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Monetary policy after the Global Financial Crisis

An empirical essay on the transmission mechanisms of monetary policy

Department of Economics and Law
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To everyone who has been there,
who has walked this path,
who has experienced these moments.

The difficulty lies, not in the new idea,
but in escaping from old ones.
J. M. Keynes

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Introduction

This thesis is a product of research work and internship experiences I undertook at my university and central banks, aiming to offer fresh insights into the analysis of monetary policy transmission mechanisms. The first two chapters focus on the United States, exploring the interaction between monetary policy and financial markets. These chapters consider financial stability (Chapter 1) and the risk-taking channel of non-bank financial intermediaries (Chapter 2). The third chapter shifts focus to the Euro Area, examining how banks' confidence can alter monetary policy transmission. In all three chapters, the analysis is empirical to understand the dynamics of monetary policy pass-through better. The first work employs a VAR identified through mixed zero-sign restrictions as the applied empirical methodology, and the second and last chapters present panel Local Projections in both linear and non-linear specifications. Here, I briefly summarize the content of the three chapters.

Chapter 1 - - "Shedding Lights on Leaning Against the Wind" - - is designed to investigate the effectiveness of monetary policy in stabilizing financial markets, with instability represented by stock market bubbles. The effectiveness of monetary policy intervention against stock market bubbles hinges on identifying monetary policy shocks. We estimate a Bayesian VAR identified with mixed zero-sign restrictions, where we distinguish a pure monetary policy shock from a central bank information shock, following the approach of Jarociński and Karadi (2020). These two shocks impact the components of asset prices differently, where the asset price is the sum of the fundamental and bubbly components. A pure tightening monetary policy shock reduces the S&P500 Index but causes the bubble to increase. Conversely, a central bank information shock, by revealing information about the economy's future path, increases the fundamental component, leading to a decrease in the bubble. Ignoring the distinction between these two types of monetary shocks helps explain the ambiguity surrounding the effectiveness of leaning against the wind policy regarding its ability to deflate a bubble.

In Chapter 2 - - "Monetary Policy and Investment Funds: Hungry for Risk?" - - we explore the role of investment funds in the transmission of monetary policy, given their interconnectedness with banks and their significance in terms of assets under management. We investigate the transmission of monetary policy through the portfolio allocation decisions of US investment funds, focusing on the daily net flows of all US-domiciled investment funds on Federal Open Market Committee (FOMC) days. We decompose the announcement into the monetary policy stance, information channel, and the risk-shift component (Kroencke et al., 2021) to capture the risk-taking channel better. The risk-shift component represents a positive shift in investors' risk appetite. Our findings indicate that funds significantly adjust their portfolios in response to monetary policy announcements. We observe that contractionary monetary policy shocks lead to net outflows, especially in the short term for riskier fund types (i.e., equity) and in the long term for less risky ones (i.e., bonds). We also find strong evidence of a risk-taking channel: funds significantly reallocate towards riskier positions, both domestic and foreign, following a positive shift in risk attitude. Additionally, we note a symmetric behaviour in equity funds' investment decisions concerning past performance and rating: flows follow positive returns and higher risk rewards. We isolate the risk-taking channel of monetary policy, noting that even restrictive monetary policy can stimulate a buildup in riskier positions in the non-bank-related financial sector.

Chapter 3 - - "Decomposing the Transmission Channel of Monetary Policy" - - shifts focus to the Euro Area after discussing the interaction between monetary policy and financial markets in the US. In the Eurozone, the role of banks in channelling monetary policy stimuli is pivotal. Indeed, banks' confidence in the economy also matters for monetary policy transmission. This work examines the impact of conventional and unconventional monetary policy shocks on bank balance sheets based on their level of confidence. We construct a bank confidence index using sentiment analysis with a specific financial lexicon on Significant Institution's earnings call transcripts. Banks with higher confidence respond more effectively to conventional expansionary policy shocks, enhancing lending activities and portfolio balance adjustments. In contrast, when bank confidence is low, unconventional policy easing mainly boosts household loan issuance and shifts towards riskier investments. These insights underscore central banks' importance in considering bank confidence as a crucial factor influencing monetary policy transmission.

Chapter 1

Shedding Lights on Leaning Against the Wind

JEL Codes: E4, E5, G1
Keywords: Monetary Policy, Bubbles, LAW, BVAR

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1.1 Introduction

The Global Financial Crisis reignited a vigorous debate on the appropriateness and efficacy of the leaning against the wind (henceforth LAW) policy, which involves central banks using monetary policy tools to counteract financial imbalances, particularly asset bubbles (Gambacorta and Signoretti, 2013). The critical question is whether central banks should target financial stability directly through asset prices, in addition to their traditional mandates of price stability and full employment. Before the crisis, the consensus leaned towards aggressive inflation targeting to maintain overall macroeconomic stability (Bernanke, 2010). However, the crisis revealed the potential limitations of this approach, prompting a reassessment of LAW policies. Despite this renewed interest, the literature presents mixed and often contradictory evidence on the efficacy of LAW policies. While some studies argue for their effectiveness in mitigating financial risks and enhancing economic stability (see, among others, Miao et al. 2019 and Allen et al. 2018), others highlight potential drawbacks, including the risk of inducing economic slowdowns or failing to control bubbles effectively (Galì 2014 among others). Recent empirical research underscores that the outcomes of monetary tightening policies are susceptible to the theoretical assumptions underlying macroeconomic models (Giglio et al., 2016), the identification and measurement of bubbles in empirical research (see the Greewood et al. 2018 's joint hypothesis problem), and the prevailing monetary-financial regimes in place (Corsi and Sornette 2014, Galì and Gambetti 2015, Nneji 2015, Bianchi and Nicolò 2021, Herwartz and Roestel 2022 , Ciccarone et al. 2023).

Given the extreme contrast in outcomes produced by different approaches, both in identifying the effects of monetary policy shocks and defining bubbles, a more detailed analysis of these methods is necessary to understand why the results diverge significantly. Thus, this chapter aims to clarify the ambiguous findings surrounding LAW policies on the empirical side by examining the differential impacts of various monetary policy shocks. Specifically, we distinguish between pure monetary policy shocks and central bank information shocks using a Bayesian VAR identified with mixed zero-sign restrictions. Following Jarociński and Karadi (2020) (hereafter JK), we augment the Bayesian VAR model by the S&P500 estimated bubble.[1] This specification enables us to evaluate the effect of the monetary policy shocks (pure monetary versus information shock) on the asset price compositions, i.e. the fundamental and bubble components. A pure monetary policy tightening shock increases the official interest rate and leads to a drop in S&P500 prices; conversely, an information shock reveals the central bank's expectations about future economic growth, thereby boosting stock prices through investors' anticipations of future positive returns. The impact of these two types of shocks on the bubbly component of asset prices varies between the two shocks, determining the effectiveness of LAW policies.

The analysis delivers three main results. First, a pure monetary policy tightening reduces the S&P500 price via the fundamental component, whereas the bubble expands via the interest rate increase. This result corroborate those by (Galì and Gambetti, 2015) and of

[1] In line with Tirole (1985), we use the term bubble and "non-fundamental" asset price component interchangeably, as we consider it as excessive price movements (Brunnermeier and Schnabel, 2015).

the literature against a central bank intervention. However, it straightly depends on the definition of the monetary policy shock. In fact, the second main finding is that a central bank information shock increases the fundamental component and the S&P500 index because anticipated economic growth enhances expected future dividend flows, thereby increasing the fundamental component. The bubble component simultaneously decrease. Third, asset price components react uniformly to an interest rate hike across different bubble definitions.

To provide additional evidence on the importance of identification of monetary policy shocks, we also leverage the monetary surprise identified by JK and by Miranda-Agrippino and Ricco (2021) to estimate local projection models that allow the use of the asset price components individually. Using this close substitute for the JK shocks, we confirm the main finding that the identification of monetary policy is crucial when assessing the efficacy of LAW. Meanwhile, asset price components consistently respond to an interest rate hike across various bubble definitions.

Thus, as Allen et al. (2018) show that the results from Galì (2014) are sensitive to model specifications, with minor parameter changes leading to significantly different outcomes in the theoretical framework (see Section 1.2 for further details on the debate). Our contribution to the empirical discussion on LAW efficacy is twofold. First, we demonstrate that a pure monetary policy shock reduces the fundamental component while increasing the bubble. Second, we show that asset price components respond differently to a central bank information shock. Therefore, when assessing the efficacy of LAW policy, the identification of monetary shocks is of significance, nor how we compute the bubble. The remainder of this chapter is organized as follows: Section 1.2 focuses on the effects of different approaches to assess LAW efficacy, Section 1.3 describes the variables. In contrast, Section 1.4 describes the empirical methodology and the identification strategy, and Section 1.5 presents the results. Section 1.6 shows some robustness exercises while Section 1.7 concludes.

1.2 Estimating the effects of LAW

The existing literature on the LAW policy can be broadly categorized into theoretical and empirical studies. Theoretical works often explore the foundational concepts of asset bubbles and the role of monetary policy in managing them. Samuelson (1957), Diamond (1965), and Tirole (1985) laid the groundwork by developing models that illustrate how bubbles can form in the presence of financial friction. These models were later expanded to include rational bubbles and their implications for macroeconomic stability (Blanchard and Watson 1982,Farhi and Tirole 2012, Martin and Ventura 2012, Ikeda and Phan 2016, and Ikeda and Phan 2019). The central debate within the theoretical literature revolves around whether central banks should intervene in the presence of stock market bubbles. On one side, proponents of non-intervention argue that central banks should adopt a "wait and see" approach due to the potential unintended consequences and difficulties in detecting actual bubble episodes (Bernanke and Gertler 1999, Bernanke and Gertler 2001 and Greenspan et al. 2002). This perspective suggests that attempting to prevent a rise in asset prices without an overheated economy might limit the central bank's ability to lower interest rates during the fallout phase, potentially exacerbating economic downturns (Barlevy et al., 2018). Bernanke and Gertler (1999) further argue that targeting asset prices could interfere with the central bank's mandate of macroeconomic stability, an approach known as the "Jackson Hole Consensus" or "lean against clean" (Mishkin and Serletis, 2011). The "lean against clean" policy contrasts with the LAW. Further contributions come from Hirano et al. (2017) who shows that, provided that the central bank can deflate the bubble, this comes at the cost of an economic slowdown. Svensson (2014) and Svensson (2017) works are an essential contribution to this debate, who argues against the LAW policy based on cost-benefit analyses. Svensson contends that the costs of such policies, including potential economic slowdowns, often outweigh the benefits of bubble mitigation. He contrasts those who advocate for systematic LAW policies, which incorporate asset prices into the central bank's reaction function.

In support of intervention, Castelnuovo and Nistico (2010) develop a theoretical model where the central bank follows an "augmented" Taylor rule, which responds to inflation, output gaps, and the stock price gap. They find evidence of the Federal Reserve systematically responding to stock price fluctuations driven by non-fundamental components Ciccarone et al. (2019). Gambacorta and Signoretti (2013) argue that LAW is desirable during supply shocks, aiming to stabilize financial markets and the real economy. Martin and Ventura (2016) finds that LAW policies can maximizes output and consumption and Ikeda and Phan (2016) alerts that policy interventions are warranted. Later, Martin and Ventura (2018) provide a guide on incorporating rational bubbles into macroeconomic models to account for critical phenomena. This is consistent with Caballero and Simsek (2020), who sustain that the central bank should feed the bubble for rapid economic recovery.

Ambiguous results about the efficacy of LAW in managing bubbles are also evident. Allen et al. (2017) challenge Galì (2014) work, showing that small changes in model parameters can lead to different outcomes, such as bubble dampening instead of growth. Galì (2014) suggests that bubbles can cause economic instability and that increasing interest rates systematically in response to growing bubbles can positively affect bubble growth. Allen et al. (2017) argue that bubbles are most dangerous when they arise, not when they burst, suggesting that central bank intervention can enhance economic well-being. In response, Galí (2021) develops an OLG New Keynesian model, indicating that bubbles and their fluctuations are detrimental to the economy and should be offset by the central bank to prevent aggregate demand fluctuations. Allen et al. (2022) find that policy responses are more effective when discouraging risky investments rather than targeting asset prices, suggesting macroprudential policy as the appropriate tool for addressing bubbles, with LAW policies being discretionary and responsive only during financial booms (Schularick et al., 2021).

Also empirical studies on the efficacy of LAW policies present a mixed picture. The exploration is relatively limited on the empirical side of the literature and largely hinges on the work by Galì and Gambetti (2015). They concentrate on US monetary policy and the US stock market, finding that a tightening monetary policy is ineffective in deflating bubbles using a Time-Varying SVAR. Their findings are supported by Galì and Gambetti (2015), who emphasize the role of leveraged bubbles in exacerbating financial instability. Conversely, other studies, like those by Aastveit et al. (2017) and Allen et al. (2018) highlight the model-dependent nature of these results, suggesting that different assumptions and identification strategies can lead to varying conclusions.

In this context, we aim to provide further clarity on the effectiveness of LAW. We examine this issue in a novel empirical setup à la JK to avoid any confusion between actual policy interventions and the information revealed by the Fed's actions. By design, these two shocks affect the S&P500 Index differently. Therefore, by focusing on the composition of asset prices, we can assert that the ambiguity about the effectiveness of LAW in managing the asset price bubble depends on the identification of the monetary policy shock.

1.3 Dataset

The dataset spans from February 1991 to June 2019, encompassing 11 instances of financial turmoils. We deliberately exclude the COVID-19 period to sidestep the additional monetary policy easing measures implemented in response to the pandemic restrictions.

1.3.1 The non-fundamental components

Numerous empirical studies have made bubble estimations accessible through market data. Drawing on the theory of rational bubbles, Cochrane (2001) defines a log-linearised model to calculate the bubble as the difference between the price and the present value sum of future dividends, building on Tirole (1985). This approach has been recently further developed by Giglio et al. (2016). Bubbles can be perceived as significant deviations from the stock market trend, as suggested by the statistical approaches of Jordà et al. (2015) and Phillips et al. (2015). Additionally, Forni et al. (2017) define bubbles as noise shocks affecting both the asset price and dividend. Recent studies investigate real-time bubble detection via implied option prices (Jarrow et al. 2011, Jarrow 2015, Greenwood et al.

2019, and Fusari et al. 2020). However, these approaches rely on limited market data. Moreover, as there is not a universally accepted definition of a bubble or non-fundamental component, and some strands of literature even express scepticism about their existence we rely on two mainstream techniques in macro-financial literature for the estimation of the bubble: one is based on a dividend discount model (Cochrane, 2001), akin to the theory of rational bubbles; the other is devoid of any rationality assumptions and is based on a bivariate VAR with prices and dividends, where the bubble is extracted as a noisy shock (Forni et al., 2017). Our analysis utilizes the mainstream technique in macro-financial literature, suggesting that rational bubbles yield the same results as non-rational bubbles when augmented with risk premium.

In the macro-financial literature, seminal works by Jordà et al. (2015) and Phillips et al. (2015) statistically test for their existence, consistently finding positive results. Also, studies in pure financial literature validate the existence of bubbles based on options data (Jarrow et al. 2011, Jarrow 2015, Greenwood et al. 2019, and Fusari et al. 2020). Given the lack of consensus on the definition of a bubble, we rely on the theory of rational bubbles and non-rational assumptions. The theory of rational bubbles is mainstream in macroeconomic and macro-financial literature (Giglio et al., 2016), and we estimate non-fundamental components for the S&P500 Index starting from there.

Rational bubbles The theory of rational bubbles posits that when the transversality condition does not hold, a rational bubble grows at the same pace as the real interest rate. Thus, the present value of a bubble is a function of the real interest rate:

$$B_t = E_t\left(\frac{B_{t+1}}{R}\right) \tag{1.1}$$

Tirole (1985) defines bubbles as the difference between the price and the fundamental component:

$$B_t = E_t\left[\frac{P_t}{R^{T-t}}\right] - E_t\left[\frac{\sum_{k=1}^{T-t} D_{t+k}}{R^k}\right] \tag{1.2}$$

whit D_t dividends and $R_t = 1 + r_t$, where r_t is the real interest rate. Given this definition, we use the formula by Cochrane (2001) for deriving the fundamental component that, in log-linearised terms, is

$$q_t^F = K + \sum_{j=0}^{\infty} \Lambda^j [(1-\Lambda)d_{t+j} - r_{t+j}] \tag{1.3}$$

where K is a constant equal to $\log(1 + P/D) - \frac{P/D}{1+P/D}$ and P/D is the price to dividend ratio in level. Λ represents the ratio between the growth rate of dividend g and the real interest rate R, d_{t+j} is the dividend series in logs and r_{t+j} is the approximate one-year return in logs, in our case the real interest rate. Hence, we derive the bubble as the difference between the price and the fundamental component:

$$q_{i,t}^B = p_t - q_{i,t}^F \quad \text{with} \quad i = 1, 2 \tag{1.4}$$

with p_t the log of S&P500 Price Index and q_t^F obtained from Equation 1.3. For more accuracy, we regress the price, dividends, and real interest rate series on their mean and apply Equation 1.3 to the dividend residuals. From Equation 1.4, we derive the two rational bubbles: when $i = 1$ the discount rate Λ_1 is estimated as defined in Equation 1.3, which is $\Lambda_1 = 0.94$[2]. When $i = 2$, we augment the real interest rate with the risk premium (Blanchard and Watson, 1982) to remove asset price fluctuations due to variations in investors' risk attitude.[3] The discount rate becomes $\Lambda_2 = 0.76$. We will use the bubble augmented with risk premium to control for the generic changes in financial conditions. Indeed, the novelty of this work is that we directly estimate the bubbly component of the S&P500 Index to use it as a variable.

Non-rational bubble The methodology from Forni et al. (2017) identifies three sources of stock price volatility: the dividend shock, the interest rate shock, and the noise shock. The non-fundamental component arises from the noise shock. Also, bubbles are considered a measure of the percentage deviation (positive or negative) of prices from their fundamental values. The theoretical representation of asset price is:

$$\Delta p_t = \frac{\sigma_a^2}{\sigma_s^2}(a_t + \frac{\sigma_e^2}{\sigma_a^2} a_{t-1}) + \frac{\sigma_a^2}{\sigma_s^2}(e_t - e_{t-1}) \tag{1.5}$$

where a_t is the information set regarding dividend and σ_a^2 the variance of dividend shocks, σ_s^2 is the variance of interest rate shock and σ_e^2 the variance of noise shock and e_t the relative bubbles. Thus, prices are also derived as the sum of fundamental and non-fundamental components. What differs in equation 1.5 is that the fundamental component depends on both observable (a_t) and non-observable (e_t) information set about the future path of dividends. Therefore, after some manipulation, Equation 1.5 can be represent as:

$$p_t = q_t^F + q_t^B \tag{1.6}$$

$$\Delta q_t^F = \alpha(L) a_t + n(L) \nu_t \tag{1.7}$$

$$\Delta q_t^B = (1 - L)\tilde{\beta}(L) e_t \tag{1.8}$$

[2] Λ_1 is obtained from observed data and the sample size is long enough to assume the estimated parameter converges to its true value.

