynesian view that a more responsive monetary policy (higher α_{mp}) mitigates cyclical fluctuations in the SDF, making the assumption $\sigma > 1$ reasonable.

Second, the evidence from Section 2.2 supports $\mathrm{Cov}\left(\Delta\tilde{\alpha}_1, MPS_{1_m}\right) < 0$. Proposition 3 shows that belief revisions about the policy rule move in the same direction as monetary policy surprises during expansions but in the opposite direction during downturns. Thus, if belief revisions predominantly occur during recessions, it is likely that $\mathrm{Cov}\left(\Delta\tilde{\alpha}_1, MPS_{1_m}\right) < 0$. Consistent with this prediction, Figure 2 shows that monetary policy surprises are highly procyclical, with large movements concentrated around recessions, and that the large negative surprises observed during the 2001 recession and the Great Recession of 2008–09 are largely driven by the predictable component. These patterns suggest that market misperceptions about the monetary policy rule become more pronounced during downturns, implying that recessions, rather than expansions, are the primary periods during which markets learn about the policy responsiveness parameter α.[19] Taken together, these considerations suggest that the condition $(\sigma-1)\,\mathrm{Cov}\left(\Delta\tilde{\alpha}_1, MPS_{1_m}\right) < 0$ is indeed plausible.

[19] In Figure D.5 (Supplementary Appendix D), we find that the estimation bias is more pronounced during recessions.

4 Discussion

The preceding section presented evidence of estimation bias arising from the endogeneity of high-frequency monetary policy surprises, based on comparisons between estimates using original and residualized surprise measures. It highlighted the confounding role of publicly available macro-financial information, which simultaneously influences both measured surprises and firm-level stock returns on FOMC days. To formally capture the underlying mechanism, we developed a theoretical model in which investors update their beliefs about the central bank's policy rule.

In this section, we further discuss the implications of these findings from two perspectives. First, we investigate how well the residualized monetary policy surprise, $\widehat{MPS}_t$, serves as an instrument for isolating exogenous policy shocks. By construction, $\widehat{MPS}_t$ removes the influence of pre-announcement public information and is employed in Section 2.3 to detect endogeneity in conventional high-frequency identification. While it improves upon raw surprise measures and functions as a useful, though imperfect, instrument, we complement this approach by comparing it with an alternative strategy for extracting exogenous policy shocks.

To benchmark $\widehat{MPS}_t$, we present the estimates of γ_k with those based on the refined surprise measure developed by Bu, Rogers, and Wu (2021, BRW, henceforth), shown in Figure D.6 (Supplementary Appendix D). Their measure is derived using Fama and MacBeth (1973) regressions that extract the common component in changes of zero-coupon Treasury yields across maturities. Notably, this series shows minimal predictability from public information and is orthogonal to Fed-internal signals, making it a widely accepted proxy for exogenous policy shocks. Estimates of γ_k based on $\widehat{MPS}_t$ closely track those from the BRW's series, with both pointing to substantially less heterogeneity in stock price responses across firm sizes than conventional high-frequency methods suggest.

The second part of our discussion focuses on the underlying channel through which endogeneity arises. In the predictability regression (1), we highlight the role of publicly available macro-financial information—observable to both market participants and the central bank. However, this public information may also be correlated with the Fed's private information. Indeed, Miranda-Agrippino and Ricco (2021) show that high-frequency monetary policy surprises are partially predictable using Greenbook forecasts, which are internal to the Fed and unavailable to the public in real time. This highlights an alternative source of endogeneity: monetary policy surprises convey the Fed's private assessment of economic conditions to markets, a mechanism often referred to as the Fed information effect.

Our empirical results, however, are not consistent with this interpretation. In Figure D.7, we compare the estimated γ_k coefficients using the raw MPS_t and those based on residualized surprises after removing the component predictable from Greenbook forecasts. If the Fed information effect were the main driver of endogeneity, we would expect stock return responses to increase in magnitude once this component is excluded. Contrary to this expectation, the results indicate a general *decrease* in the estimated responses, particularly for larger firms. To further investigate, Supplementary Appendix E applies the decomposition using the sign restriction employed by Jarociński and Karadi (2020), which isolates the Fed information component. Consistent with theory, this approach shows stronger market responses after the information effect is removed. Overall, these findings suggest that while the Fed information effect exists, it is unlikely to be the dominant source of endogeneity. Rather, our results point to public macroeconomic news as the more substantial confounding factor.

5 Conclusion

This study examined how firm-level estimates of stock price responses to monetary policy shocks—when based on high-frequency measures of monetary policy surprises—can be distorted by endogeneity, particularly due to the predictability of these surprises. Our first contribution is to empirically demonstrate that the stock price responses of large firms are especially susceptible to overestimation bias. This finding suggests that the stronger stock price responses of large firms reported in earlier studies may, at least in part, reflect endogeneity rather than genuine differences in sensitivity to monetary policy shocks.

Our second contribution is to identify the source of this bias, namely, the confounding effect of macroeconomic and financial market information publicly available prior to FOMC announcements. We show that such information not only helps predict monetary policy surprises but also directly influences stock returns on FOMC days. This dual influence creates endogeneity in conventional empirical designs. The confounding effect is particularly pronounced for large firms, whose performance is more closely linked to the macroeconomic indicators that shape expectations of monetary policy.

Our third contribution is to develop a macroeconomic model that formally explains why public news acts as a confounder, how this mechanism generates estimation bias, and why the resulting bias is more pronounced for larger firms. The model combines money-in-utility preferences with granular-origin aggregate fluctuations and investor learning about the central bank's policy rule. It shows that belief revisions following monetary policy announcements induce heterogeneous adjustments in risk premia across firms. Even when monetary policy shocks have uniform effects on firm fundamentals, the stock prices of larger firms react more strongly due to their tighter connection to aggregate conditions and investor expectations.

Appendix

A Additional Tables

Table A.1: Correlations among Firm Characteristics

	Assets	Sales	Book equity	Market equity	Leverage	Cash ratio	Short-term debt	Interest burden
Assets	1.00	0.89	0.95	0.89	0.32	-0.33	-0.24	0.03
Sales		1.00	0.84	0.79	0.27	-0.43	-0.18	0.00
Book equity			1.00	0.90	0.12	-0.24	-0.24	-0.10
Market equity				1.00	0.10	-0.11	-0.10	-0.08
Leverage					1.00	-0.44	-0.02	0.56
Cash ratio						1.00	0.37	-0.20
Short-term debt							1.00	0.00
Interest burden								1.00

Note: "Assets" refer to total assets; "Sales" to gross sales; "Book equity" to the book value of equity; and "Market equity" to the market value of equity. These four variables are expressed in logarithms. "Leverage" is defined as total liabilities divided by total assets. "Cash ratio" is cash and cash equivalents divided by total assets. "Short-term debt" is defined as short-term debt divided by total debt. "Interest burden" is defined as interest expense relative to total assets. Correlations are computed by first calculating the correlation matrix for each quarter and then taking the time-series average across quarters.