[3] As a proxy for the risk premium, we consider the interest rate on BAA 10Y Bonds rated by Moody's (Caldara and Herbst, 2019a).

where p_t is the sum of fundamental q_t^F and bubbly component q_t^B. The fundamental component Δq_t^F (Equation 1.7) is a function of dividend and interest rate shock (a_t and ν_t respectively). The non-fundamental component Δq_t^B (Equation 1.8) is a function of the noise shock e_t, which is stationary and orthogonal to economic fundamentals a_t and ν_t. In conclusion, the noise shock is obtained via a bivariate structural VAR:

$$\begin{bmatrix} \Delta d_t \\ \\ \Delta p_t \end{bmatrix} = \begin{bmatrix} C(L)\sigma_a & 0 \\ \\ \alpha(L)\sigma_a & \beta(L)\sigma_e \end{bmatrix} \begin{bmatrix} a_t/\sigma_a \\ \\ e_t/\sigma_e \end{bmatrix} \tag{1.9}$$

Figure 1.1 encapsulates the three bubble series, with market booms and fallout marked by red dashed vertical lines. The green line represents the bubble series augmented with the risk premium. As anticipated, it is smoother than the one without the risk premium (depicted by the blue line) because it captures fluctuations solely in the bubbly component, not in the risk premium. Accounting for the risk premium allows us to extract the pure bubbly component. The red line represents the bubble obtained with the bivariate VAR (Forni et al., 2017). Its variability underscores that it depends on a noise shock. The S&P500 Index and its dividend series are sourced from the "Online Data Robert Shiller".[4]

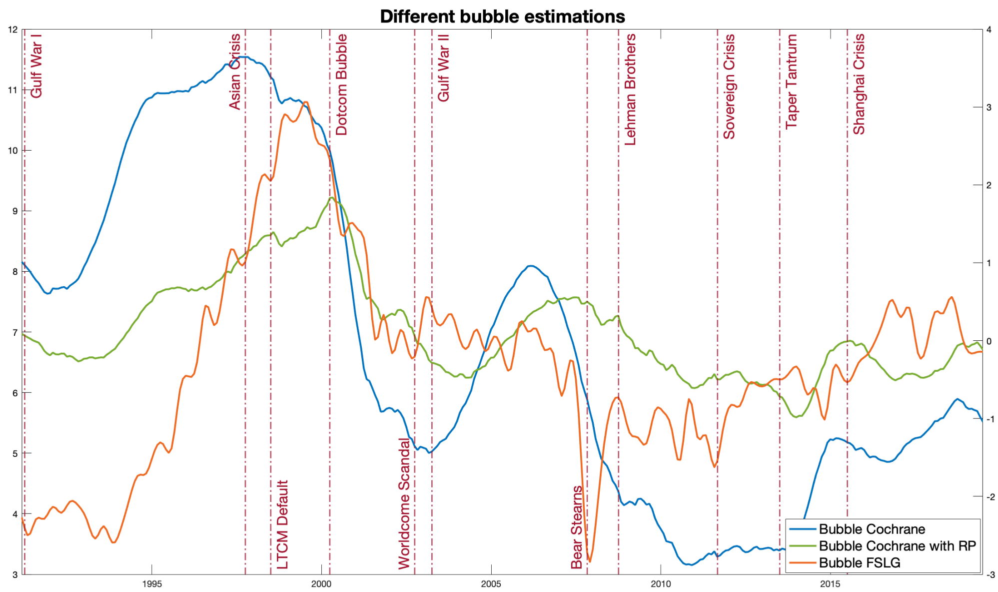

Figure 1.1. Bubble series for the S&P500 Index. The figure shows the bubble series for the S&P500 Index with different specification: blue line rational bubble with $\Lambda_1 = 0.94$ (Cochrane, 2001), green line rational bubble with $\Lambda_2 = 0.76$, red line rational bubble with bivariate VAR (Forni et al., 2017). Data are in logs.

[4]For additional details on data, see Appendix A.1.

1.3.2 U.S. Monetary Policy and remaining variables

U.S. Monetary Policy The main objective of this chapter is to evaluate the effectiveness of LAW by differentiating the shock of pure monetary policy from the shock of central bank information. Therefore, we utilize the data and methodology provided by JK. The data refers to the surprise in the "policy indicator", which is the first principal component of the surprises in interest rate futures with maturities ranging from 1 month to 1 year, and the surprise in the S&P500 near the FOMC meetings. In contrast, to represent the conventional monetary policy behaviour in the US, we opt for the Federal Funds Rate (FFR), a standard choice in the literature. Despite some criticisms regarding its ability to capture pure monetary policy decisions, we follow Arias et al. (2019), who demonstrate that the FFR is the best instrument for identifying monetary policy actions as it reacts only to itself. Also, for the Zero Lower Bound period, which begins with the announcement of the first Quantitative Easing (November 2008) and ends with the 2015 tapering, we substitute the FFR with the shadow rate. The shadow rate is the shortest maturity rate that would generate the observed yield curve if the ZLB had not been binding. Thus, it can be damaging. Additionally, the Shadow Rate accounts for unconventional monetary policy as in Debortoli et al. (2019) and Wu and Zhang (2017). This approach allows the interest rate series to be more sensitive than it would have been if we had maintained values close to zero. We use the shadow rate estimated by Wu and Xia (2016).

Other Variables The remaining variables in the study are the real GDP and the inflation rate. All variables are monthly, seasonally adjusted, and in logarithm, sourced from the FRED Saint Louis. The inflation rate is the annualized rate of change in the GDP deflator. GDP is derived from Chow-Lin interpolation with the Industrial Production Index. In summary, the set of variables is as follows:

- FFR_t^{hf}: The high-frequency surprise in the "policy rate";
- $S\&P500_t^{hf}$: The high-frequency surprise in the S&P500 Index;
- FFR_t: The policy rate;
- EBP_t: The Excess Bond Premium (Gilchrist and Zakrajšek, 2012);
- $q_{i,t}^B$: The bubble component. The subscript i in q^B indicates one of the two non-fundamental components: the rational (Equations 1.4) and the non-rational (Equation 1.8);
- $S\&P500$: The S&P500 Index in log real terms;
- GDP_t: The real U.S. GDP;
- π_t: The inflation rate.

1.4 Methodology

This chapter seeks to illuminate the effectiveness of the LAW policy and examine whether the traditional identification of monetary policy shock is accountable for the ambiguous effects of the LAW policy documented in the literature. This examination necessitates an empirical framework with two essential characteristics. One is the ability to separate a pure monetary shock from a central bank information shock. The other is to remain neutral regarding the relationship between monetary shocks and asset price composition. Therefore, in the first regard, we utilize the Bayesian VAR framework by JK, and for the second, we identify the BVAR via mixed zero-sign restrictions.

1.4.1 Model set-up

To trace out the dynamics of the response of S&P500 Index components to monetary shocks, we estimate a Bayesian VAR that, in its reduced form, is:

$$\mathbf{y}_t = \sum_{i=1}^{p} \mathbf{A}_i \mathbf{y}_{t-i} + \mathbf{u}_t \tag{1.10}$$

where $\mathbf{y}_t$ is the vector of variables listed in Section 1.3.2, $\mathbf{A}$ is the matrix of reduce-form parameters and $\mathbf{u}_t \sim N(0, \Sigma_u)$ is the vector of reduced form shocks. Following JK, we use the original Minnesota prior (Litterman et al., 1986) and estimate the VAR with 12 lags. We assume that the variables are close but not fully stationary; hence, the diagonal elements of $\mathbf{A}_1$ are fixed to 0.8, and the off-diagonal equals zero. Indeed, the prior variability is specified for the ij^{th} element of the matrix $\mathbf{A}_i$, and it follows a hierarchical structure related to four fundamental hyperparameters.

$$\sigma^2_{a_{ij}} = \left(\frac{\lambda_1}{\text{lag}^{\lambda_3}}\right)^2 \tag{1.11}$$

$$\sigma^2_{a_{ij}} = \left(\frac{\sigma_i^2}{\sigma_j^2}\right)\left(\frac{\lambda_1 \lambda_2}{\text{lag}^{\lambda_3}}\right)^2 \tag{1.12}$$

$$\sigma^2_{c_i} = \sigma_i^2(\lambda_1 \lambda_4) \tag{1.13}$$

where the hyperparameter λ_1 is the overall tightness hyperparameter, λ_2 is the cross-variance hyperparameter, λ_3 is the scaling hyperpamater controlling the shrinkages of lag decay λ_4 is another tightness parameter. All the hyperparameters are optimized according to Giannone et al. (2015). Finally, σ_i^2 and σ_j^2 are the residual variances of the autoregressive model estimated with OLS for variable i and j (Alistair et al., 2018).

1.4.2 Identification Strategy

To derive the impulse response functions (IRF) from the VAR reduced form, we need to define an identification strategy for the matrix of structural coefficients. It is common in empirical literature to map reduced-form shocks to innovation in the structural form using the lower triangular Cholesky decomposition (Galì and Gambetti 2015, Aastveit et al. 2017), which involves imposing a recursive scheme on the matrix of the structural coefficients. This chapter's model identification strategy relies on mixed zero-sign restrictions (Arias et al., 2018). Mixed zero-sign restrictions imply that the impact effects matrix is set-identified rather than point-identified. In other words, we only constrain the sign of the parameters of interest without estimating the true value, and we can impose orthogonality via the zero.

The algorithm by Arias et al. (2018) leverages the QR decomposition in the Haar space and the concept of Haar orthogonality. The QR decomposition utilizes the definition of a VAR in its reduced form, as in Equation 1.10, and defines the reduced form errors as:

$$\mathbf{u}_t = \mathbf{P}\mathbf{Q}\mathbf{Q}'\mathbf{e}_t = \mathbf{P}\mathbf{Q}\varepsilon_t^* \tag{1.14}$$

Where $\mathbf{e}_t = \mathbf{P}^{-1}\mathbf{u}_t$ is the transformed error from the Cholesky factorization of the reduced covariance matrix $\mathbf{\Omega}$ such that $E(\mathbf{e}_t\mathbf{e}_t') = \mathbf{P}^{-1}\mathbf{\Omega}\mathbf{P}^{-1'} = \mathbf{P}^{-1}\mathbf{P}\mathbf{P}'\mathbf{P}^{-1'} = \mathbf{I}_m$. Then, the algorithm searches for a large number of combinations between ε_t^* and $\mathbf{e}_t$ and between $\mathbf{u}_t$ and $\mathbf{e}_t$ knowing that $\varepsilon_t^* = \mathbf{Q}'\mathbf{e}_t$ where $\mathbf{Q}'$ is an orthogonal matrix such that that sign restrictions are satisfied. Hence, the ε_t^* is admissible for $\mathbf{e}_t$ if, given the estimates of $\mathbf{u}_t$ and $\mathbf{\Omega}$ from the reduced form VAR, the implied structural impact matrix $\mathbf{PQ}$ satisfies sign restrictions. The procedure consists in generating a large number of candidates $\mathbf{Q}$ from the set of all orthogonal matrices $\upsilon_m = \mathbf{Q}|\mathbf{Q}\mathbf{Q}' = \mathbf{I}_m$ and retaining only those consistent with the set of restrictions. Hence, sign restrictions are imposed only on the draws from the posterior distribution. There is no need to set any further artificial restrictions when estimating the IRF, as it was with the previous algorithms (Jordà 2005, Rubio-Ramirez et al. 2010, Fry and Pagan 2011).

Table 1.4.2 outlines our assumptions for the baseline model identification strategy. The critical aspect of this chapter is to distinguish between the pure monetary policy shock and the central bank information shock. We achieve this separation using the JK identification, which combines High-Frequency Identification (HFI, see Caldara and Herbst (2019b) among others) with sign restrictions, without imposing any restrictions on monthly macroeconomic and financial variables.

The HFI assumption is based on the hypothesis that the two structural shocks are transmitted through central bank announcements and not by other shocks. The assumption of sign restrictions is based on the simultaneous effects of the surprise on interest rates and stock prices. Specifically, a negative co-movement shock is associated with an increase in interest rates and a decrease in stock prices. In contrast, a positive co-movement shock is the orthogonal shock associated with an increase in both interest rates and stock prices.

The negative co-movement shock aligns with news about monetary policy and can be approximated as a monetary policy shock. A pure monetary policy tightening shock increases the official interest rate, leading to a drop in the S&P500 high-frequency index. This occurs because monetary tightening generates a contraction that reduces the expected value of future dividends, and the higher interest rates increase the discount rate applied to these dividends. Consequently, stock prices, which represent the present discounted value of future dividends in standard asset pricing theory, decline.

Conversely, the positive co-movement shock is associated with an information shock that reveals the central bank's expectations about future economic growth, thereby boosting stock prices through investors' anticipations of future positive returns. Since these shocks are identified via HFI, they are orthogonal to slow-moving variables like GDP and other real-side shocks, as per JK. We leave all other variables unrestricted, and all restrictions are applied only to the impact (Canova and Paustian, 2011).

	Pure Monetary	CBI	Supply	Demand	Fundamental	Non-Fundamental	Risk-Bearing
FFR^{hf}	+	+	0	0	0	0	0
$S\&P500^{hf}$	-	+	0	0	0	0	0
GDP							
Inflation							
S&P500							
Q^B							
EBP							

Table 1.1. The Table shows the restrictions for each variable (rows) for each shock (columns). Blank boxes mean that the variable is unrestricted.

1.5 The implication for financial stability

In this Section, we reassess the impact of the monetary shock on both the S&P500 Index and its components, focusing specifically on the influence of a pure monetary shock and a central bank information shock. Shocks are normalized to a 1% increase in the standard deviation.

Old school Firstly, we revisit the widely recognized results in the literature. Galì and Gambetti (2015) provide the primary results in the empirical LAW literature. We replicate this model with our monthly data and the two rational bubble estimations. We maintain the same variable ordering but, for simplicity, we omit the World Consumer Price Index. As a result, the findings display a price and output puzzle. In both scenarios, the bubbly

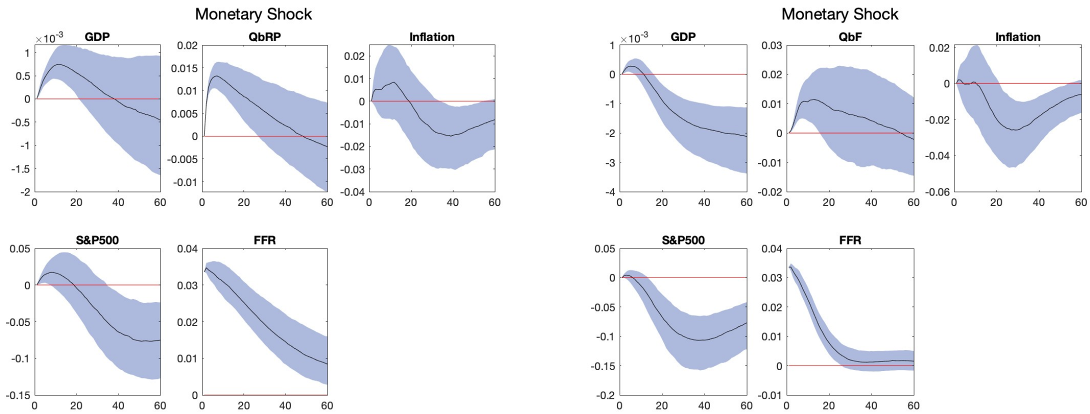

Figure 1.2. Impact of monetary policy shock in the BVAR model. IRF to a monetary shock as in the model by Galì and Gambetti (2015) with rational non-fundamental component as in Equation 1.4 (LHS) and non-rational 1.8 (RHS). Confidence bands at 68%.

component rises following a tightening monetary policy, consistent with the baseline specification by Galì and Gambetti (2015). However, as Allen et al. (2018) show that the results from Galì (2014) with minor parameter changes leading to significantly different outcomes in the theoretical framework. Our contribution to the empirical discussion is twofold. First, we demonstrate that a pure monetary policy shock reduces the fundamental component while increasing the bubble. Second, we show that asset price components respond differently to a central bank information shock.

The effects of a pure monetary shock Our BVAR model's baseline specification follows JK and is described in Section 1.3.2, where the vector $\mathbf{y}$ contains the variables listed. We begin by analyzing the responses to the pure monetary shock (see Figure 1.3). The shock results in a roughly 10% drop in the S&P500 within the first three months, and an increase by about 0.01% over three months for the rational bubble as per Equation 1.4. A more persistent increase occurs for the non-rational bubble obtained by Equation 1.8. This response indicates that the bubble is growing faster than the stock prices. This finding aligns with the theory of rational bubbles. The shock also triggers a decrease in GDP and inflation. We interpret the findings about the bubble as follows: given that the bubble grows at the same rate as the actual interest rate, a rise in the policy rate causes the bubble to expand. Also, consider that the asset price is the sum of the fundamental and the bubble components, where the fundamental value is the discounted sum of dividend flows. A rate hike causes the discount rate to jump higher, reducing the discounted value of the dividend. Thus, the fundamental component declines instead of the bubble, which comes at the cost of a mild recession. These results broadly align with the literature. Firstly, the seminal work by Galì and Gambetti (2015) demonstrates that monetary policy is unsuccessful in deflating the bubble, followed by the more recent empirical investigation by Forni et al. (2017). Also, Aastveit et al. (2017) highlights the role of an interest rate increase in feeding the non-fundamental component. Finally, Svensson (2017) supports the inefficacy of preventing a bubble from rising using an interest rate increase, as does Schularick et al. (2021).