Table A.2: Predictability of Monetary Policy Surprise

	(1) Baseline	(2) ED1	(3) ED2	(4) ED3	(5) ED4
Constant	-0.0072*	-0.0089**	-0.0158***	-0.0197***	-0.0210***
	(0.0043)	(0.0038)	(0.0041)	(0.0045)	(0.0049)
Payrolls Surprise	0.0063*	0.0072**	0.0071**	0.0054	0.0043
	(0.0033)	(0.0029)	(0.0032)	(0.0035)	(0.0038)
Payrolls Change	0.0045**	0.0021	0.0043**	0.0056**	0.0053**
	(0.0021)	(0.0019)	(0.0021)	(0.0022)	(0.0025)
S&P 500 Change	0.0887*	0.0556	0.0758*	0.1016**	0.1087**
	(0.0477)	(0.0422)	(0.0459)	(0.0499)	(0.0549)
Slope Change	-0.0063	-0.0041	-0.0060	-0.0069	-0.0073
	(0.0074)	(0.0065)	(0.0071)	(0.0077)	(0.0085)
Commodity Price Change	0.1118***	0.0633*	0.0989**	0.1235***	0.1461***
	(0.0419)	(0.0371)	(0.0403)	(0.0439)	(0.0482)
Treasury Skewness	0.0249**	0.0098	0.0216**	0.0315***	0.0335**
	(0.0114)	(0.0100)	(0.0109)	(0.0119)	(0.0131)
R^2	0.13717	0.07879	0.12847	0.15700	0.14634
Observations	240	240	240	240	240

Notes: The dependent variable is MPS_t, measured using the first principal component approach in column (1), and the changes in the first four quarterly Eurodollar futures contracts (ED1 through ED4) surrounding FOMC press releases in columns (2) through (5), respectively. The independent variables capture information about macroeconomic conditions available to private sector agents prior to FOMC announcements. Payrolls Surprise represent the surprise component of the most recent Nonfarm Payrolls release. Payrolls Change 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 before the announcement to the day before the announcement. Slope Change measures 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 announcement. Treasury Skewness refers to the implied skewness of the 10-year Treasury yield, as introduced by Bauer and Chernov (2024). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

References

Aruoba, S. Borağan, Francis X. Diebold, and Chiara Scotti. 2009. "Real-Time Measurement of Business Conditions." *Journal of Business & Economic Statistics* 27 (4):417–427.

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

Bauer, Michael D., Carolin E. Pflueger, and Adi Sunderam. 2024. "Perceptions about Monetary Policy." *Quarterly Journal of Economics* 139 (4):2227–2278.

Bauer, Michael D. and Eric T. Swanson. 2023a. "An Alternative Explanation for the 'Fed Information Effect'." *American Economic Review* 113 (3):664–700.

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

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

Brave, Scott A., R. Andrew Butters, and David Kelley. 2019. "A New 'Big Data' Index of U.S. Economic Activity." *Economic Perspectives* (1):1–30.

Brennan, Connor M., Margaret M. Jacobson, Christian Matthes, and Todd B. Walker. 2024. "Monetary Policy Shocks: Data or Methods?" Finance and Economics Discussion Series 2024-011, Board of Governors of the Federal Reserve System (U.S.).

Bu, Chunya, John Rogers, and Wenbin Wu. 2021. "A Unified Measure of Fed Monetary Policy Shocks." *Journal of Monetary Economics* 118:331–349.

Camara, Santiago. 2025. "Spillovers of US Interest Rates: Monetary Policy & Information Effects." *Journal of International Economics* 154:104059.

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

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

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

Fama, Eugene F. and James D. MacBeth. 1973. "Risk, Return, and Equilibrium: Empirical Tests." *Journal of Political Economy* 81 (3):607–636.

Fischer, Stanley. 1979. "Anticipations and the Nonneutrality of Money." *Journal of Political Economy* 87 (2):225–252.

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

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

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

Graves, Sebastian, Christopher K. Huckfeldt, and Eric T. Swanson. 2023. "The Labor Demand and Labor Supply Channels of Monetary Policy." Working Paper 31770, National Bureau of Economic Research.

Gürkaynak, Refet S., Hatice Gökçe Karasoy-Can, and Sang Seok Lee. 2022. "Stock Market's Assessment of Monetary Policy Transmission: The Cash Flow Effect." *Journal of Finance* 77 (4):2375–2421.

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

Ippolito, Filippo, Ali K. Ozdagli, and Ander Perez-Orive. 2018. "The Transmission of Monetary Policy through Bank Lending: The Floating Rate Channel." *Journal of Monetary Economics* 95:49–71.

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

Jeenas, Priit. 2023. "Firm Balance Sheet Liquidity, Monetary Policy Shocks, and Investment Dynamics." Working Papers 1409, Barcelona School of Economics.

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

Kiyotaki, Nobuhiro and John Moore. 1997. "Credit Cycles." *Journal of Political Economy* 105 (2):211–248.

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

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

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

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

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

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

Romer, Christina D. and David H. Romer. 2000. "Federal Reserve Information and the Behavior of Interest Rates." *American Economic Review* 90 (3):429–457.

Sastry, Karthik A. forthcoming. "Disagreement About Monetary Policy." *American Economic Journal: Macroeconomics* Forthcoming.

Taylor, John B. 1993. "Discretion versus Policy Rules in Practice." *Carnegie-Rochester Conference Series on Public Policy* 39:195–214.

Walsh, Carl E. 2010. *Monetary Theory and Policy, Third Edition*, *MIT Press Books*, vol. 1. The MIT Press.

Supplementary Appendix (Not for Publication)

B Proofs

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

Proof of Proposition 2. The growth rate of y_t is given

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

$\square$

In the first line, $\int_{j \in J_S} \Delta y_{j,t+1}\, dj = 0$ by the law of large numbers and the assumption that the mean of productivity growth among small firms is zero. Note that $\sum_{j \in J_L} \Delta y_{j,t+1}$ is not necessarily zero because the number of large firms is finite.

Proof of Lemma 1.

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

$\square$

Proof of Proposition 4. Approximating $\Lambda_{t,t+1}$ with respect to $g_{Y,t+1}$ and $\varepsilon_{mp,t+1}$ up to second order yields:

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

Since $\mathbb{E}\left[\frac{\Delta y_{j,t+1}}{y_{j,t}}\right] = 0$, we have:

$$\mathrm{Cov}_t\left(\Lambda_{t,t+1}, \frac{y_{j,t+1}}{y_{j,t}}\right) = \mathrm{Cov}_t\left(\Lambda_{t,t+1}, \frac{\Delta y_{j,t+1}}{y_{j,t}}\right) = \mathbb{E}_t\left[\Lambda_{t,t+1}\frac{\Delta y_{j,t+1}}{y_{j,t}}\right].$$

Thus,

$$\begin{aligned} \mathbb{E}_t\left[\Lambda_{t,t+1}\frac{\Delta y_{j,t+1}}{y_{j,t}}\right] =& \mathbb{E}_t\left[\Lambda_{t,t+1}\sigma_g\varepsilon_{j,t+1}\right] \\ \approx& \beta\sigma_g\mathbb{E}_t\left[-\left(\sigma + \theta(1-\sigma)\alpha_{mp}\right) g_{Y,t+1}\varepsilon_{j,t+1}\right] \\ &+ \frac{\beta\sigma_g}{2}\mathbb{E}_t\left[\left(\sigma + \theta(1-\sigma)\alpha_{mp}\right)^2 g_{Y,t+1}^2\varepsilon_{j,t+1}\right]. \end{aligned}$$

Proposition 2 has shown that $g_{Y,t+1} = \sigma_g \sum_{j\in J_L}(y_{j,t}/y_t)\varepsilon_{j,t+1}$. Hence, for small firms $j \in J_S$,

$$\mathbb{E}_t\left[\Lambda_{t,t+1}\frac{\Delta y_{j,t+1}}{y_{j,t}}\right] = 0,$$

which implies

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

Now consider large firms $j \in J_L$. Using $\mathbb{E}[\varepsilon_{j,t+1}^2] = 1$ and $\mathbb{E}[\varepsilon_{j,t+1}^3] = 0$, we have

$$\begin{aligned} \mathbb{E}_t\left[\Lambda_{t,t+1}\frac{\Delta y_{j,t+1}}{y_{j,t}}\right] &\approx -\beta\sigma_g^2\mathbb{E}_t\left[\left(\sigma + \theta(1-\sigma)\alpha_{mp}\right)\frac{y_{j,t}}{y_t}\varepsilon_{j,t+1}^2\right] \\ &= -\beta\frac{y_{j,t}}{y_t}\sigma_g^2\left[\sigma + \theta(1-\sigma)\alpha_{mp}\right]. \end{aligned}$$