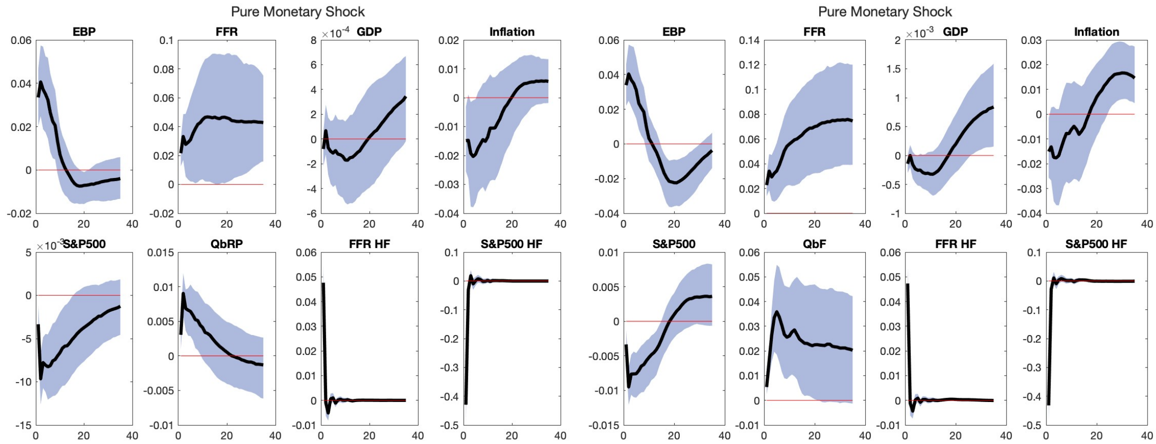

Figure 1.3. Impact of pure monetary policy shock in the BVAR model. IRF to a pure monetary shock identified as JK with rational non-fundamental component as in Equation 1.4 (LHS) and non-rational 1.8 (RHS). Confidence bands at 68%.

The effects of a central bank information shock The subsequent two panels display the responses to the central bank information shock (see Figure 1.4). By design, the central bank information shock is entirely distinct from the pure monetary policy shock. It reveals positive information about the central bank's expectations for the future trajectory of the economy, leading to different outcomes. It prompts a 1% increase in the S&P500 Index over roughly six months before returning to the steady state. The rational bubble as per Equation 1.4 (LHS panel) exhibits a significant negative drop of 5%, which remains stable over time. In this context, the anticipated economic growth strengthens expectations about positive future dividend flows more than the increase in the discount rate, causing the fundamental component to expand. We find a hump-shaped response of the opposite sign for the non-rational bubble as per Equation 1.8, which tends to be positive after almost two years but lacks significance. We may interpret this result considering that according to Forni et al. (2017), investors observe the shock but they are not able to distinguish between news and noise shock. The transitory effects of the information conveyed by the announcement are consistent with the definition and the effect of a noise shock. Consistent with the monetary authority conveying positive economic information, GDP and inflation respond positively, in line with the JK baseline and poor man model. These results support the literature's portion favouring monetary policy intervention. We observe that monetary policy maximizes all its targets: it controls inflation and reduces the bubble without causing a recession (Martin and Ventura 2016, and Martin and Ventura 2018). Also, we can interpret this policy intervention as a mild *laissez-faire*. The central bank allows the bubble to grow to the point where it stimulates economic growth (Caballero and Simsek, 2020). If the monetary authority intervenes at this point, the bubbly component drops in favour of the fundamental, fueled by economic growth.

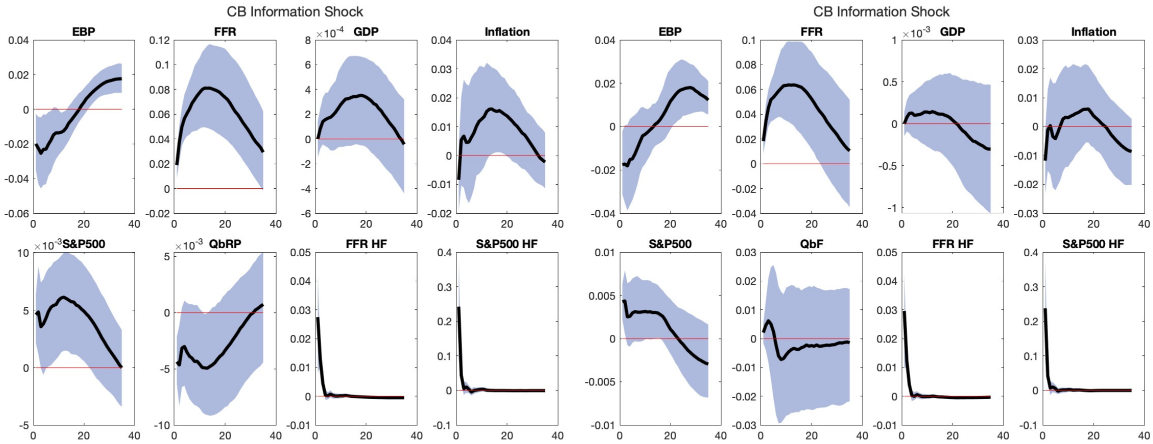

Figure 1.4. Impact of central bank information shock in the BVAR model. IRF to a central bank information identified as JK with rational non-fundamental component as in Equation 1.4 (LHS) and non-rational 1.8 (RHS). Confidence bands at 68%.

1.6 Robustness checks

We conduct two different exercises to evaluate the robustness of our baseline models. First, we test if the BVAR aligns with local projections model (Jordà, 2005), where shocks are externally identified. Since the seminal work by Jordà (2005), linear projections have emerged as a practical, cost-effective method for exploring the dynamics in the transmission of shocks. Furthermore, Stock and Watson (2018) expanded the application and effectiveness of linear projections by proposing externally identified shocks. We then use the monetary factors extracted in JK as external shocks, one for pure monetary shock and one for central bank information shock. Later, we repeat the same exercise using the factors obtained by Miranda-Agrippino and Ricco (2021) (MAG from now on) as external shocks.[5] Moreover, thanks to the flexibility of the linear projections model, we can directly investigate the impact of the two shocks on the asset price composition, namely on the asset price itself and the bubbly component. As a final exercise, we also perform a

[5]MAG's available shock series run from 1991M1 to 2015M12. Thus, we select 24 horizons for the local projections estimates to avoid excessive sample cutting and maintain consistency in estimation.

counterfactual analysis to observe how real variables would have behaved had the central bank not responded to the bubble.

1.6.1 Alternative model

The alternative specification of the baseline model is the linear projections model, described by Equation 1.15. The variable on the left-hand side is alternately represented by the S&P500 Index and the bubble itself as per Equation 1.4 or 1.8. The primary regressors are the monetary surprise series constructed by JK. We include GDP, inflation, S&P500, and the complementary monetary shock among the controls, with 12 lags. The estimation sample spans from February 1991 to June 2019.[6]

$$y_{t\to h} = \alpha_h MP_t^i + \beta_h y_{t-1} + \Gamma_h(L)X_{t-s} + \varepsilon_{t,h} \qquad h = 0, ..., 24 \tag{1.15}$$

Where y is the variable of interest, MP represents the JK surprise series, where i refers to the pure monetary policy shock and the central bank information shock. X is the set of control variables. When calculating the IRF, we focus on the representative pure monetary policy shock associated with a median increase of 5 basis points in the three-month fed funds futures and a median drop of 42 basis points in the S&P500 Index in the 30 minutes surrounding the FOMC statements. Figure 1.5 displays the impulse response for the S&P500 Index. Consistent with the baseline specification, the pure monetary tightening has a recessionary impact on the S&P500 Index, but of smaller magnitude, in contrast to the central bank information shock that boost the S&P500 price. Now, we directly examine

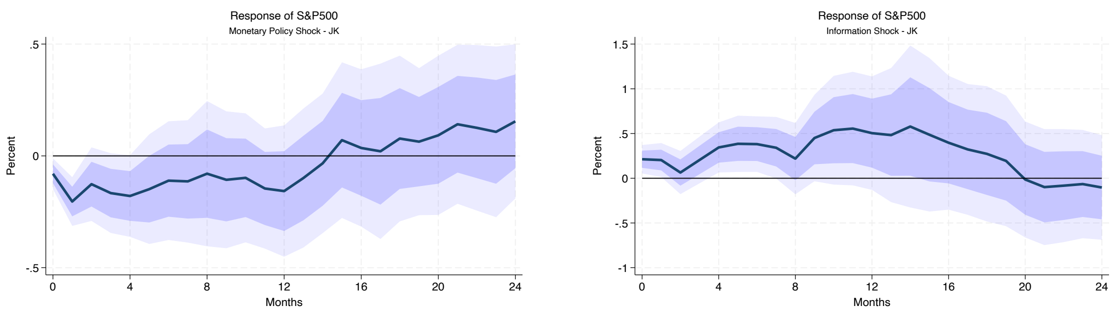

Figure 1.5. Impact of monetary policy shocks in the linear model. The figure shows the impact of monetary policy shocks identified by JK - pure monetary on the LHS and information shock on the RHS - on S&P500. Confidence bands at 68% and 90%.

the effect of pure tightening on the non-fundamental component. Figure 1.6 displays the impulse response functions (IRFs) for the two types of bubbles. The response of the rational non-fundamental component (as per Equation 1.4) suggests an increase in the bubble (+1%), although the response is quite noisy. Conversely, the non-rational bubble

[6] All the IRF are calculated considering the Newey-West correction for error terms.

(as per Equation 1.8) exhibits a more coherent dynamic, showing a positive hill-shaped response (peaking at +1.5%) that tends to fade after two years. The responses of the

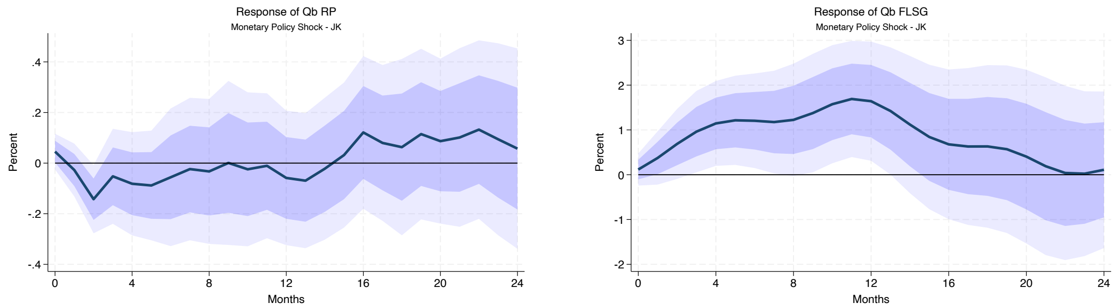

Figure 1.6. Impact of monetary policy shocks in the linear model. The figure shows the impact of monetary policy shocks identified by JK on the non-fundamental component defined as in Equation 1.4 (LHS) and 1.8 (RHS). Confidence bands at 68% and 90%.

asset price composition to the pure monetary policy shock align with the findings of Galì and Gambetti (2015) and Jordà et al. (2015). An increase in the interest rate promotes bubble growth, as demonstrated by Galì and Gambetti (2015) in their Time Varying VAR, and this effect is even more pronounced when the bubbles are leveraged, as per Jordà et al. (2015). Additionally, Aastveit et al. (2017) highlights that an increase in the interest rate fuels the non-fundamental component of stock prices. Remember that the bubble is calculated as the difference between the price and the fundamental component. Given that the fundamental component is the discounted sum of dividend flows, a higher interest rate increases the discount factor at which dividends are discounted, reducing the fundamental value. As a result, the bubble becomes larger. From a theoretical perspective, these results are also consistent with Schularick et al. (2021), who argue that a monetary intervention against asset booms may trigger a crisis due to the bubble's bursting.

The next step is to investigate whether the propagation mechanism changes when considering the information channel, as explored by Jarociński et al. (2018), Jarociński and Karadi (2020), and Miranda-Agrippino and Ricco (2021). The central bank information shock is associated with a median increase of 3 basis points in fed funds futures and a median increase of 28 basis points in the S&P500 Index in the 30 minutes surrounding the FOMC statements. Figure 1.7 presents the impulse response functions, which reveal a completely different dynamic triggered by the central bank information shocks. In line with the idea that the central bank discloses information about the economy's future path, we observe for both non-fundamental components a persistent decline (-1% for the rational bubble and -4% for the non-rational bubble)[7] that either does not revert to zero values after two years. The responses to the central bank information shocks are opposed to the pure monetary

[7] When considering LP model, the IRF does not exhibit the transitory effect as in the baseline specification, making us thinking about the effect of a news shock. Clarify the premise of superior

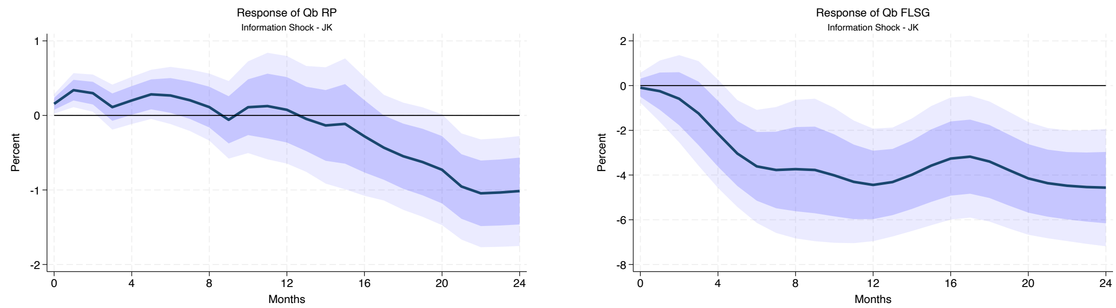

Figure 1.7. Impact of the central bank information shocks in the linear model. The figure shows the impact of the central bank information shocks identified by JK on the non-fundamental component defined as in Equation 1.4 (LHS) and 1.8 (RHS). Confidence bands at 68% and 90%.

shock. The monetary tightening succeeds in reducing the bubble by disclosing information about the economy. This result is not surprising, as the fundamental component depends on the expected dividend growth, making the information channel crucial.

In line with Allen et al. (2017) and Allen et al. (2018), a central bank's commitment to target bubbles for macroeconomic stability can enhance social welfare. According to Caballero and Simsek (2020), if the central bank nurtures the bubble to a certain point, it can stimulate economic growth. Therefore, an increase in the interest rate when the economy is expected to grow can prevent the bubble from expanding. The fundamental component supplants the bubble in the price composition, thus mitigating the risk of the bubble's growth and supporting economic well-being, as per Allen et al. (2018). Furthermore, the anticipated dividend growth makes riskier investments less appealing, favouring the fundamental component over the bubble, as suggested by Allen et al. (2022).

1.6.2 Alternative shocks

The alternative specification of the model in Equation 1.15 employs the monetary surprises constructed by MAG as the primary regressors. Unlike JK, MAG does not use sign restrictions for shock identification. Instead, they utilize a novel instrument incorporating high-frequency and narrative approaches. This instrument is obtained as the residuals of the regression of high-frequency movements in the fourth federal funds' futures on the deviation of the expected economic forecast. They extract two factors using the instruments: one represents the monetary policy shock, and the other represents the information shock. These are normalized to represent a 1% increase in the policy rate.

information of central bank and how investors interpret the announcement would be a further development of this chapter.

Figure 1.8 presents the dynamic responses of the S&P500 Index to the pure monetary policy and information shocks, following the approach of MAG. In this case, we can observe a declining path (on average, -0.2%) over the two years considered, confirming that a tightening monetary policy decrease stock prices while the reverse holds for the information shock (on average, +0.1%). We delve deeper into the dynamics of the bubbles' responses

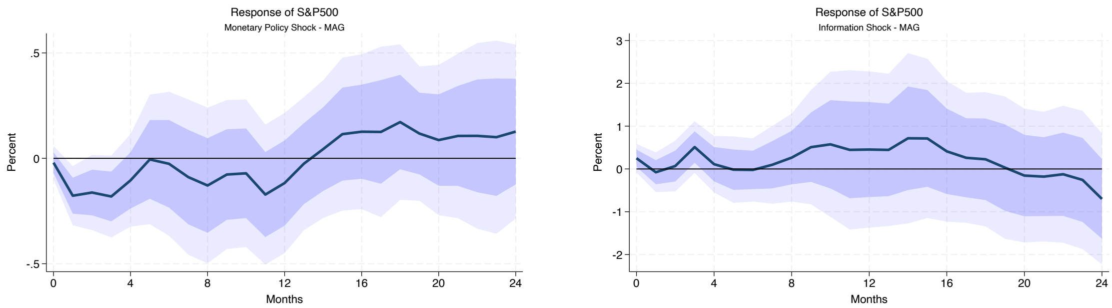

Figure 1.8. Impact of the monetary policy shocks in the linear model. The figure shows the impact of the monetary policy shocks identified by MAG - pure monetary on the LHS and information shock on the RHS - on S&P500. Confidence bands at 68% and 90%.

by directly examining them in Figure 1.9. In this case, we do not observe a clear and persistent increase: the rational bubble from Equation 1.4 exhibits much noise. On the other hand, the non-rational bubble from Equation 1.8 increases in the first five months up to +1.5%, but it quickly reverts to zero, lacking statistical significance. Lastly, we

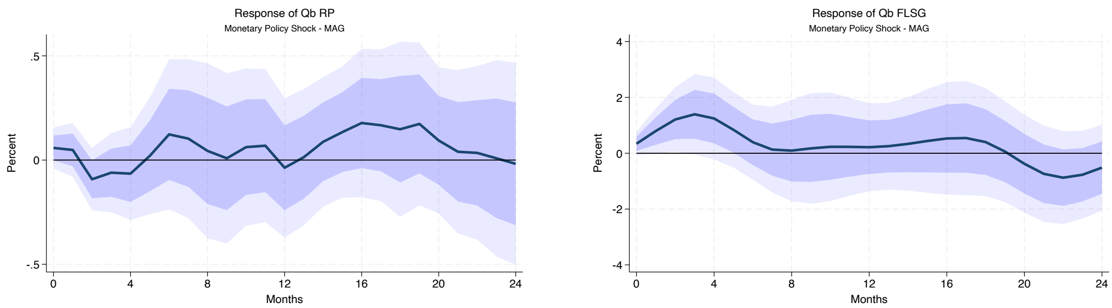

Figure 1.9. Impact of the monetary policy shocks in the linear model. The figure shows the impact of the monetary policy shocks identified by MAG on the non-fundamental component defined as in Equation 1.4 (LHS) and 1.8 (RHS). Confidence bands at 68% and 90%.

present the results for the central bank information shock in the spirit of MAG, which are more robust than the responses to the pure monetary shock. Figure 1.10 displays IRF for the central bank information shock to the S&P500 Index bubble component. Consistently with the previously discussed results, we find an enduring decline in the value of the non-fundamental component.

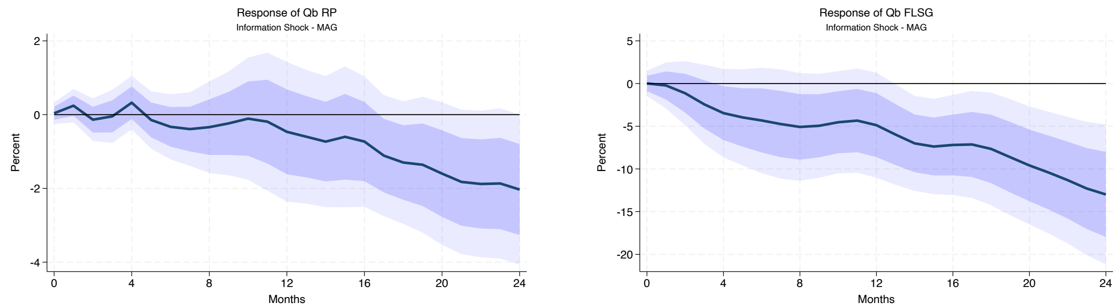

Figure 1.10. Impact of the central bank information shocks in the linear model. The figure shows the impact of the central bank information shocks identified by MAG on the non-fundamental component defined as in Equation 1.4 (LHS) and 1.8 (RHS). Confidence bands at 68% and 90%.

1.6.3 Counterfactual analysis

As a final exercise, we also perform a counterfactual analysis to observe how real variables would have behaved had the central bank not responded to the bubble. This analysis is essential to answer the original question "Should the central bank react to stock market bubble?". To perform a counterfactual analysis on VAR specification, we apply the same methodology of Kilian and Lewis (2011) but in the recent and direct formulation of Chen (2023). Their idea is easy to implement. Consider our VAR model, but in its structural representation:

$$A_0 y_t = A_1 y_{t-1} + ... + A_p y_{t-p} + e_t \tag{1.16}$$

where $y_t = (y_{1,t}, y_{2,t}, ..., y_{k,t})'$ is our k-vector of endogenous variables and p is the number of lags (in our case $k = 8, p = 12$). The SVAR can be also represented as:

$$y_t = (I - A_0)y_t + A_1 y_{t-1} + ... + A_p y_{t-p} + e_t \tag{1.17}$$
$$y_t = Cy_t + A_1 y_{t-1} + ... + A_p y_{t-p} + e_t \tag{1.18}$$

where $C = [c_{ij}]$ and $A_k = [a_{ij}^k]$ for $k = 1, 2, ..., 12$. To obtain the counterfactual response, we construct the matrix $\tilde{C}$ such that the coefficient that monetary policy variable (High-Frequency FFR - the seventh variable in our ordering) reacts to fluctuations in all variables in the SVAR model except the financial and non-fundamental shock (the fifth and sixth variables in our ordering). To do so, the matrix $\tilde{C}$ has the same coefficient of matrix C except that the elements $[\tilde{c}_{7,5}] = 0$ and $[\tilde{c}_{7,5}] = 0$. Also, we construct matrices $\tilde{A}_k$ for $k = 1, 2, ..., 12$ as $\tilde{A}_k = [\tilde{a}_{ij}^k]$, where $[\tilde{a}_{ij}^k] = 0$ for $(i, j) = (7, 5)$ and $(i, j) = (7, 5)$. In full matrix notation:

$$\tilde{C} = \begin{bmatrix} \tilde{c}_{1,1} & \tilde{c}_{1,2} & \tilde{c}_{1,3} & \tilde{c}_{1,4} & \tilde{c}_{1,5} & \tilde{c}_{1,6} & 0 & 0 \\ \tilde{c}_{2,1} & \tilde{c}_{2,2} & \tilde{c}_{2,3} & \tilde{c}_{2,4} & \tilde{c}_{2,5} & \tilde{c}_{2,6} & 0 & 0 \\ \tilde{c}_{3,1} & \tilde{c}_{3,2} & \tilde{c}_{3,3} & \tilde{c}_{3,4} & \tilde{c}_{3,5} & \tilde{c}_{3,6} & 0 & 0 \\ \tilde{c}_{4,1} & \tilde{c}_{4,2} & \tilde{c}_{4,3} & \tilde{c}_{4,4} & \tilde{c}_{4,5} & \tilde{c}_{4,6} & 0 & 0 \\ \tilde{c}_{5,1} & \tilde{c}_{5,2} & \tilde{c}_{5,3} & \tilde{c}_{5,4} & \tilde{c}_{5,5} & \tilde{c}_{5,6} & 0 & 0 \\ \tilde{c}_{6,1} & \tilde{c}_{6,2} & \tilde{c}_{6,3} & \tilde{c}_{6,4} & \tilde{c}_{6,5} & \tilde{c}_{6,6} & 0 & 0 \\ \tilde{c}_{7,1} & \tilde{c}_{7,2} & \tilde{c}_{7,3} & \tilde{c}_{7,4} & 0 & 0 & + & - \\ \tilde{c}_{8,1} & \tilde{c}_{8,2} & \tilde{c}_{8,3} & \tilde{c}_{8,4} & \tilde{c}_{8,5} & \tilde{c}_{8,6} & + & + \end{bmatrix} \quad \tilde{A} = \begin{bmatrix} \tilde{a}_{1,1} & \tilde{a}_{1,2} & \tilde{a}_{1,3} & \tilde{a}_{1,4} & \tilde{a}_{1,5} & \tilde{a}_{1,6} & \tilde{a}_{1,7} & \tilde{a}_{1,8} \\ \tilde{a}_{2,1} & \tilde{a}_{2,2} & \tilde{a}_{2,3} & \tilde{a}_{2,4} & \tilde{a}_{2,5} & \tilde{a}_{2,6} & \tilde{a}_{2,7} & \tilde{a}_{2,8} \\ \tilde{a}_{3,1} & \tilde{a}_{3,2} & \tilde{a}_{3,3} & \tilde{a}_{3,4} & \tilde{a}_{3,5} & \tilde{a}_{3,6} & \tilde{a}_{3,7} & \tilde{a}_{3,8} \\ \tilde{a}_{4,1} & \tilde{a}_{4,2} & \tilde{a}_{4,3} & \tilde{a}_{4,4} & \tilde{a}_{4,5} & \tilde{a}_{4,6} & \tilde{a}_{4,7} & \tilde{a}_{4,8} \\ \tilde{a}_{5,1} & \tilde{a}_{5,2} & \tilde{a}_{5,3} & \tilde{a}_{5,4} & \tilde{a}_{5,5} & \tilde{a}_{5,6} & \tilde{a}_{5,7} & \tilde{a}_{5,8} \\ \tilde{a}_{6,1} & \tilde{a}_{6,2} & \tilde{a}_{6,3} & \tilde{a}_{6,4} & \tilde{a}_{6,5} & \tilde{a}_{6,6} & \tilde{a}_{6,7} & \tilde{a}_{6,8} \\ \tilde{a}_{7,1} & \tilde{a}_{7,2} & \tilde{a}_{7,3} & \tilde{a}_{7,4} & 0 & 0 & \tilde{a}_{7,7} & \tilde{a}_{7,8} \\ \tilde{a}_{8,1} & \tilde{a}_{8,2} & \tilde{a}_{8,3} & \tilde{a}_{8,4} & \tilde{a}_{8,5} & \tilde{a}_{8,6} & \tilde{a}_{8,7} & \tilde{a}_{8,8} \end{bmatrix}$$

Figure 1.11 compares the original and counterfactual impulse response functions of the key variables in response to the pure monetary policy shock using the proposed approach to implement the Kilian–Lewis counterfactual. Shutting down the direct response to financial and non non-fundamental shocks has virtually some effect on inflation and little effect on real output. The Federal Reserve still would have raised interest rates by a roughly similar number of basis points in response to an exogenous positive financial and non-fundamental shocks. We observe slightly different outcomes depending on the bubble definition. In

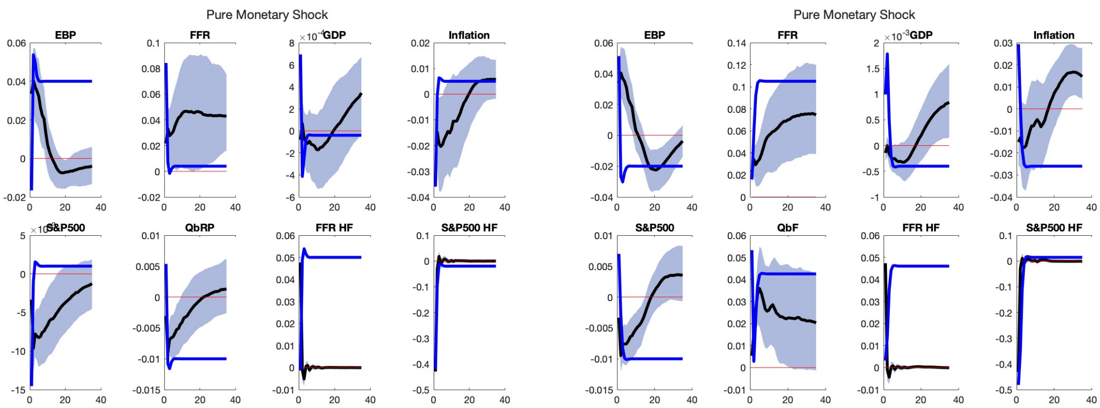

Figure 1.11. Impact of the pure monetary poicy shock in the counterfactual scenario. The figure shows the impact of the pure monetary policy shock identified by JK on the non-fundamental component defined as in Equation 1.4 (LHS) and 1.8 (RHS) and counterfactual scenario. Confidence bands at 68% and 90%.

the case of a rational bubble (LHS), a pure monetary policy shock causes the bubble to grow and remain persistently high, along with an increase in risk perception. This shock also leads to a sharp drop in GDP and a simultaneous rise in inflation, resulting in a price puzzle. Since shocks to the non-fundamental component can be considered a type of demand shock, monetary policy appears more effective in managing macroeconomic imbalances when it also targets financial stability.

On the other hand, when the bubble is non-rational (RHS panel), monetary policy intervention seems more effective in stabilizing the economy. The tightening shock reduces both GDP and inflation without causing a price puzzle.

1.7 Conclusion

This chapter explores the impact of the leaning against the wind policy on asset price composition and provides clarity on the ambiguity surrounding the efficacy of LAW. We demonstrate that the ambiguity in the well-known results in the literature hinges on the identification of the monetary policy shock.

To investigate this mechanism, we adopt the approach by Jarociński and Karadi (2020) and Miranda-Agrippino and Ricco (2021) to distinguish a pure monetary policy shock from a central bank information shock. The analysis indicates that asset price and bubble responses vary depending on the type of monetary shock. On average, a pure monetary tightening is associated with a general decrease in the S&P500 Index due to the inverse relationship between asset prices and interest rates. Additionally, the bubble component expands, consistent with the rational bubble definition and the fundamental component's dampening. In contrast, a central bank information shock reduces the bubble component, favouring the fundamental component driven by expected economic growth. Therefore, the efficacy of the LAW policy depends on the reason for monetary tightening.

Our results underscore that if a bubble exists, the central bank should intervene once the bubble has stimulated economic growth. The fundamental value can displace the bubble in the asset price composition.

Appendix A

Additional material

A.1 Data

We use monthly data in logarithms for the US economy spanning from 1991M2-2019M6. All the variables are seasonally adjusted with the TRAMO-SEATS filter. Table A.1 provides all the details. Monthly series as GDP is obtained with Chow-Lin interpolation with Industrial Production. Column *Bubble Contribution* indicates to which non-fundamental component estimation the variable contributes. Bubble 1 is obtained by Equation 1.4 with risk-premium and 2 by Equation 1.8.

Table A.1. Data source

Variable	Source	Derivation	Bubble Contribution
Excess Bond Premium	Gilchrist and Zakrajšek (2012)		
Real Gross Domestic Product	FRED St. Louis		
Gross Domestic Product	FRED St. Louis		
Inflation		Annualized rate of change of GDP deflator	1, 2
Personal Consumption Expenditure - Durable Goods	FRED St. Louis		2
Personal Consumption Expenditure - Non Durable Goods	FRED St. Louis		2
Fixed Private Investment	FRED St. Louis		2
Federal Funds Rate	FRED St. Louis		1, 2
Industrial Production Index	FRED St. Louis		
BAA 10Y Moody's	FRED St. Louis		1
Real Disposable Income	FRED St. Louis		2
Shadow Rate	Wu and Xia (2016)		1, 2
S&P500 Price Index	Robert Shiller On-line		1, 2
S&P500 Divided	Robert Shiller On-line		1, 2
S&P500 HF	Marek Jarocinski web-site		
FFR HF	Marek Jarocinski web-site		
Monetary Factor JK	Marek Jarocinski web-site		
CBI Factor JK	Marek Jarocinski web-site		
Monetary Factor MAG	Giovvanni Ricco web-site		
CBI Factor MAG	Giovanni Ricco web-site		

A.2 Structural Shocks

Since we present the IRFs of the reduced form VAR, we provide an insight into the Structural Shocks in this Section. All the shocks behave as mean-reverting series.

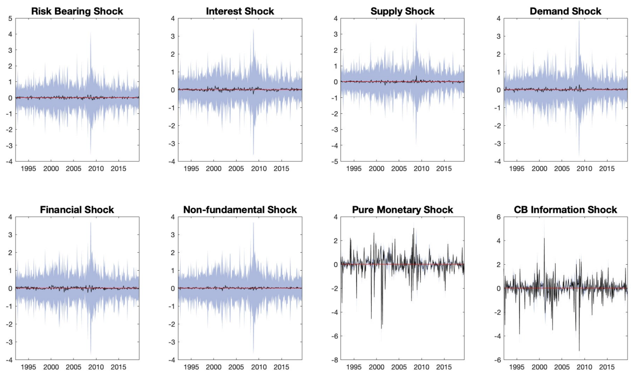

Figure A.1. Structural Shocks. Structural Shocks of the baseline model estimated with the non-fundamental component in Equation 1.4.

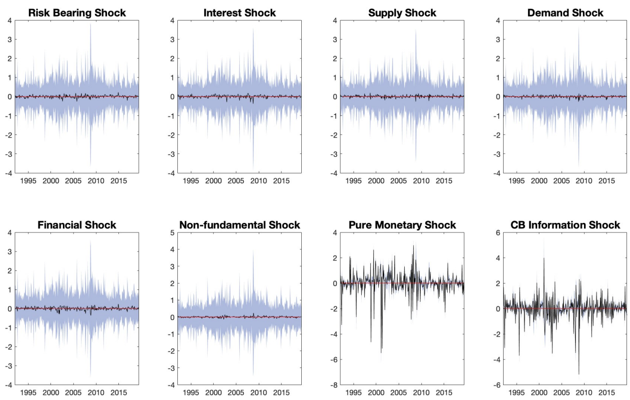

Figure A.2. Structural Shocks. Structural Shocks of the baseline model estimated with the non-fundamental component in Equation 1.8.

A.3 Cholesky Identification

For completeness of exposition, we report in this Section the full set of IRFs, i.e. the response of each variable to each shock, for the Galì and Gambetti (2015) identification

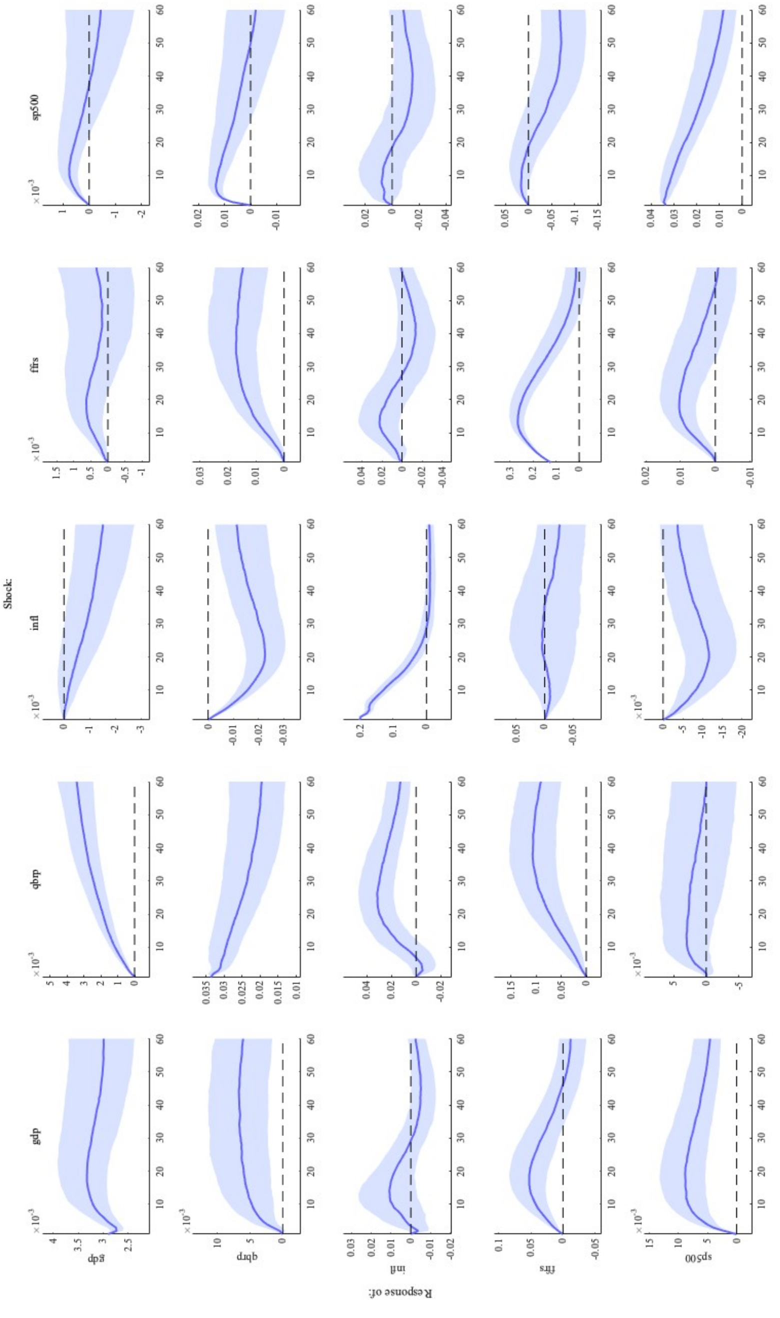

Figure A.3. Impact of all shocks on all variables. IRFs of the model à la Galì and Gambetti (2015) estimated with non-fundamental component in Equation 1.4.