Therefore,

$$\mathrm{Cov}_t\left(\Lambda_{t,t+1}, \frac{y_{j,t+1}}{y_{j,t}}\right) \approx -\beta \frac{y_{j,t}}{y_t} \sigma_g^2 \left[\sigma + \theta(1-\sigma)\alpha_{mp}\right].$$

□

Proof of Lemma 2. Thus, we have

$$\begin{aligned}
\mathbb{E}\left[\tilde{\Lambda}_{1,2}^{(0)}\right] &= \mathbb{E}\left[\tilde{\Lambda}_{1,2}^{(0)} \mid \mathcal{F}_{1_m^-}\right] \\
&\approx \beta\left(1 + \frac{1}{2}\left\{\left[\sigma^2 + 2\theta\sigma(1-\sigma)\tilde{\alpha}_0 + (\theta(1-\sigma))^2 \tilde{\sigma}_{\alpha,0}^2\right] \sigma_{g_Y,1}^2 + (\theta(1-\sigma))^2 \sigma_{mp}^2\right\}\right).
\end{aligned}$$

Similarly, we have

$$\mathbb{E}\left[\tilde{\Lambda}_{1,2}^{(1)}\right] \approx \beta\left(1 + \frac{1}{2}\left\{\left[\sigma^2 + 2\theta\sigma(1-\sigma)\tilde{\alpha}_1 + (\theta(1-\sigma))^2 \tilde{\sigma}_{\alpha,1}^2\right] \sigma_{g_Y,1}^2 + (\theta(1-\sigma))^2 \sigma_{mp}^2\right\}\right).$$

So, we have

$$\mathbb{E}\left[\tilde{\Lambda}_{1,2}^{(1)}\right] - \mathbb{E}\left[\tilde{\Lambda}_{1,2}^{(0)}\right] \approx \theta(1-\sigma)\left[\sigma(\tilde{\alpha}_1 - \tilde{\alpha}_0) + \frac{(\theta(1-\sigma))^2}{2}\left(\tilde{\sigma}_{\alpha,1}^2 - \tilde{\sigma}_{\alpha,0}^2\right)\right] \sigma_{g_Y,1}^2.$$

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 $j \in J_L$,

$$\begin{aligned}
\mathrm{Cov}\left(\tilde{\Lambda}_{1,2}^{(0)}, \frac{y_{j,2}}{y_{j,1}}\right) =& \mathbb{E}\left[\exp\left(-\left(\sigma + \theta(1-\sigma)\alpha_{mp}\right)\sigma_g \sum_{j \in J_L} \frac{y_{j,1}}{y_1}\varepsilon_{j,2}\right)\sigma_g \varepsilon_{j,2} \mid \mathcal{F}_{1_m^-}\right] \\
\approx& \mathbb{E}\left[\left(1 - \left(\sigma + \theta(1-\sigma)\alpha_{mp}\right)\sigma_g \frac{y_{j,1}}{y_1}\varepsilon_{j,2}\right)\sigma_g \varepsilon_{j,2} \mid \mathcal{F}_{1_m^-}\right] \\
=& -\frac{y_{j,1}}{y_1}\mathbb{E}\left[\left(\sigma + \theta(1-\sigma)\alpha_{mp}\right)\sigma_g^2 \varepsilon_{j,2}^2 \mid \mathcal{F}_{1_m^-}\right] \\
=& -\frac{y_{j,1}}{y_1}\sigma_g^2\left[\sigma + \theta(1-\sigma)\tilde{\alpha}_0\right]
\end{aligned}$$

Similarly, we have

$$\mathrm{Cov}\left(\tilde{\Lambda}_{1,2}^{(1)}, \frac{y_{j,2}}{y_{j,1}}\right) = -\frac{y_{j,1}}{y_1}\sigma_g^2\left[\sigma + \theta(1-\sigma)\tilde{\alpha}_1\right].$$

So, we have

$$\text{Cov}\left(\tilde{\Lambda}^{(1)}_{1,2}, \frac{y_{j,2}}{y_{j,1}}\right) - \text{Cov}\left(\tilde{\Lambda}^{(0)}_{1,2}, \frac{y_{j,2}}{y_{j,1}}\right) = \frac{y_{j,1}}{y_1}\sigma_g^2\theta(\sigma-1)\left(\tilde{\alpha}_1 - \tilde{\alpha}_0\right).$$

$\square$

Derivation of (12)

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

C Additional Empirical Analyses

C.1 Alternative Firm Size Grouping

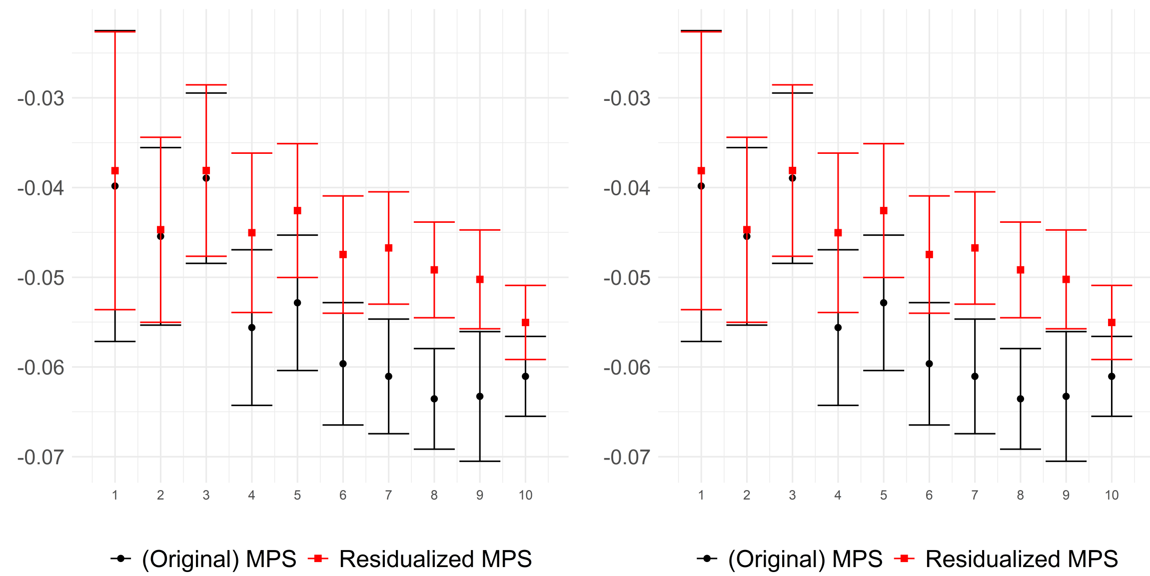
In the baseline analysis in Section 2, firms are sorted into ten groups based on size, with rankings rebalanced quarterly using firm size measured in the preceding quarter. To assess the robustness of our findings to alternative portfolio formation strategies, we consider a lower-frequency rebalancing scheme. Specifically, we implement a biennial reclassification, in which firm size rankings are updated every two years using the average firm size over the preceding eight quarters. This approach reduces the frequency of reclassification and helps smooth transitory fluctuations in firm size that may not reflect persistent firm fundamentals. Figure C.1 compares the estimated coefficients γ_k using the original monetary policy surprise measure (MPS_t) and the residualized surprise ($\widehat{MPS}_t$) under this alternative scheme. The results confirm the robustness of our baseline findings, showing similar patterns of stock return responses across firm size deciles and continued evidence of upward bias when using the non-residualized measure.