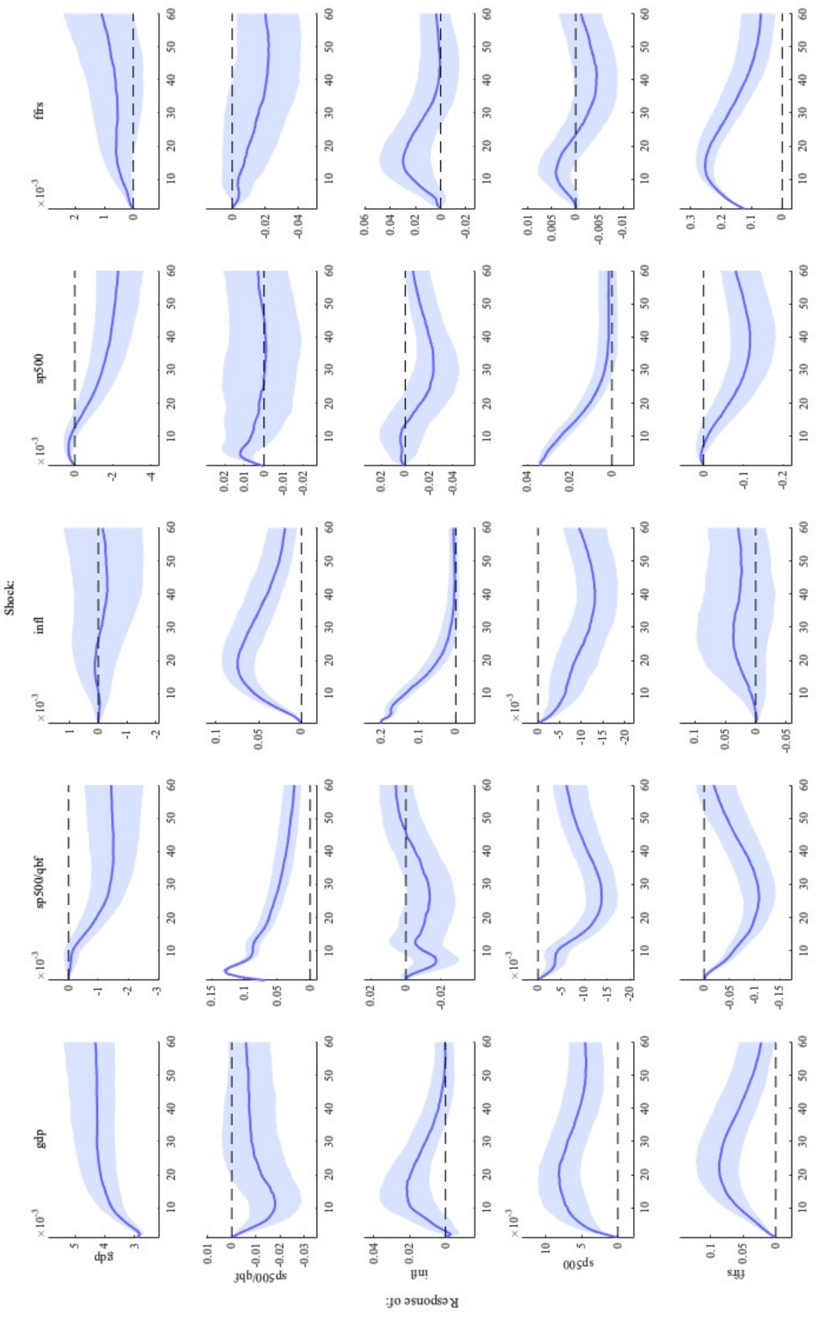

Figure A.4. Impact of all shocks on all variables. IRFs of the model à la Galì and Gambetti (2015) estimated with non-fundamental component in Equation 1.8.

Chapter 2

Monetary Policy and Investment Funds: Hungry for Risk?

JEL Codes: E4, E5, G1, G2
Keywords: Investment funds, funds flows, NBFI, Monetary policy, Risk.

Notes and Acknowledgements

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2.1 Introduction

The non-bank financial institutions (NBFI) sector has seen dramatic growth. In 2021, the NBFI sector expanded by 8.9%, surpassing its five-year average growth rate of 6.6% and reaching a staggering $239.3 trillion. Consequently, the NBFI sector increased its share of global financial assets from 48.6% to 49.2% in 2021. Investment funds, particularly equity funds, primarily drove the growth of the NBFI sector in 2021. The expansion in investment fund assets was supported by a combination of flows and valuation effects, with the growth of equity funds predominantly driven by valuation increases during 2021 (FBS, 2022). The investment funds industry in the U.S., the largest in the world, accounted for USD 21.3 trillion in total net assets, equivalent to 125% of the US GDP in 2019.[1] This substantial presence in the financial market highlights the growing importance of NBFI, which is increasingly recognized as a potential new channel for monetary policy. Specifically, investment funds might play a key role in the monetary policy transmission process through the risk-taking and portfolio rebalancing channels (IMF, 2016).

In this chapter, we analyze the impact of monetary policy shocks on the portfolio allocation decisions of U.S. mutual funds from 2008 to 2020. We observe the daily net flows of over 6000 investment funds domiciled in the U.S. towards equity, bond, and money market funds at the asset class level. We aim to understand how investors' responses to monetary policy shocks influence the sector's size, composition, and risk profile. This understanding is crucial for elucidating the mechanisms through which the Fed's unconventional policies may sway portfolio decisions.

The first of these mechanisms is the portfolio rebalancing channel, which operates via risk and liquidity premiums. Large-scale asset purchase programs in the bond sector affect yields and asset availability. The reduction of bond risk premium boosts asset prices and prompts a shift towards riskier assets to the extent that they are not perfectly substituted (Bernanke et al., 2010). Concurrently, the purchase programs enhance market functioning by decreasing liquidity premiums and facilitating position switching. A second mechanism operates via the signalling channel, which also impacts yields. Similarly, signalling future low policy rates affects the pure portfolio balance (Fratzscher et al., 2018).

We employ the event-study methodology from financial economics to analyze the response of investment funds on Federal Open Market Committee (FOMC) announcement days. Specifically, we use the monetary shocks identified by Kroencke et al. (2021), which extend beyond the identification by Jarociński and Karadi (2020).
The risk-taking channel is particularly relevant to the investment funds allocation decision. In this context, Kroencke et al. (2021) expands the identification of monetary policy shocks beyond stance and information shock by identifying a third component that alters investors' risk appetite. This concept departs from traditional approaches that focus on changes in risk-free rates by targeting the unaccounted factors in stock price fluctuations like growth news and shifts in risk premia. Referred to as "risk shifts", this additional aspect of monetary policy news is fundamental to comprehending the financial market's response to monetary policy announcements.

This study primarily investigates how monetary policy shocks affect the portfolio allocations of funds. We find distinct responses across asset classes to shocks: pure monetary

[1] FRED St. Louis data. Series: DDDI07USA156NWDB

policy, information, and risk-shift shocks. We deliver two main results. First, monetary shocks tied to risk-free rates consistently result in substantial withdrawals from higher-risk funds, regardless of maturity. Secondly, in scenarios where monetary policy enhances risk appetite, there is a notable surge in investments into funds with higher risk profiles.

A tightening in monetary policy, encompassing both pure monetary shocks and information shocks, consistently leads to withdrawals from funds invested in equities and bonds. This behaviour aligns with the portfolio rebalancing theory, where investors adjust their holdings in response to changing economic conditions and monetary policies, shifting away from riskier assets like stocks and bonds to maintain their preferred risk levels. A tightening carries a high recession risk; thus, investors seek safe assets - a phenomenon known as the "dash for cash". This inclination towards safety extends beyond domestic markets; it manifests globally. There is a pronounced shift from bonds and equity funds investments in non-U.S. markets, especially in Emerging Market Economies and Asia. This global flight-to-safety attitude leads to significant capital withdrawal from these regions, reflecting a broader risk-averse sentiment among investors in tumultuous economic times.
The risk-shift surprise alters investors' risk appetite, making them more willing to bear the risk. This shift results in substantial inflows towards equity funds, particularly U.S. funds, EMEs, and non-U.S. bonds. This search for yield behaviour is also driven by fund performance: funds with positive returns over the last month and quarter, as do those with better risk-return performance, attract substantial inflows.

Related Literature Our chapter contributes to the growing literature exploring the relationship between monetary policy and investment funds. The International Monetary Fund (IMF) first highlighted the potential impact of the burgeoning NBFI sector on traditional monetary policy transmission channels (IMF, 2016). The literature often distinguishes between conventional and unconventional monetary policy. For instance, Bubeck et al. (2018) investigated the signalling and portfolio rebalancing channels, finding no significant active reallocation among Euro Area investment funds. However, Giuzio et al. (2021) contradicted this, demonstrating significant portfolio rebalancing towards riskier positions during periods of unconventional monetary policy easing.

Most studies focus on the U.S. investment funds industry, given its significant role in global financial markets. Fratzscher et al. (2018) and Daniel et al. (2021) both found that the Federal Reserve's unconventional measures led to portfolio reallocation and market risk re-pricing, with investors shifting towards high-yield assets in a low-interest rate environment. Banegas et al. (2022) reported similar findings, with unexpected monetary tightening associated with outflows from bond funds. Ciminelli et al. (2022) introduced a novel approach by distinguishing between pure monetary and information shocks rather

than focusing solely on conventional and unconventional measures. They found pure contractionary monetary policy shocks resulted in outflows from U.S. and emerging market economy (EME) mutual funds. Meanwhile, interest rate increases carrying positive future economic information prompted investors to reallocate towards riskier positions.
Additional studies worth noting include Kaufmann (2023), which demonstrated that a loosening of U.S. monetary policy led to higher global investment fund inflows into equities and debt. Silva et al. (2019) found a positive relationship between portfolio turnover and the performance of equity investment funds in Brazil. Döttling and Ratnovski (2023) contrasted how monetary policy affects intangible relative to tangible investment, documenting that the stock prices of firms with more intangible assets react less to monetary policy shocks. Lastly, Hernandez-Vega (2021) studied how unconventional monetary policy announcements affected foreign investment in debt and equity in Mexico, finding that both equity and debt flows reacted immediately to unexpected U.S. monetary policy announcements.

Our study builds on this literature by using the monetary shock identification approach of Kroencke et al. (2021) to isolate the component that stimulates the risk-taking channel, and some of our results reinforce well-established findings in the literature. However, our analysis contributes to the ongoing debate in three significant ways. Firstly, we exploit a highly granular dataset with daily flows for more than 6000 US-domiciled mutual funds, a level of detail not typically seen in fund flow data. Secondly, we primarily focus on the impact of monetary policy announcements on the investment decisions of mutual funds in the U.S., thereby adopting a perspective oriented towards the domestic transmission channel rather than international spillover. Thirdly, we provide evidence that monetary surprises stimulate risk-taking through investment funds, which reallocate towards riskier positions when correctly isolated.

The remainder of this chapter is organized as follows: Section 2.2 extensively describes the dataset, and Section 2.3 describes the empirical strategy to study the funds flow reallocation following monetary shocks. Section 2.4 discusses the main results and alternative specifications in Section 2.5. Section 2.6 presents the conclusions.

2.2 Data

2.2.1 Investment Funds

Our mutual fund data is sourced from Morningstar, a premier data provider in the asset management industry known for its detailed and accurate information on various mutual fund characteristics. The analysis period spans from January 2008 to June 2019, covering numerous Federal Open Market Committee (FOMC) meetings and announcements related to conventional and unconventional monetary policy. Our empirical study focuses on open-end funds and exchange-traded funds domiciled in the U.S., included in the Morningstar categories that we consider are *Equity, U.S. Equity, Advanced Economy Equity and Emerging Market Equity* for the stock market and the bond market *Fixed Income, U.S. Bond, Government Bond, Advanced Economy Fixed Income and Emerging Market Fixed Income*. We also consider the category *Cash* for the money market. Figure 2.1 shows the asset allocation of U.S. domiciled mutual funds. More than 50% of the shares are invested in equity, around 20% in bonds and the residual part in Cash and other assets. The investment strategy of these categories differs in terms of financial assets making up the fund portfolio. Throughout the sample period, the number of unique mutual funds equals 6000. In the Equity category, around 70-78% of the shares are invested in U.S.

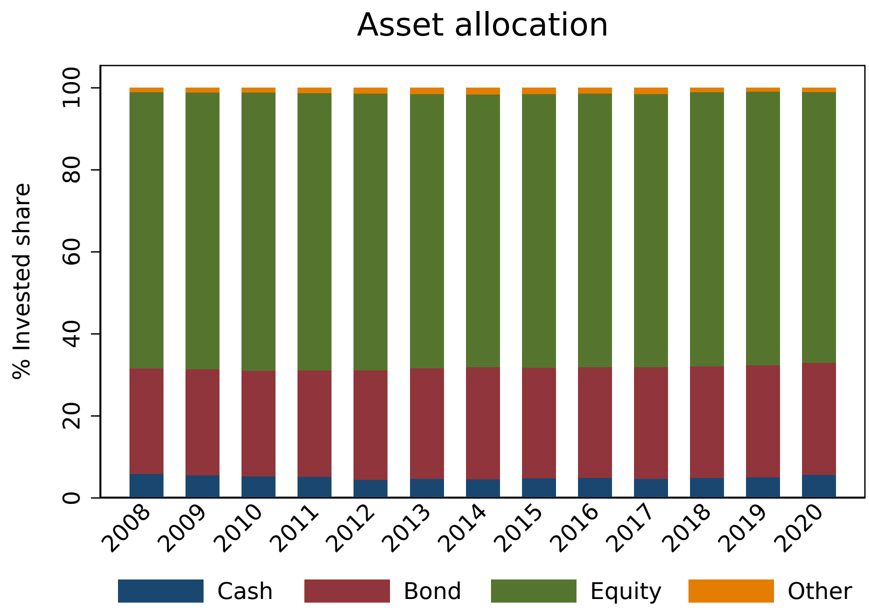


Figure 2.1. Asset allocation breakdown. Breakdown of asset allocation of mutual funds domiciled in the US.

equity, despite a decreasing trend in the last ten years. Given the prominent role of investment in U.S. Equity, the same pattern could be observed when considering advanced and emerging economies (Figure 2.2 We observe now the geographical allocation of bond - or fixed income instruments - in Figure 2.3, where the concentration in domestic - i.e. U.S. - is even higher than equity, which mimics the one of Advanced Economy. Despite this, we also observe a slightly declining trend here. The U.S. investment funds industry has experienced significant growth over the past decade. The Morningstar dataset provides information on daily net flows into U.S. mutual funds. For a given day t, these flows are

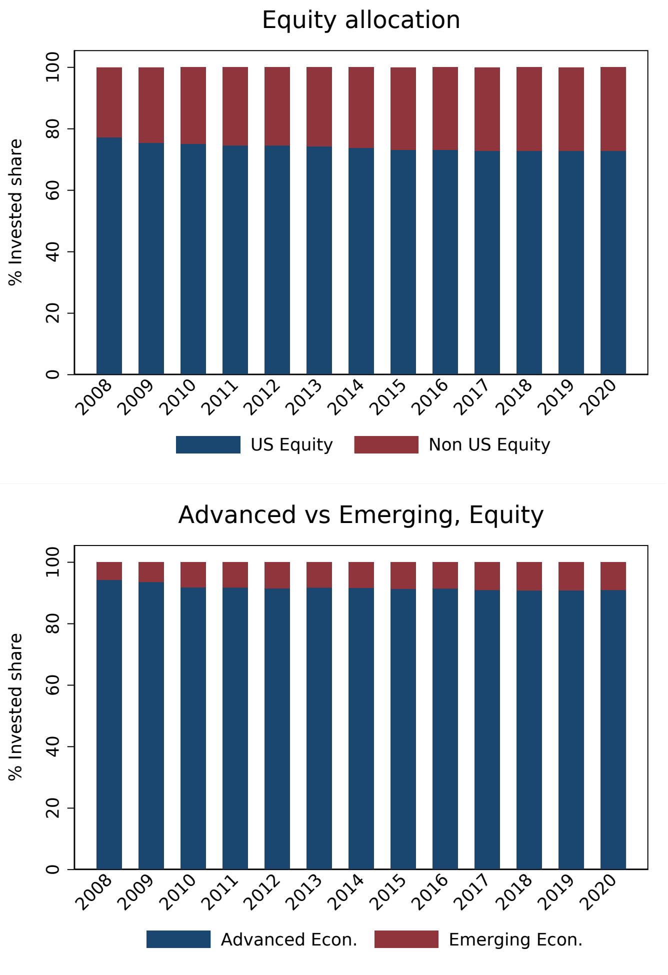


Figure 2.2. Geographical breakdown of equity funds. Geographical breakdown of investment funds domiciled in the U.S. in U.S. and non-U.S. Equity - upper panel - and in Advanced and Emerging Economy - lower panel - in the Morningstar category equity. For a more detailed breakdown see Figure B.3 in the Appendix B.2.

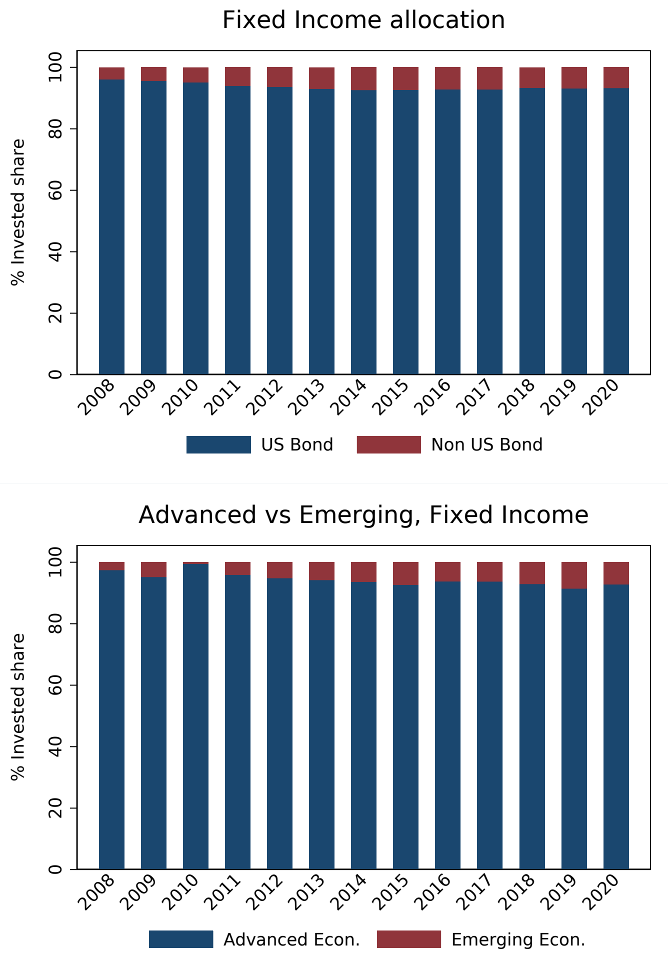


Figure 2.3. Geographical breakdown of equity funds. Geographical breakdown of investment funds domiciled in the U.S. in U.S. and non-U.S. Bond - upper panel - and in Advanced and Emerging Economy - lower panel - in the Morningstar category Fixed Income. For a more detailed breakdown see Figure B.4 in the Appendix B.2.

defined as:

$$F_{i,t} = TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t}) \tag{2.1}$$

In this equation, $F_{i,t}$ represents the flow to fund i, which can be either positive (inflows) or negative (outflows). $TNA_{i,t}$ is the total net asset value of the fund, and $R_{i,t}$ is the return of fund i over the observation period t. This definition of fund flows is widely accepted in the literature (Barber et al. 2016, Pástor and Vorsatz 2020, Kroencke et al. 2021, Ciminelli et al. 2022). It is based on the variation in TNA, which depends solely on the asset change under management, net of the fund's asset returns. Our dataset provides information on fund flows at a daily frequency, which is more granular than the data available from alternative sources used in similar studies.[2] This aspect is vital for conducting timely analysis and accurately identifying the specific asset classes that experience withdrawals or subscriptions following monetary policy announcements on a given day. Understanding the immediate market response to these announcements and the resulting financial behaviour is essential. As depicted in Figure 2.4, there is a clear upward trend in net flows in the industry (with exceptions during critical events like the Taper Tantrum in 2013 and the Covid-19 outbreak). Cumulatively, these net flows exceeded 400 billion U.S. dollars by mid-2020. The descriptive statistics in Table 2.1 provide additional details about net

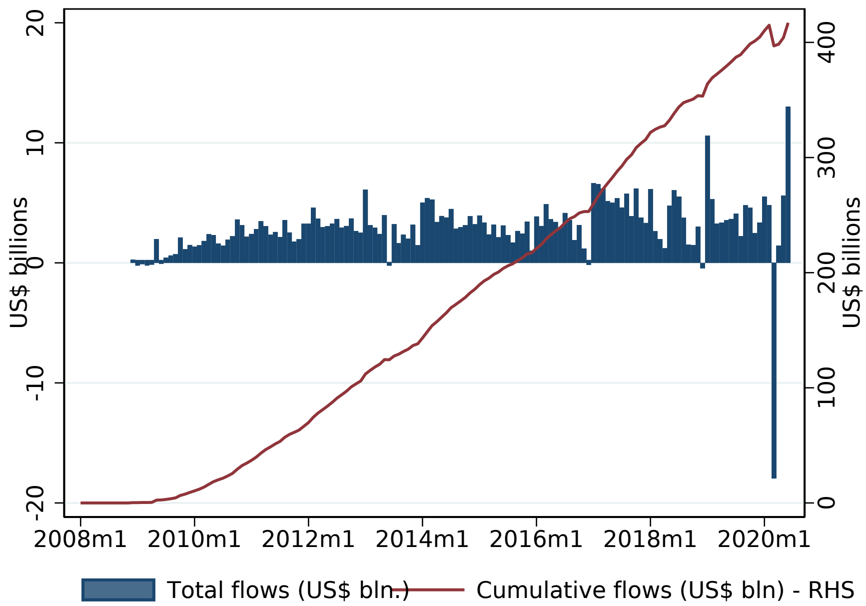


Figure 2.4. Monthly net flows and cumulative flows. Monthly net flows - blue bars - and cumulative flows - red line - of U.S. domiciled mutual funds investments.

flows and mutual fund characteristics in our dataset. The first observation is a high

[2]For instance, the EPFR data used in the studies by Ciminelli et al. (2022) and Giuzio et al. (2021) only offer weekly updates.

variation in net flows and assets under management (Size in Table 2.1). The fourth and fifth rows present descriptive statistics for dummy variables identifying exchange-traded funds (ETFs) and funds where investment is restricted to institutional investors. ETFs, which are mutual funds traded on a stock exchange with the primary goal of replicating the return of a stock index, bond index, or commodity index, represent 36% of the total funds. This trend is not surprising given the significant increase in their share over the past decade (IMF, 2019). Institutional funds, i.e. those with investment constraints such as minimum shares, represent 38% of the sample. Therefore, our sample predominantly consists of retail actively managed investment funds.
As shown in Figure 2.1, over 50% of fund shares are invested in equity (56.68% on average, of which 82.54% is in Advanced Economies, primarily the U.S., and the remainder in Emerging Markets). In contrast, 35.86% is invested in Bonds (of which 90% is in Advanced Economies, mainly the U.S.). The share of liquid assets (Cash 5.76% on average) is widely regarded as an indicator of a fund's resilience during periods of financial distress. Large cash buffers enable asset managers to mitigate the disruptive effects of forced sales, as fund liquidity can act as a countercyclical factor (Chernenko and Sunderam, 2020).

Lastly, we consider information about fund performance and portfolio managers. On average, actively managed funds do not outperform the market (average Alpha[3] value of -0.01). Based on risk-adjusted performance, the average Morningstar rating is 3 out of 5 and can be interpreted as the Sharpe ratio. Finally, portfolio managers' tendency to concentrate fund holdings on a limited number of assets is also evident: almost all the funds in the sample invest their entire portfolio in the top 10 holdings. This strategy can be justified for several reasons. Generally, fund managers prefer industrial sectors and geographical areas where they are more likely to have an informational advantage. To minimize potential measurement errors, we consider the main share class for each fund and exclude funds that are less than one year old and small funds (those with a size smaller than $10 million) from the sample. We also winsorize the sample at the first percentile on both tails.

2.2.2 Monetary Policy

Identifying monetary policy shocks through high-frequency interest rate changes around the FOMC announcements, also known as monetary policy surprises, has become common over the past two decades. The monetary policy surprises are particularly useful because they focus on interest rate changes in a narrow time window around FOMC announcements. This effectively eliminates issues of reverse causality and other endogeneity problems. The high-frequency study originated from the works of Kuttner (2001), Cochrane and Piazzesi

[3]Alpha describes an investment strategy's ability to beat the market, often considered as "excess return".

Table 2.1. Descriptive statistics

	Mean	St.Dev.	25p	50p	75p
Net flow (US$ mln)	0.55	15.00	-0.01	0.00	0.06
Size (US$ mln)	1490.39	8473.88	42.59	182.94	688.81
Institutional fund	0.38	0.48	0.00	0.00	1.00
ETF	0.36	0.48	0.00	0.00	1.00
% Equity	56.68	46.87	0.00	91.20	98.64
% Bond	35.86	45.08	0.00	0.00	92.28
% Cash	5.76	12.34	0.22	1.83	5.57
% Government	10.44	24.87	0.00	0.00	1.83
% Equity AEs	82.54	32.09	84.46	99.81	100.00
% Equity EMEs	17.38	32.01	0.00	0.19	15.38
% Bond AEs	90.61	24.73	98.34	100.00	100.00
% Bond EMEs	9.39	24.73	0.00	0.00	1.66
Alpha	-0.01	0.40	-0.09	-0.01	0.09
Morningstar rating	3.14	1.17	2.00	3.00	4.00
Concentration 10	98.93	10.30	100.00	100.00	100.00

(2002), and Faust et al. (2004). However, the seminal work in this area is by Gürkaynak et al. (2004), who used principal components analysis and factor loading rotation on high-frequency variations of Federal Funds Rate (FFR) futures around the FOMC to identify conventional and unconventional monetary policy shocks. This methodology has been adopted in subsequent studies such as Altavilla et al. (2019a), Inoue and Rossi (2021), and Kroencke et al. (2021). Another line of research uses structural vector autoregression (SVAR) for high-frequency identification, as seen in the works of Gertler and Karadi (2015), Caldara and Herbst (2019b), and Jarociński and Karadi (2020).

In this context, Jarociński and Karadi (2020) (also see Miranda-Agrippino and Ricco 2021, Bu et al. 2021) expanded the identification of monetary policy shocks by distinguishing between pure monetary policy shocks and information shocks. This separation allows for the resolution of specific puzzling issues. In essence, a tightening monetary policy conveys a pure monetary shock when the rise in interest rates is associated with a decrease in stock prices. Conversely, an information shock occurs when an unexpected tightening of monetary policy reveals the central bank's private information about the economy's future (and positively co-moves with stock prices). Building on this, Kroencke et al. (2021) combined the methodology of Gürkaynak et al. (2004) and extended the idea of Jarociński and Karadi (2020) by identifying a third component: the risk-shift. According to Kroencke et al. (2021), a risk-shift shock occurs when a rise in interest rates is associated with a reduction in the VIX, CDS premiums, and the dollar index, which are all proxies for risk. Figure 2.5 helps clarify the extension made by Kroencke et al. (2021), where the risk-shift component essentially extends the information channel. The methodology employed by

	news captured by risk-free rates	news captured by risky asset prices but not captured by risk-free rates
news about current and future short-term rates	**"risk-free rate surprises"** direct effect of risk-free rates	-
news about economic growth and risk premia	**"risk-free rate surprises"** information channel	**"risk shifts"** extended information channel

Figure 2.5. Taxonomy of monetary policy news. Taxonomy identified by Kroencke et al. (2021) about the information carried by monetary policy announcements.

Kroencke et al. (2021), which builds upon the work of Gürkaynak et al. (2004), involves two steps. Initially, they extract the first three principal components based on high-frequency changes in treasury futures, volatility, CDS index, and a portfolio of foreign exchange futures in a window of 90 minutes around the FOMC. Subsequently, they apply a standard orthogonal factor rotation to derive the monetary policy surprises. In essence, these three monetary policy surprises can be described as follows:

1. **Short-Rate Surprises**: This factor is primarily associated with the short-term segment of the yield curve and has a mild exposure to market-based risk proxies. As such, this surprise measure predominantly captures changes in the central bank's policy target and its stance;
2. **Long-Rate Surprises**: The second factor has a significant load on 5- and 10-year yields, capturing news about asset purchases that impact the yields on long-term bonds through signalling and portfolio rebalancing channels. While it has virtually no exposure to short-term yields, it does have some exposure to risk proxies. However, these exposures are small in magnitude and have opposing signs (negative for VIX but positive for the U.S. dollar), indicating no clear connection to risky asset prices.
3. **Risk-Shifts**: The third factor consistently loads negatively on all three market-based risk proxies but does not have a substantial load on yields. An increase in this surprise measure coincides with a drop in the VIX, a weakening of the Dollar Index, and a compression in CDS premiums.

Figure 2.6 depicts the realization of the three surprises. Based on the FOMC calendar, Kroencke et al. (2021) note that large risk-shift surprises occur on days with important monetary news, like the introduction of the Quantitative Easing 2 and 3 (positive shift) or the announcement of a "taper tantrum" in mid-2013 (negative shift).

2.2.3 Other Variables

We expand our dataset with additional variables that act as controls in our baseline model. These variables include the S&P500 Price Index, the CBOE Volatility Index (VIX), and the Dollar Index (DXY). These data are collected daily from the Federal Reserve Bank of St. Louis' FRED database.

2.3 Methodology

To capture the dynamics of fund flow responses to the monetary surprises outlined in Section 2.2.2, we employ local projections (Jordà, 2005) and consider a 12-business day horizon. We construct the dependent variable as the ratio of cumulative flows to the primary share class in fund i over the horizon $t+h$ to the assets under management of fund i at time t, expressed in USD millions. Subsequently, we interact the monetary surprises with a dummy variable that we create to identify the asset class. To create this dummy, we consider the distribution of investment in a specific asset class (e.g., U.S. Equity) and

Figure 2.6. Monetary policy surprise. Monetary policy surprises identified by Kroencke et al. (2021) standardise to a unit of standard deviation.

assign a value of 1 for all the funds above the 50th and 75th percentiles.[4] This approach allows us to measure the overall effect of the monetary surprise on funds' allocation to a given asset class. Therefore, the model we estimate for $h = 0, ..., 12$ is as follows:

$$\frac{\sum_{h=0}^{H} F_{i,t+h}}{A_{i,t}} = \beta^h MP^1 j, t + \Gamma^h \boldsymbol{X} t - 1 + \gamma^h MP^0 j, t + \varepsilon i, t \tag{2.2}$$

Here, the subscripts i and t denote the fund and time, respectively, while the superscript h represents the horizon considered. $F_{i,t}$ is the fund flows as defined in Equation 2.2.1, expressed in USD millions; $A_{i,t}$ is the volume of assets under management by fund i at time t, also in USD millions. $MP^1 j, t = MP_j \times assetclass_i$, where MP_j is one of the monetary surprise (Short-Run, Long-Run and Risk-Shift) interacted with the dummy denoting the asset class(i.e. U.S. equity, U.S. bond etc.), and $MP^0 j, t = MP_j \times (1 - assetclass_i)$ is one the monetary surprise interacted with one minus the dummy. This term serves as a control to isolate the overall effect of the monetary shock on the fund flows. The monetary surprises have a value on the FOMC days and 0 elsewhere. $\boldsymbol{X}_{t-1}$ is a set of controls with one lag that includes the log of VIX, DXY, and S&P500 Index and the lagged measure of assets under management in USD millions.[5] β^h is the coefficient of interest and captures the mean cumulative response over the $t + h$ horizon of fund flows to a one-point increase in standard deviation in the monetary surprise.

We estimate the panel linear projections with Driscoll and Kraay (1998) robust standard errors and fixed effects. We leave the maximum lag order of autocorrelation set by default equal to $m(T) = floor[4(T/100)^{(2/9)}]$ given the large number of $T = 2750$. To present the results, we plot the impulse response functions (IRF) constructed using the point estimates for $\hat{\beta}^h$ at 68% and 90% confidence levels.

2.4 Results

In this Section, we present the IRFs of fund flows in response to short-run surprises (pure monetary shocks), long-run surprises (information shocks), and risk-shift surprises.

[4] For a comprehensive list of all the created asset classes, see Appendix B.4.

[5] We further tested the Excess Bond Premium (EBP), as estimated in the seminal work by Gilchrist and Zakrajšek (2012), as a control variable. The EBP is considered a proxy for investors' risk-bearing capacity, potentially relevant to this study. However, the impulse response functions controlling for risk-bearing capacity do not change, except for slightly smaller confidence bands. This outcome is not surprising, given that the Risk-Shift surprise loads on market-based risk proxies provide comprehensive risk information. For example, the VIX signals market-perceived uncertainty, and a rise in the VIX correlates with reduced asset prices. The Dollar Index measures the dollar's value against a basket of other currencies. It indicates the dollar's value in global markets, where it is commonly recognized as a safe asset. Finally, CDS transfers the credit exposure of fixed-income products, with the premium representing the fair reward for bearing the risk. Thus, it is not unexpected that using the EBP does not add further helpful information.

2.4.1 The effects of Short-Run Surprise

We begin by examining the impact of short-run surprises. When calculating the IRF, we focus on a representative one-standard-deviation monetary policy surprise on FOMC days (refer to Figure 2.6 in Kroencke et al. 2021). Figure 2.7 presents the results for various asset classes: we plot the responses for all U.S. domiciled mutual funds above the 75th percentile[6] in the distribution of investments in equity, U.S. equity, non-U.S. equity, bond, U.S. bond, and non-U.S. bond.

A tightening monetary shock implicitly carries a recession risk, making investors willing to hold safe assets. This has a negative and persistent effect on flows to all asset classes. Equity funds experience a more significant immediate impact than bonds, but the outflow for both types of funds is 0.05% after 12 business days from the announcement. We find the same pattern as the primary category when we specifically focus on U.S. equity and U.S. bonds. The fact that U.S.-based responses drive the main category is unsurprising given the geographical allocation shown in Figure 2.2 and Figure 2.3. The dynamic of the outflows is even more pronounced in non-U.S. equity and non-U.S. bond funds, where outflows reach -0.1%. Non-U.S. funds are riskier than domestic ones due to the presence of Emerging Market Economies (EME) countries (see Figure B.3 and B.4), thus in a risk-averse environment, they experience more substantial outflows.

2.4.2 The effects of Long-Run Surprise

We now focus on the effects of long-run surprises, which can be considered information shocks. Figure 2.8 illustrates that the impacts of long-run surprises on fund flows vary from those of short-run surprises and depend on the type of asset class.

Looking at equity funds, the overall effect on the main category is slightly negative at the outset (-0.02% the day after the announcement), but it becomes neutral and statistically insignificant after one week. However, we observe different behaviours when considering the breakdown into U.S. and non-U.S. equity. For U.S. equity, we see positive inflows one week after the announcement, reaching an overall +0.05% in positive inflows. Conversely, following a tightening long-run surprise, we observe significant outflows from non-U.S. equity of about -0.07% after 12 business days. Given the information conveyed by the long-run surprise in a Delphic interpretation of the announcement, an optimistic economic growth forecast makes investors more willing to invest in the domestic market.

The story is different for bond funds. A positive long-run surprise prompts investors to redeem shares from bond funds, both overall and from U.S. and non-U.S. bonds (0.1% of redemption after 12 business days on average). Indeed, a shock to the long-term segment

[6] The standard representation is above the 50th percentile; however, we decided to narrow the distribution.