C.2 Different Time Spans

The baseline specification covers a 30-year period from 1990 to 2019. We consider two alternative subsamples: (a) 1990–2010, which excludes the last 10 years, and (b) 2000–2019,

Figure C.1: Estimates of γ_k $(k = 1, \ldots, 10)$: Biennial Size Group Revision

(a) Assets (b) Sales

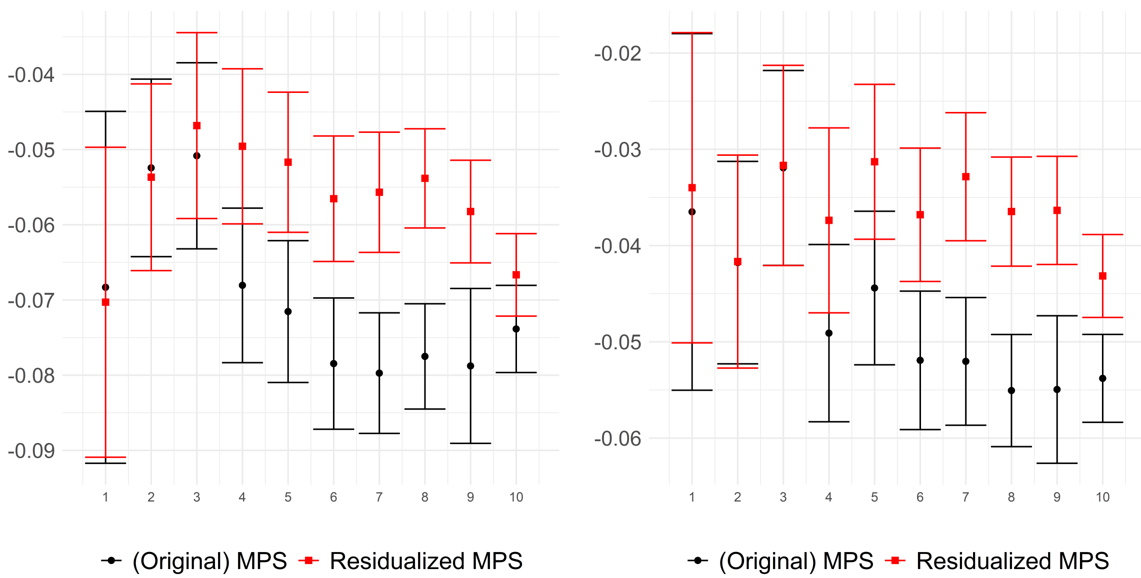


Note: This figure presents the estimates of γ_k $(k = 1, \ldots, 10)$ from (2). The estimates based on the original monetary policy surprise measure (MPS_t) are shown with circular markers, while those based on the residualized surprises $(\widehat{MPS}_t)$ are shown with square markers. The residualized monetary policy surprise is obtained by regressing the original monetary policy surprise on a set of macroeconomic and financial market news variables, X_{t-1} (see Table A.2). Firm size is measured using total assets in Panel (a) and sales in Panel (b). The composition of firm size groups is rebalanced for every two years. The bars indicate 95% confidence intervals, and standard errors are clustered at the firm level.

which excludes the first 10 years. Figure C.2 presents the results and confirms that the choice of time samples does not drive the findings.

Figure C.2: Estimates of γ_k ($k = 1, \ldots, 10$): Selected Time Periods

(a) 2000-2019 (b) 1990-2009



Note: This figure presents the estimates of γ_k ($k = 1, \ldots, 10$) from (2). The estimates based on the original monetary policy surprise measure (MPS_t) are shown with circular markers, while those based on the residualized surprises ($\widehat{MPS_t}$) are shown with square markers. The residualized measure is constructed by regressing the original surprise on a set of macroeconomic and financial news variables X_{t-1} (see Table A.2). Firm size is measured using total assets, and firm groups are rebalanced quarterly. Panel (a) uses samples 2000-2019. Panel (b) uses 1990-2009. The bars indicate 95% confidence intervals, and standard errors are clustered at the firm level.

D Additional Figures and Tables

Table D.1: Estimates of δ_k ($k = 1, \ldots, 10$)

News Variable	$k=1$	$k=2$	$k=3$	$k=4$	$k=5$	$k=6$	$k=7$	$k=8$	$k=9$	$k=10$
Commodity	-0.016	-0.028	-0.026	-0.035	-0.031	-0.031	-0.036	-0.038	-0.038	-0.031
	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Payroll Surprise	-0.119	-0.069	-0.070	-0.103	-0.115	-0.135	-0.104	-0.114	-0.123	-0.086
	(0.045)	(0.024)	(0.015)	(0.013)	(0.012)	(0.011)	(0.009)	(0.010)	(0.018)	(0.007)
Payroll Change	0.001	0.000	0.001	0.000	0.001	0.000	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Slope Change	0.035	-0.008	0.028	0.128	0.050	0.032	0.103	0.145	0.028	-0.049
	(0.100)	(0.062)	(0.054)	(0.048)	(0.044)	(0.039)	(0.038)	(0.032)	(0.034)	(0.024)
S&P 500 Change	0.000	0.012	0.006	-0.006	-0.016	-0.015	-0.022	-0.016	-0.016	-0.006
	(0.011)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.002)
Treasury Skewness	0.004	0.000	0.002	0.003	0.003	0.003	0.004	0.004	0.005	0.003
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)

Notes: This table reports the estimates of δ_k (for firm size deciles $k = 1, \ldots, 10$) from the regression model (2). Standard errors are reported in parentheses. Firm size is measured by total assets. For visibility, the coefficients and standard errors associated with Nonfarm Payroll, Employment, and Slope have been scaled by a factor of 100. Standard errors are clustered at the firm level.

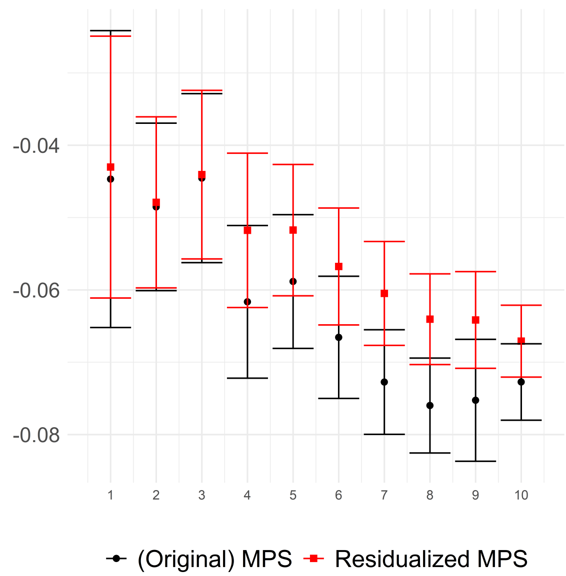
Table D.2: Monetary Policy Shock and Predictability: Additional News

	MPS		
	(1)	(2)	(3)
Constant	-3.93×10^{-5}	0.0005	-0.0449**
	(0.0036)	(0.0035)	(0.0184)
Slope Change	-0.0090	-0.0070	-0.0068
	(0.0076)	(0.0075)	(0.0076)
Commodity Price Change	0.1112**	0.0983**	0.1255***
	(0.0437)	(0.0437)	(0.0416)
Treasury Skewness	0.0221*	0.0226**	0.0236**
	(0.0113)	(0.0112)	(0.0112)
ADS	0.0093*		
	(0.0052)		
BBK		0.0136**	
		(0.0053)	
Unemp Sentiment			0.0005**
			(0.0002)
R^2	0.09153	0.10438	0.10125
Observations	240	240	240

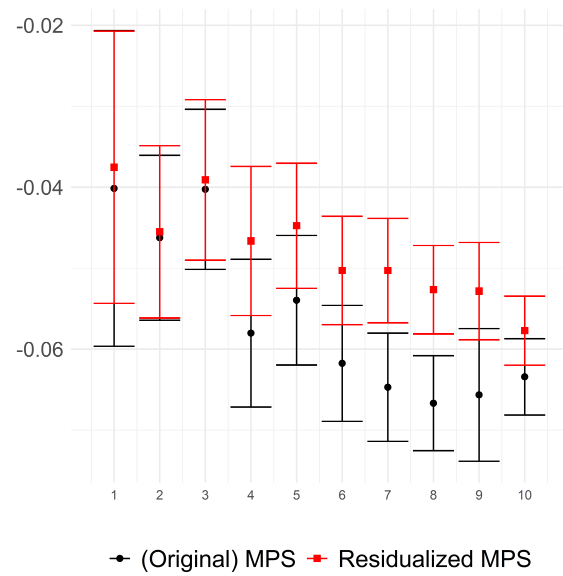
Notes: The dependent variable is MPS_t, measured using the first principal component. The independent variables capture information about macroeconomic conditions available to private sector agents prior to FOMC announcements. Slope Change measures the change in the yield curve slope. Commodity Price Change is the log change in the Bloomberg BCOM commodity price index from 13 weeks before the FOMC announcement to the day before the announcement. Treasury Skewness refers to the implied skewness of the 10-year Treasury yield, as introduced by Bauer and Chernov (2024). "ADS" denotes the ADS Business Conditions Index (Aruoba, Diebold, and Scotti, 2009) and "BBK" refers to the BBK Business Cycle Index (Brave, Butters, and Kelley, 2019). Meanwhile, "Unemp. Sentiment" refers to consumer sentiment about how unemployment will evolve in the next year, from the Michigan Survey of Consumers. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Figure D.1: Estimates of γ_k $(k = 1, \ldots, 10)$: Alternative Measures for MPS_t

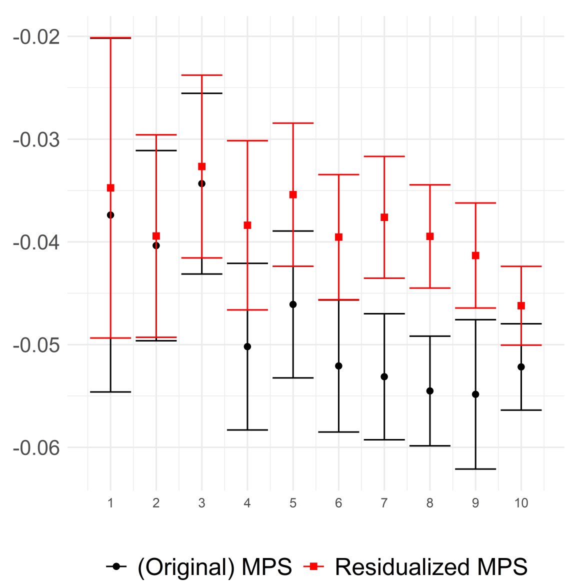
(a) ED1 for MPS_t



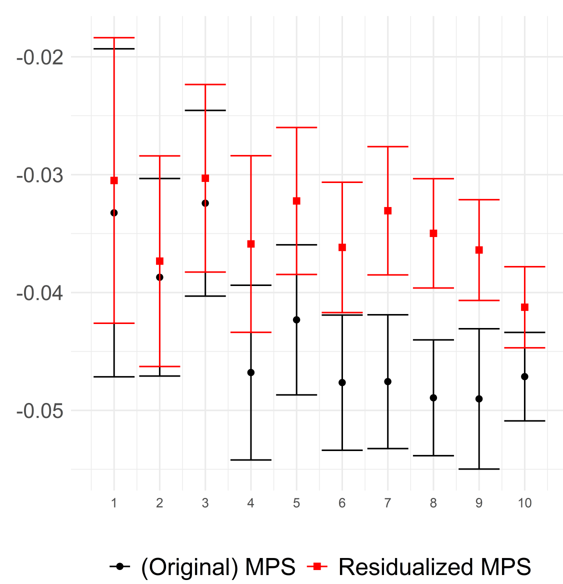
(b) ED2 for MPS_t



(c) ED3 for MPS_t

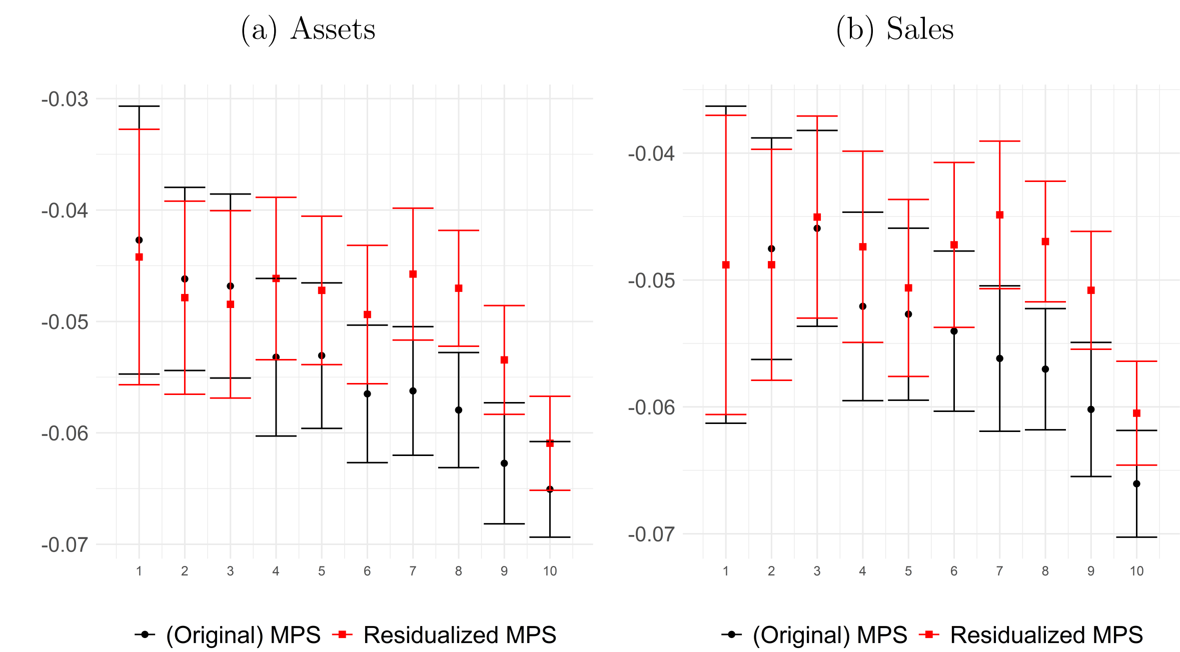


(d) ED4 for MPS_t



Note: This figure presents the estimates of γ_k $(k = 1, \ldots, 10)$ from (2). The estimates based on the original monetary policy surprise measure (MPS_t) are shown with circular markers, while those based on the residualized surprises ($\widehat{MPS}_t$) are shown with square markers. Firm size is measured using total assets. The composition of firm size groups is rebalanced for every quarter. Panels (a) through (d) use ED1 to ED4, respectively, as alternative measures of MPS_t. The residualized monetary policy surprises are obtained by regressing MPS_t on publicly available macroeconomic news. The bars indicate 95% confidence intervals, and standard errors are clustered at the firm level.