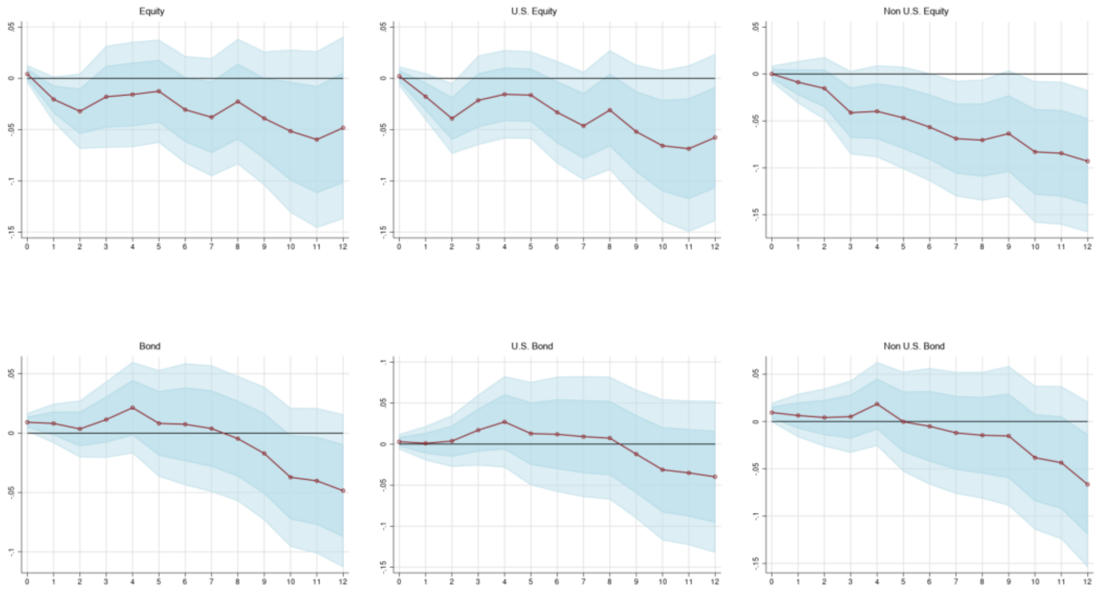


Figure 2.7. Impact of Short-Run surprise on U.S. domicile mutual fund flows across a range of asset class. The figure shows the impact of Short-Run surprise on fund flows identified by Kroencke et al. (2021) obtained from linear projections. From the top-left corner, the responses refer to equity asset class, U.S. equity and non-U.S. equity. From the bottom-left corner, the responses refer to bond asset class, U.S. bond and non-U.S. bond. Confidence bands at 68% and 90%.

of the yield curve can significantly impact investor expectations regarding potential future capital losses. When long-term interest rates are affected, it mainly influences bonds with a higher duration. By nature, such bonds are more susceptible to interest rate fluctuations, making their prices highly sensitive to these changes. Therefore, as anticipated under these conditions, a notable decrease in bond prices can lead to substantial capital losses for investors. Therefore, tightening monetary policy leads to decreased bond prices, prompting investors to redeem shares to mitigate capital account losses. Consequently, we observe evidence of portfolio rebalancing following short- and long-run surprises. These findings are broadly consistent, in both a qualitative and quantitative sense, with existing literature, such as the studies conducted (Giuzio et al. 2021 and Ciminelli et al. 2022, among others).

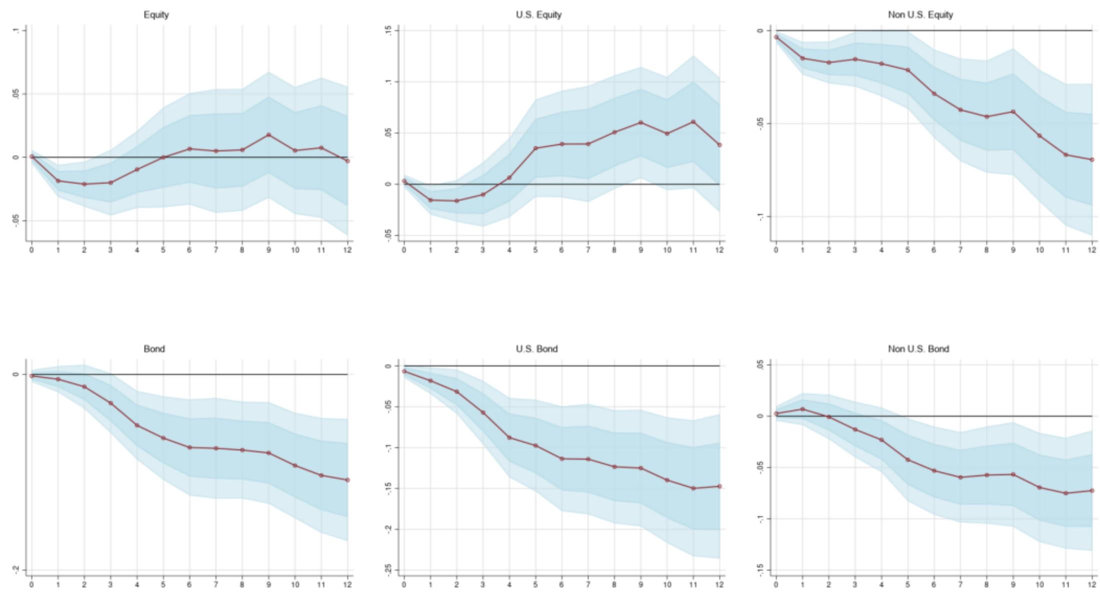


Figure 2.8. Impact of Long-Run surprise on U.S. domicile mutual fund flows across a range of asset class. The figure shows the impact of Long-Run surprise on fund flows identified by Kroencke et al. (2021) obtained from linear projections. From the top-left corner, the responses refer to equity asset class, U.S. equity and non-U.S. equity. From the bottom-left corner, the responses refer to bond asset class, U.S. bond and non-U.S. bond. Confidence bands at 68% and 90%.

2.4.3 The effects of Risk-Shift Surprise

Finally, we discuss the effects of the risk-shift surprise. As shown in Figure 2.9, the risk-shift surprise significantly and positively affects fund flows across all asset classes.

This finding is consistent with the idea that a positive risk-shift surprise, associated with a decrease in market-based risk, stimulates investors' risk appetite and inflows into riskier assets.

For equity funds, we observe a significant and positive effect on fund flows, with inflows peaking at around 0.1% after 12 business days. This effect is even more pronounced for U.S. equity funds, which see inflows of around 0.15% after the same period. Non-U.S. equity funds also experience positive inflows but to a lesser extent.

Turning to bond funds, we see a similar pattern. Overall, bond funds experience positive inflows following a risk-shift surprise, peaking at around 0.05% after 12 business days. This effect is driven primarily by non-U.S. bond funds, which see inflows of around 0.15% after the same period. U.S. bond funds also experience positive inflows, but these are smaller in magnitude, consistent with the idea that non-U.S. bonds are riskier than domestic bonds. These results suggest that risk-shift surprises can stimulate the risk-taking channel of monetary policy transmission. Following a positive risk-shift surprise, investors appear to reallocate their portfolios towards riskier assets, leading to inflows into both equity and bond funds.

2.4.4 Further Evidence

In this Section, we expand the discussion by providing additional evidence of both portfolio rebalancing and risk-taking channels in the mutual fund industry following monetary policy surprises.

Cash If fund investors react to monetary policy shocks, what role do fund managers play? While managers cannot influence the fund size, they are responsible for portfolio allocation decisions. Decisions regarding liquid asset holdings can be significant regarding the accumulation of liquidity risk in the industry. As a measure of liquidity, we consider the share of total assets held as Cash. Figure 2.10 illustrates the effect of the three surprises on mutual funds that fall either below or above the median of shares invested in Cash. Collectively, managers of mutual funds with a high concentration in Cash decide to decrease the cash buffer following a tightening monetary shock that impacts short-term interest rates. Regarding the long-term, we find evidence that funds with longer-duration bonds experience outflows. The magnitude of outflows in funds with a higher concentration of Cash is less than those less concentrated (approximately -0.02% after 12 business days compared to -0.05% respectively). Moreover, we observe a swift positive inflow in funds that invest less in Cash than those more concentrated in Cash following a positive risk shift. Managers, therefore, tend to allocate the portfolio towards less liquid funds if there is an increase in risk appetite. However, the accumulation of positions in funds with low cash buffers may heighten the risk of liquidity mismatch between assets and liabilities,

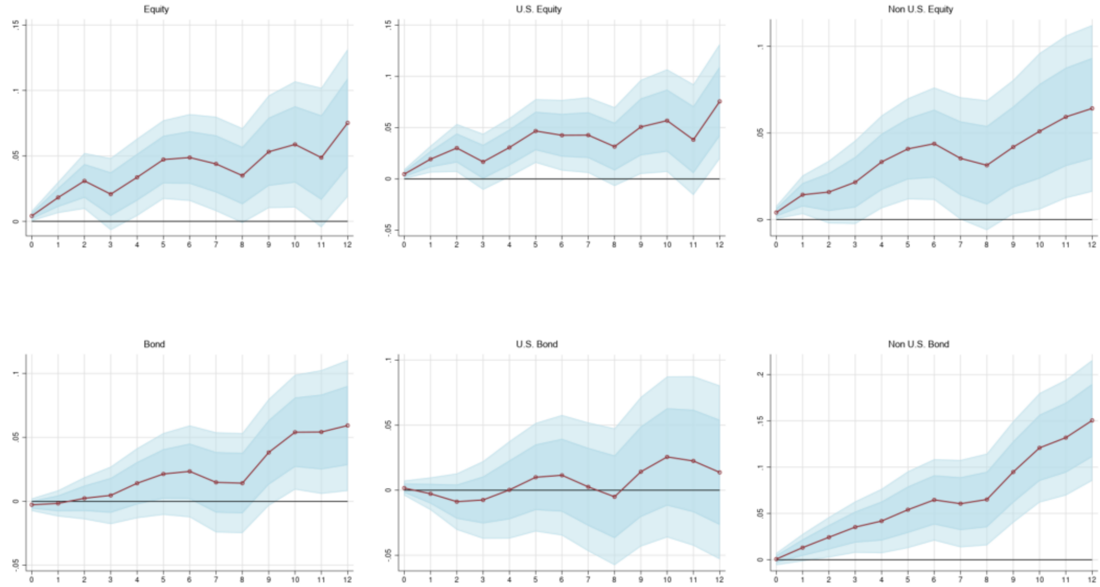


Figure 2.9. Impact of Risk-Shift surprise on U.S. domicile mutual fund flows across a range of asset class. The figure shows the impact of Risk-Shift surprise on fund flows identified by Kroencke et al. (2021) obtained from linear projections. From the top-left corner, the responses refer to equity asset class, U.S. equity and non-U.S. equity. From the bottom-left corner, the responses refer to bond asset class, U.S. bond and non-U.S. bond. Confidence bands at 68% and 90%.

thereby increasing the risk of procyclical selling during market downturns (Giuzio et al., 2021).

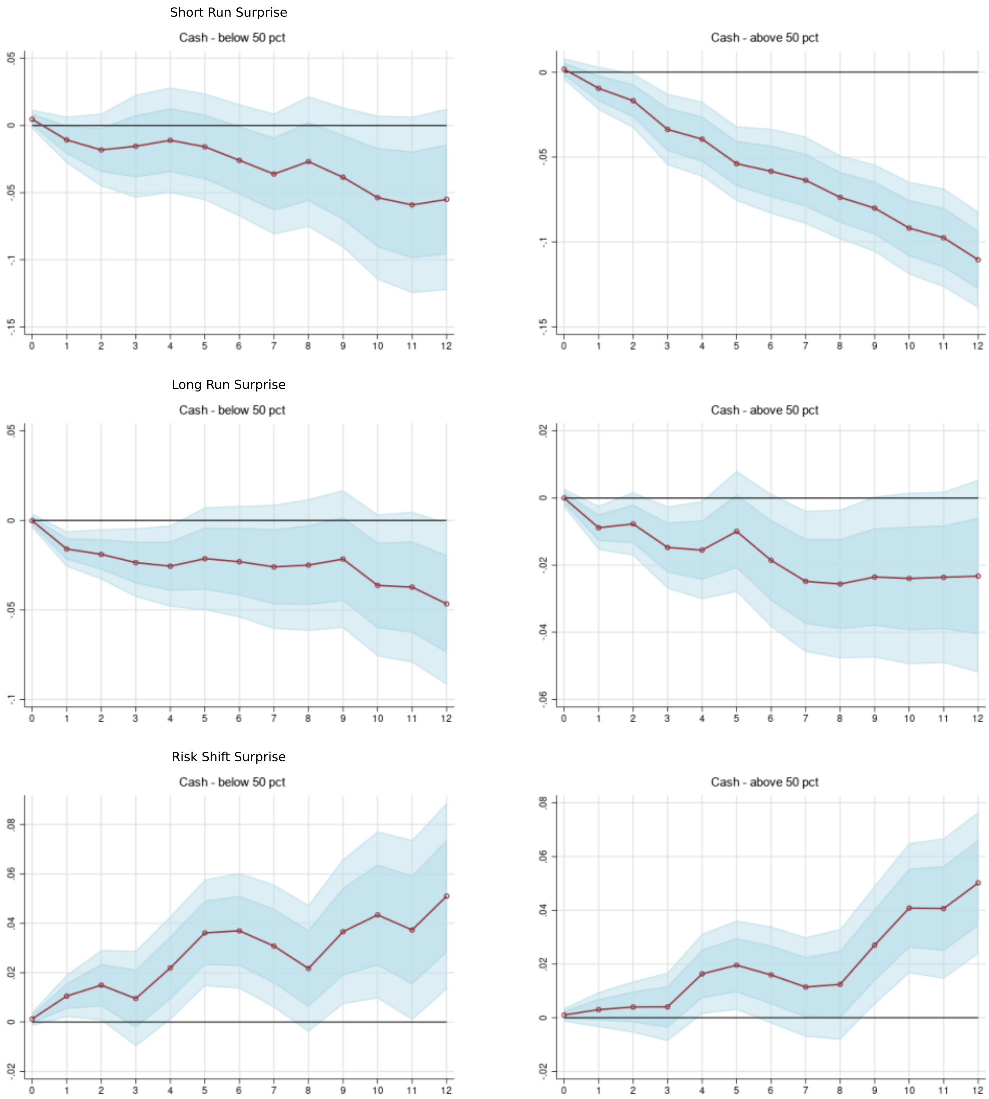


Figure 2.10. Impact of Surprise on U.S. domicile mutual fund flows towards liquid positions. The figure shows the impact of monetary surprise on fund flows identified by Kroencke et al. (2021) obtained from linear projections. In the first column, funds are below the median for shares invested in Cash. In the second column, funds are above the median for shares invested in Cash. Confidence bands at 68% and 90%.

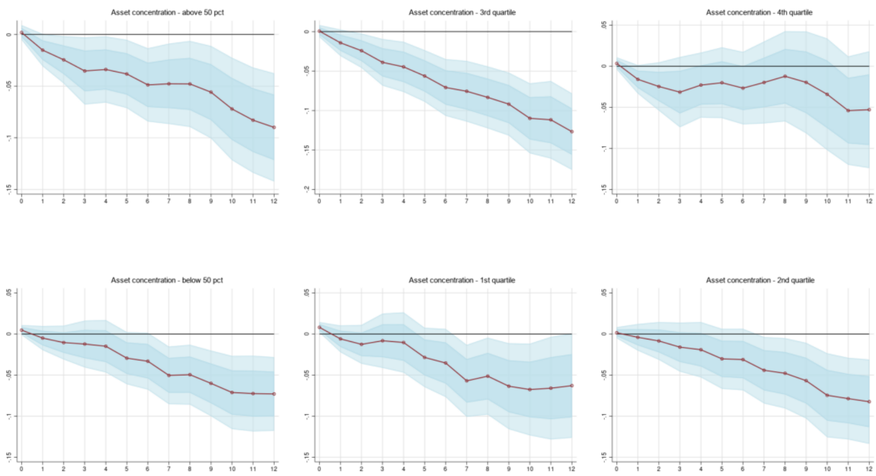
Asset Concentration We now focus on asset concentration. To define asset concentration, we consider the amount invested in the top 10 positions of the fund. We then divide the sample based on the distribution, distinguishing funds with asset concentration above and below the median and defining the quartile range. Figure 2.11 presents the effect of the short-run (upper panel) and long-run (lower panel) surprises. We observe that funds with less asset concentration are less responsive to outflows than those with more concentration. Specifically, we observe outflows ranging between -0.07% and -0.05% for funds below the median after a 12 business day horizon, while the outflows for more concentrated funds range between -0.1% and -0.07% after 12 business days. This dynamic becomes even clearer when observing the quartile distribution; the lower the quartile, the lower the sensitivity to the risk-shift surprise. We can infer that more concentrated funds experience stronger outflows due to their inherent riskiness, as we have observed for equity funds. The opposite holds for a positive surprise in risk appetite (Figure 2.12). Funds with less asset concentration attract more flows immediately after a positive shift in risk attitude, with a certain degree of persistence (+0.08% compared to a less significant +0.03% after 12 business days). This dynamic is even more pronounced when observing the quartile distribution; the lower the quartile, the higher the sensitivity to the risk-shift surprise. Due to their good diversification and return generation capabilities, we can argue that less concentrated funds may attract more investments.

Return and rating We wrap up our analysis of fund characteristics by focusing on fund performance. We consider funds that have generated positive returns in the last quarter and the last month. We also consider funds with a positive alpha, a measure of a fund's ability to outperform the market, as provided directly by Morningstar. Figure 2.13 presents the results. The effects of the short-run and long-run surprises essentially mirror those for equity funds. Pertinent to our analysis, it is noteworthy that funds capable of generating positive past returns attract significant and persistent positive inflows. Past performance of funds generally drives new investments (Sirri and Tufano 1998, Goldstein et al. 2017 and Ciminelli et al. 2022 among others), and the intense dynamic exhibited after a risk-shift shock amplifies the risk-taking channel. By definition, the risk-taking channel moves toward taking on more risk to achieve higher returns. To further substantiate this conclusion, we examine the responses of three Morningstar ratings (or stars) categories. Morningstar provides a valuation of the funds in terms of risk-adjusted return, which can be considered a Sharpe ratio. The better the risk-adjusted return, the higher the star rating. Looking at Figure 2.14, we again see the same dynamic as the equity funds for the short-run and long-run surprises. It is important to highlight that following a risk-shift surprise, the higher the Morningstar rating, the stronger the inflows (+0.28% after 12 business days from the announcement).

2.5 Alternative Specifications

Measurement Our findings could be influenced by how we define the asset class. In the baseline specification, we consider investments in equity and bonds above the 75th

Short-Run Surprise



Long-Run Surprise

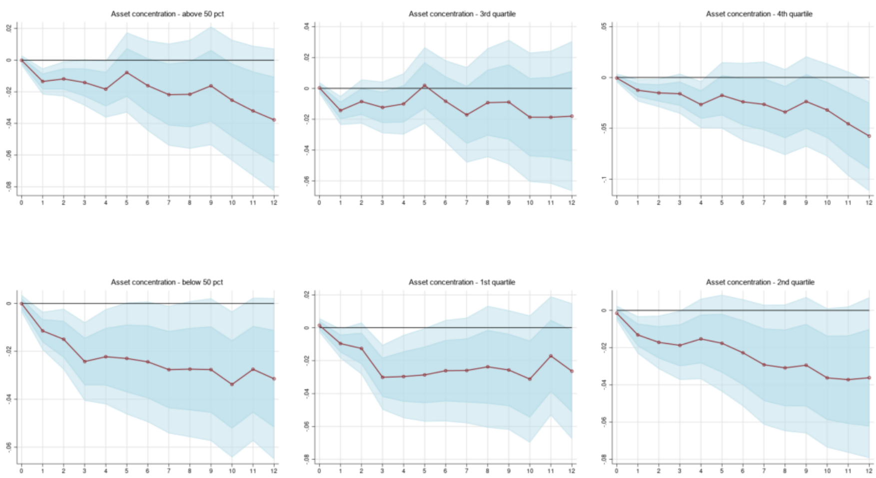


Figure 2.11. Impact of Short-Run and Long-Run surprise on U.S. domicile mutual fund flows across a range of asset class. The figure shows the impact of Short-Run (upper panel) and Long-Run (lower panel) surprise on fund flows identified by Kroencke et al. (2021) obtained from linear projections. From the top-left corner, the responses refer to funds with asset concentration above the median, the 3^{rd} quartile and the 4^{th} quartile. From the bottom-left corner, the responses refer to funds with asset concentration below the median, above the 1^{st} quartile and the 2^{nd} quartile. Confidence bands at 68% and 90%.