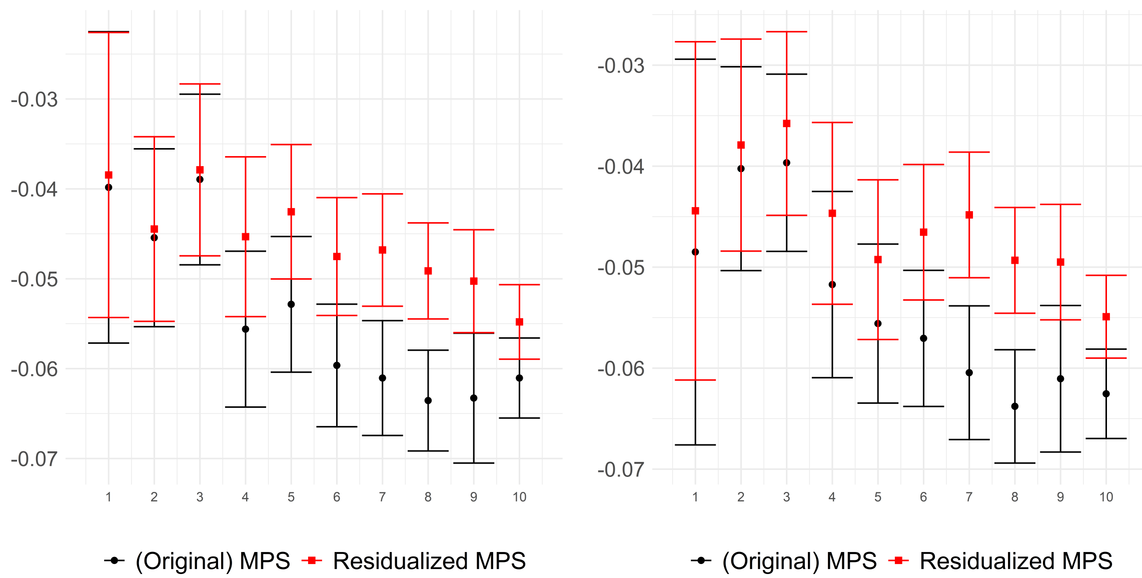
Figure D.2: Estimates of γ_k ($k = 1, \ldots, 10$): Including Unscheduled FOMC Meetings



Note: This figure presents the estimates of γ_k ($k = 1, \ldots, 10$) from (2), based on high-frequency monetary policy surprise measure surrounding both scheduled and unscheduled FOMC meetings. The estimates based on the original monetary policy surprise measure (MPS_t) are shown with circular markers, while those based on the residualized surprises ($\widehat{MPS_t}$) are shown with square markers. The residualized measure is constructed by regressing the original surprise on a vector of macroeconomic and financial market variables observed prior to the announcement (X_{t-1}; see Table A.2). Firm size is measured using total assets in Panel (a) and sales in Panel (b). The composition of firm size groups is rebalanced for every quarter. The bars indicate 95% confidence intervals, and standard errors are clustered at the firm level.

Figure D.3: Estimates of γ_k ($k = 1, \ldots, 10$): Narrower Set of Public News

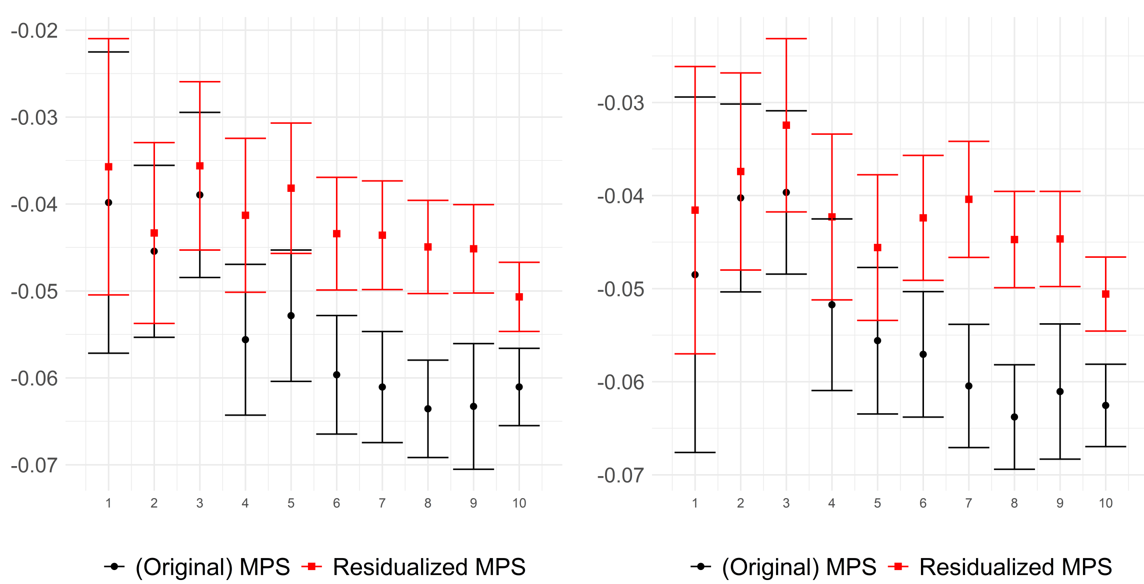
(a) Assets (b) Sales



Note: This figure presents estimates of γ_k ($k = 1, \ldots, 10$) from equation (2). The estimates based on the original monetary policy surprise measure (MPS_t) are shown with circular markers, while those based on the residualized surprises ($\widehat{MPS}_t$) are shown with square markers. The residualized surprises are obtained by regressing the original measure on payroll surprises, changes in payrolls, and changes in the S&P 500 Index. Firm size is measured using total assets in Panel (a) and sales in Panel (b). The composition of firm size groups is rebalanced for every quarter. The bars indicate 95% confidence intervals, and standard errors are clustered at the firm level.

Figure D.4: Estimates of γ_k ($k = 1, \ldots, 10$): Expanded Set of Public News

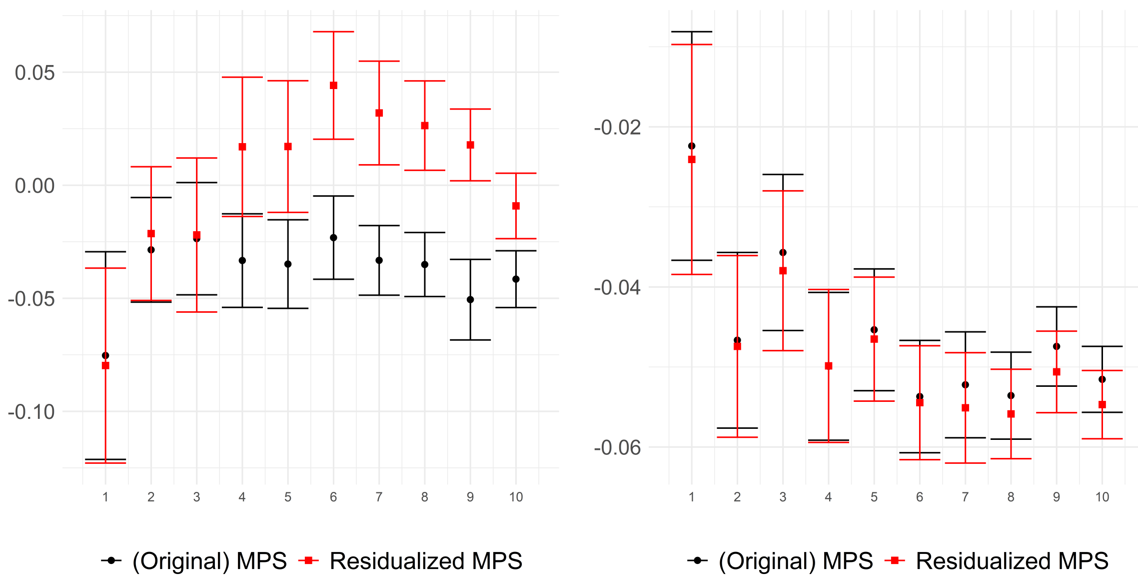
(a) Assets (b) Sales



Note: This figure presents the estimates of γ_k ($k = 1, \ldots, 10$) from equation (2). The estimates based on the original monetary policy surprise measure (MPS_t) are shown with circular markers, while those based on the residualized surprises ($\widehat{MPS_t}$) are shown with square markers. The residualized surprises are obtained by regressing the original series on an expanded set of publicly available information, including lagged values of the ADS Business Conditions Index, the BBK Business Cycle Index, and the consumer unemployment sentiment from the University of Michigan Survey of Consumers. Firm size is measured by total assets in Panel (a) and By Sales in Panel (b). The composition of firm size groups is rebalanced for every quarter. The bars indicate 95% confidence intervals, and standard errors are clustered at the firm level.

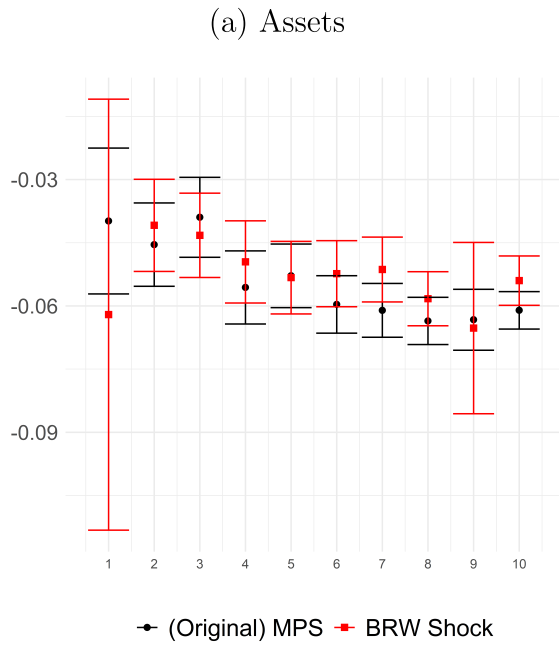
Figure D.5: Estimates of γ_k $(k = 1, \ldots, 10)$: Recessions versus Expansions

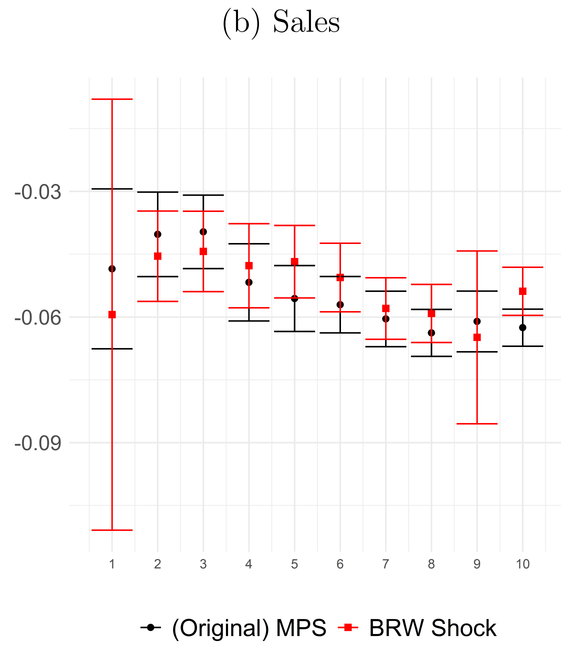
(a) Recessions (b) Expansions



Note: This figure compares the estimates of γ_k $(k = 1, \ldots, 10)$ from equation (2) between recessions (Panel (a)) and expansions (Panel (b)). In each panel, the estimates based on the original monetary policy surprise measure (MPS_t) are shown with circular markers, while those based on the residualized surprises $(\widehat{MPS}_t)$ are shown with square markers. The residualized surprises are obtained by regressing the original series on an expanded set of publicly available information. Firm size is measured by total assets. The composition of firm size groups is rebalanced for every quarter. The bars indicate 95% confidence intervals, and standard errors are clustered at the firm level.

Figure D.6: Estimates of γ_k ($k = 1, \ldots, 10$): Conventional versus Instruments by Bu, Rogers, and Wu (2021)

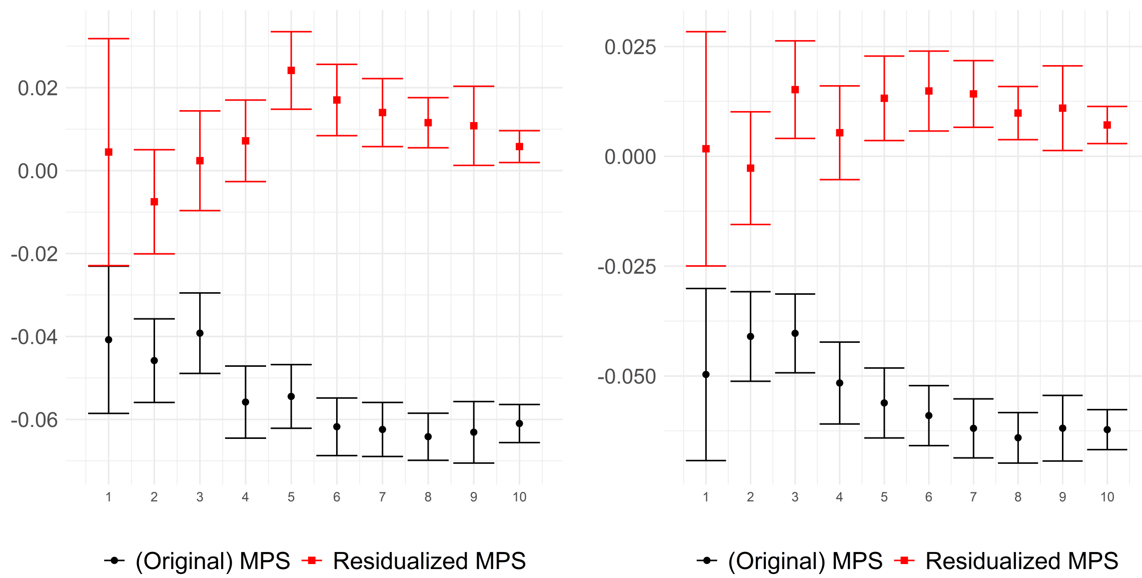




Note: This figure presents the estimates of γ_k ($k = 1, \ldots, 10$) from (2). The $\hat{\gamma}_k^{mps}$ estimates based on the original monetary policy surprise measure (MPS_t) are plotted with circular markers, while the $\hat{\gamma}_k^{rmps}$ estimates based on the residualized monetary policy surprises ($\widehat{MPS_t}$) are shown with square markers. The residualized monetary policy surprises are obtained from Bu, Rogers, and Wu (2021). Firm size is measured by total assets in Panel (a) and By Sales in Panel (b). The composition of firm size groups is rebalanced for every quarter. The bars indicate 95% confidence intervals, and standard errors are clustered at the firm level.

Figure D.7: Estimates of γ_k $(k = 1, \ldots, 10)$: Conventional versus Instruments by Miranda-Agrippino and Ricco (2021)

(a) Assets (b) Sales



Note: This figure presents the estimates of γ_k $(k = 1, \ldots, 10)$ from (2). Estimates based on the original monetary policy surprises (MPS_t) are denoted $\hat{\gamma}_k^{mps}$ and shown with circular markers, while those based on the residualized surprises $(\widehat{MPS}_t)$ are denoted $\hat{\gamma}_k^{rmps}$ and displayed with square markers. The residualized monetary policy surprise is obtained by regressing MPS_t on its lags and the Greenbook forecasts. Firm size is measured by total assets in Panel (a) and by sales in Panel (b). The composition of firm size groups is rebalanced for every quarter. The bars indicate 95% confidence intervals, and standard errors are clustered at the firm level.

E Information Disclosure Shock: Jarociński and Karadi (2020)

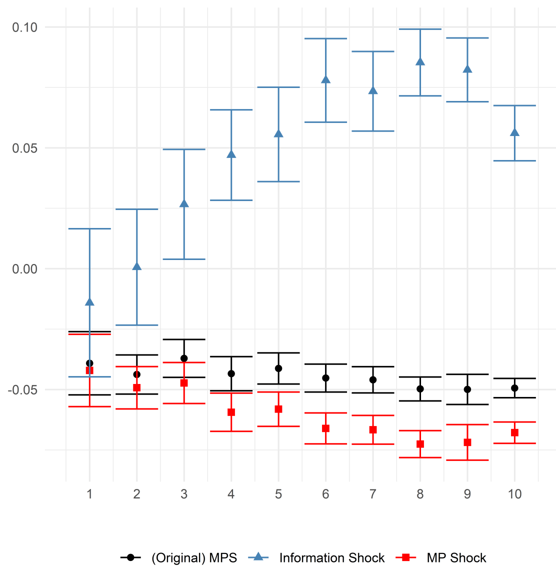
Jarociński and Karadi (2020) propose a sign-restriction-based methodology to decompose high-frequency monetary policy surprises into two distinct components: an information disclosure shock—reflecting the release of the Fed's private assessment of macroeconomic conditions—and a residual component capturing other sources of monetary policy shocks. Their identification strategy imposes that a conventional monetary tightening raises interest rates and reduces stock prices, while a positive information disclosure shock raises both.

Figure E.1 reports the estimated coefficients γ_k associated with each component across firm size deciles, allowing us to examine the differential effects of each shock. While stock returns respond positively to information disclosure shocks on average—as implied by the identification scheme—the magnitude of the response varies across firm sizes. Specifically, the smallest firms exhibit a slightly negative response ($\gamma_1 = -0.014$), while the largest firms display a substantially positive response ($\gamma_{10} = 0.056$). As a result, the estimated effects of the residual component are generally larger in magnitude than those of the raw monetary policy surprises.

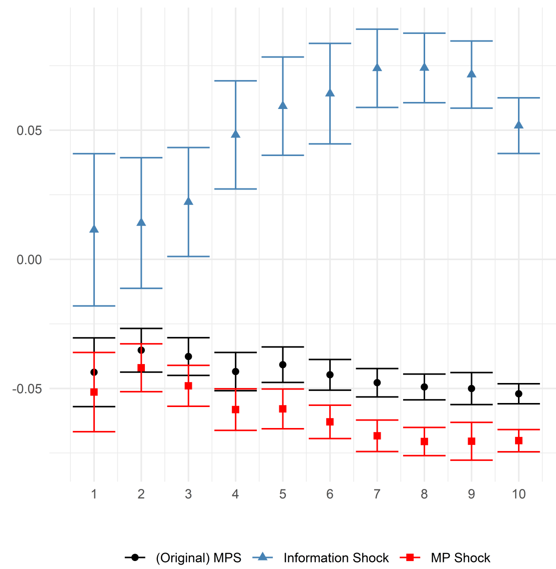
It is important to emphasize that this decomposition is conceptually distinct from the residualization approach based on pre-announcement public information. In particular, the residual monetary policy component identified in Figure E.1 may still contain predictable elements and reflect other forms of information frictions beyond the Fed's informational advantage.

Figure E.1: Response to Information Disclosure Shocks (Jarociński and Karadi, 2020)

(a) Assets



(b) Sales



Note: Estimates of γ_k based on the original monetary policy surprises (MPS_t) are shown with circular markers. Estimates associated with information disclosure shocks, following the methodology of Jarociński and Karadi (2020), are shown with triangle markers, while those corresponding to the residual component are shown with square markers. Firm size is measured using total assets in Panel (a) and sales in Panel (b), with firm size groups rebalanced quarterly. The bars represent 95% confidence intervals, and standard errors are clustered at the firm level.

F Data

- Asset is *atq*. This item represents the total value of assets reported on the Balance Sheet.
- Sales are *saleq*; Gross sales, the amount of actual billings to customers for regular sales completed during the period
- Book value of equity is
  - *seqq*: the common and preferred shareholders' interest in the company.
  - $ceqq + pstkq$ if *seqq* does not exist.
  - $atq - ltq$ if $ceqq + pstkq$ does not exist

  plus

  - *txditcq*: the accumulated tax deferrals due to timing differences between the reporting of revenues and expenses for financial statements and tax forms and investment tax credit.
  - *txdbq* if *txditcq* does not exist.
  - 0 if *txdbq* does not exist.
- Market value of equity is from monthly CRSP; the product of the number of outstanding shares *shrout* and the last traded price in a month *altprc*.

Table F.1 reports the summary statistic for firm size measures.

Table F.1: Summary Statistics for Firm Characteristics

	Summary Statistics				
	Mean	25th	Median	75th	Stdv
Assets	2244	49	220	1123	7359
Sales	484	11	54	260	1808
Book Equity	953	26	111	502	3319
Market Equity	2609	45	220	1121	11662

Note: This table reports time-series averages of quarterly cross-sectional summary statistics. All firm-level variables are measured in millions of U.S. dollars. "Stdv" represents standard deviation. "Assets" refers to total assets (`atq`); "Sales" denotes gross sales (`saleq`); "Book Equity" is the book value of equity; and "Market Equity" is the market value of equity.

G Bootstrap

This section describes the Bootstrap procedure to obtain the standard error of estimates, $\frac{1}{T}\sum_t X'_{t-1}\beta\delta'_k X_{t-1}$.

1. We estimate β in the following regression:

$$MPS_t = \beta^{'} X_{t-1} + \varepsilon_{mp,t}; \qquad \mathbb{E}\left[\varepsilon_{mp,t}|\mathcal{F}_{t^-}\right] = 0 \text{ and } \mathbb{E}\left[\varepsilon^2_{mp,t}|\mathcal{F}_{t^-}\right] = \sigma^2_{mp} > 0,$$

2. The original dataset contains N unique firms, each identified by a firm index (*gvkey*). We draw a bootstrap sample of N firms with replacement. For each selected firm (*gvkey*), we include all of its time-series observations.

3. Using the bootstrap sample obtained in the previous step, we estimate δ_k from the following regression:

$$\Delta y_{i,t} = fe_i + \sum_{k=1}^{10} \gamma_k \widehat{MPS}_t D_{\{size_{i,t}=k\}} + \delta'_k X_{t-1} D_{\{size_{i,t}=k\}} + e_{i,t},$$

4. Using the estimated coefficients, compute the quantity for each $k \in \{1, \cdots, 10\}$:

$$\frac{1}{T}\sum_t X'_{t-1}\beta\delta'_k X_{t-1}.$$

5. Repeat the procedure 10,000 times. Then, for each $k \in \{1, \cdots, 10\}$, compute the standard deviation of

$$\frac{1}{T}\sum_t X'_{t-1}\beta\delta'_k X_{t-1}.$$