Risk-Shift Surprise

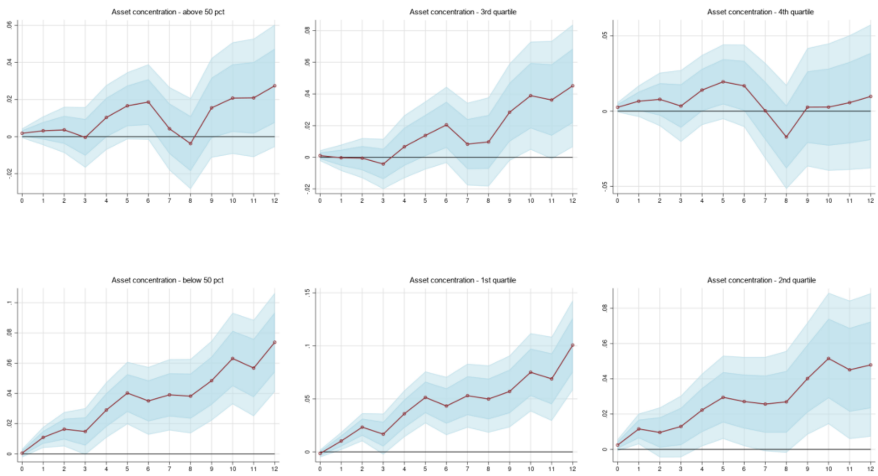


Figure 2.12. Impact of Risk-Shift surprise on U.S. domicile mutual fund flows across a range of asset class. The figure shows the impact of Risk-Shift surprise on fund flows identified by Kroencke et al. (2021) obtained from linear projections. From the top-left corner, the responses refer to funds with asset concentration above the median, the 3^{rd} quartile and the 4^{th} quartile. From the bottom-left corner, the responses refer to funds with asset concentration below the median, above the 1^{st} quartile and the 2^{nd} quartile. Confidence bands at 68% and 90%.

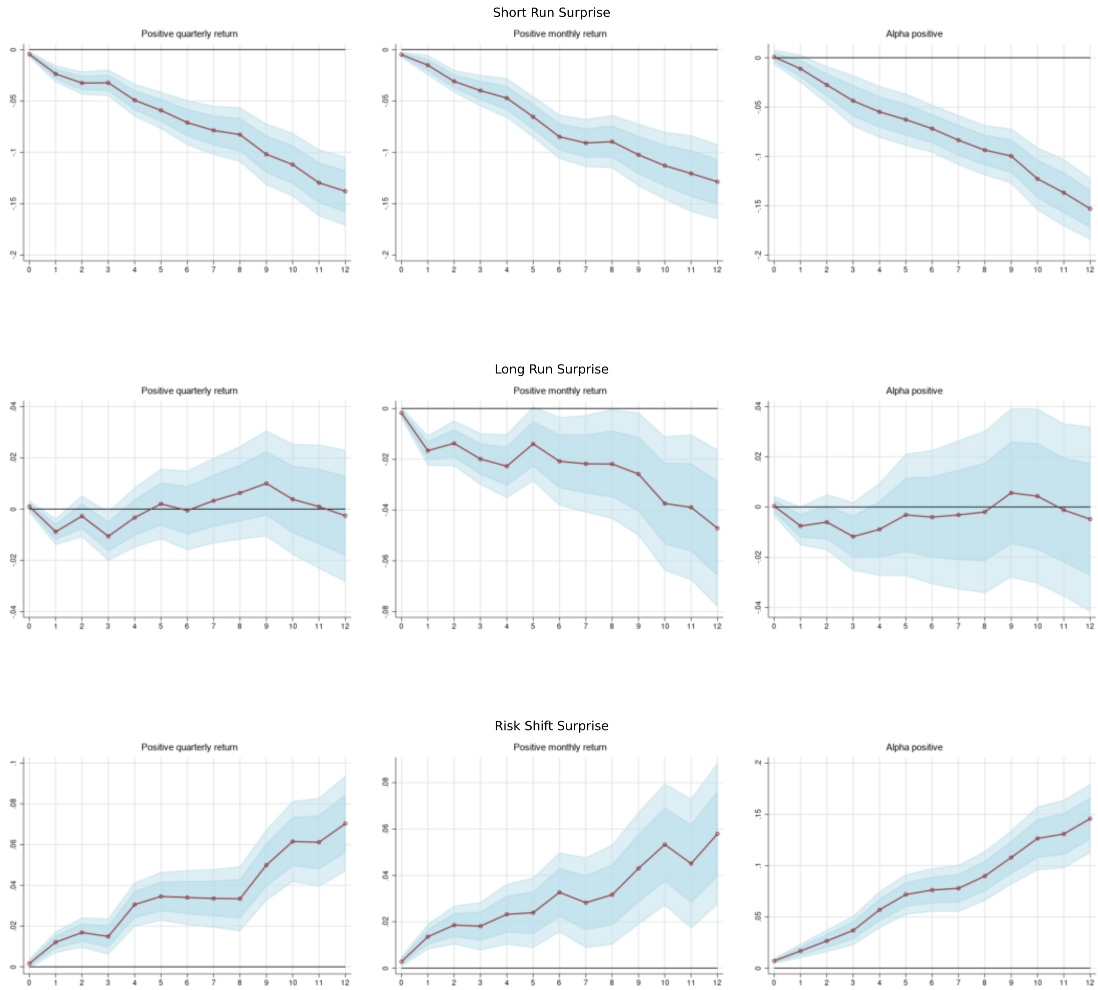


Figure 2.13. Impact of Surprise on U.S. domicile mutual fund flows towards performing funds. The figure shows the impact of monetary surprise on fund flows identified by Kroencke et al. (2021) obtained from linear projections. From the top left of each row: funds that generated positive returns over the last quarter, funds that generated positive returns over the last month, and funds that overperformed the market. Confidence bands at 68% and 90%.

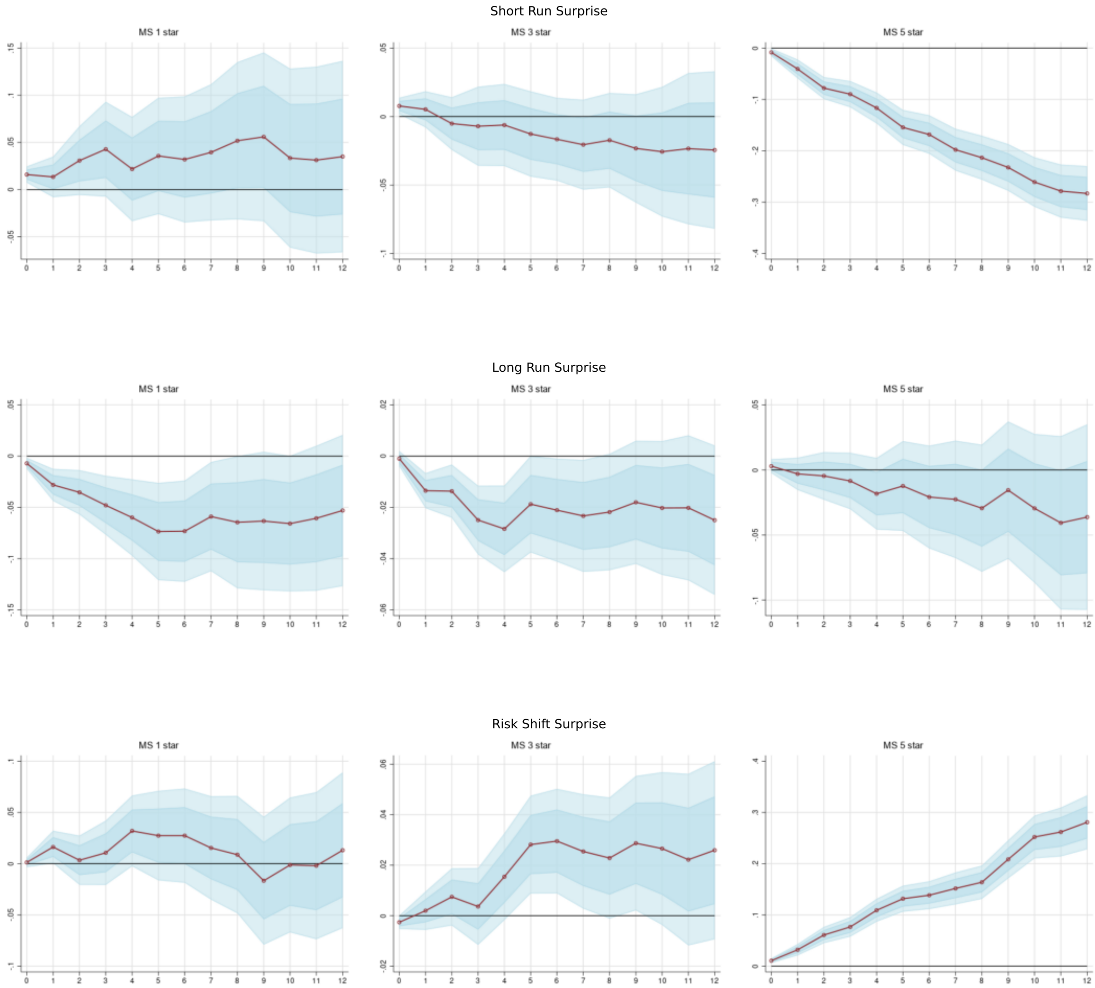


Figure 2.14. Impact of Surprise on U.S. domicile mutual fund flows towards performing funds. The figure shows the impact of monetary surprise on fund flows identified by Kroencke et al. (2021) obtained from linear projections. From the top-left of each row: funds rated 1 star, funds rated 3 star, funds rated 5 star. Confidence bands at 68% and 90%.

percentile. In this alternative specification, we lower the threshold to the median. The top line of Figure 2.15 shows that the responses of fund flows to the short-run surprise are consistent with the baseline specification regarding sign and magnitude. The middle line reports the IRF following a long-run surprise, and the consistency with the baseline specification is maintained. The bottom line also confirms that following a positive risk shift, investors are more inclined to reallocate towards riskier positions primarily driven by the U.S. market. The results also hold when considering the Morningstar category design.

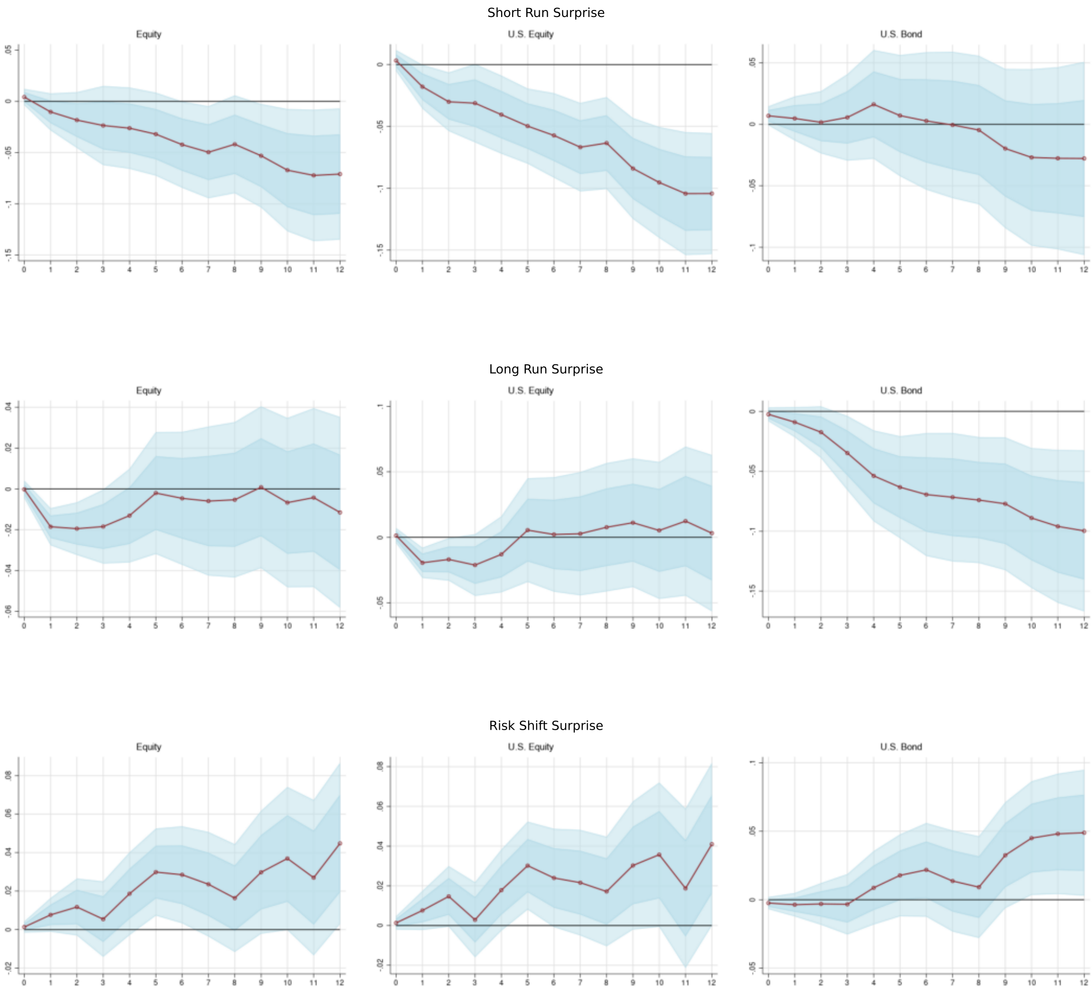


Figure 2.15. Impact of Surprise on U.S. domicile mutual fund flows towards performing funds. The figure shows the impact of monetary surprise on fund flows identified by Kroencke et al. (2021) obtained from linear projections. From the top left of each row are U.S. equity and U.S. bonds, as defined by the Morningstar category. Confidence bands at 68% and 90%.

As a data provider, Morningstar classifies each fund within a specific category based on its investment strategy. Therefore, we also utilize Morningstar's U.S. equity and U.S. bond funds classification to corroborate further our baseline results (see Figure 2.16).

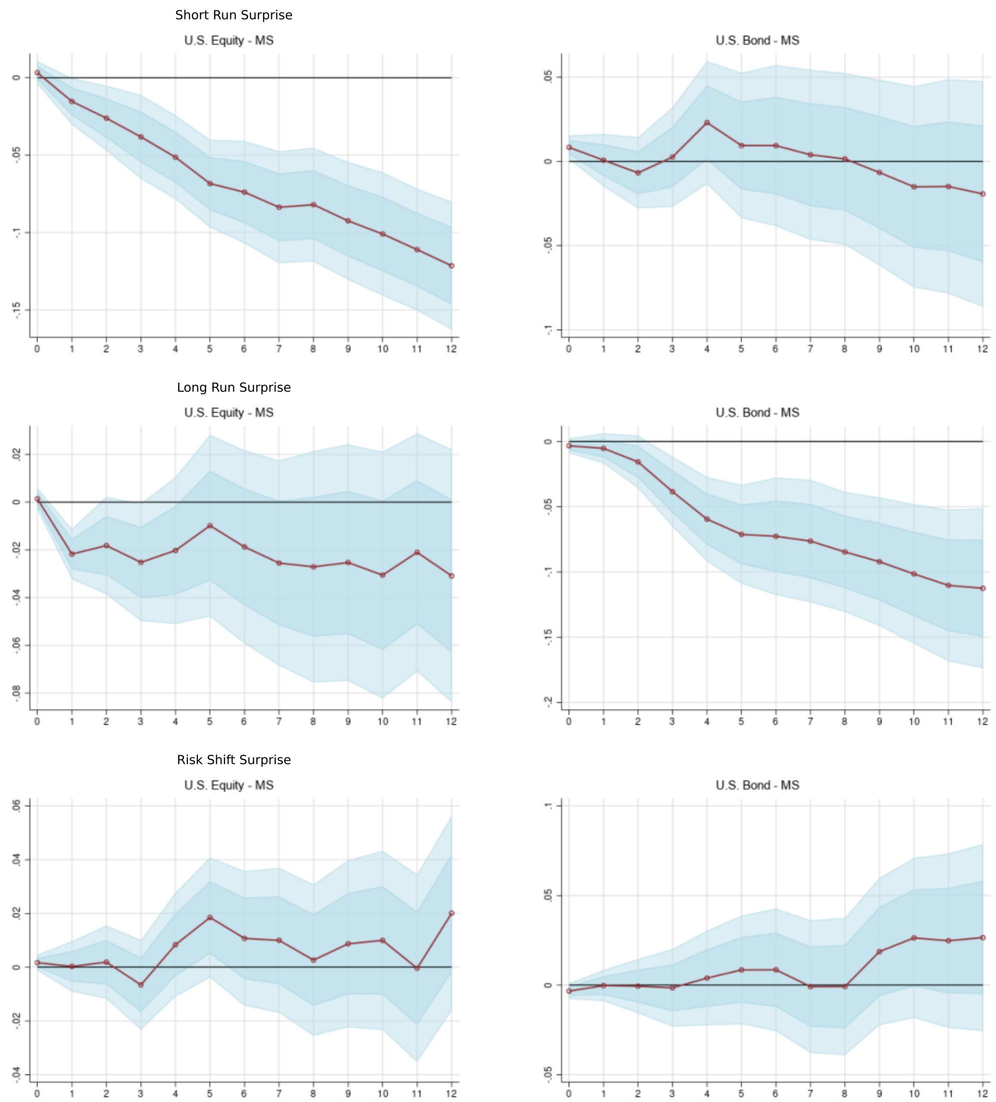
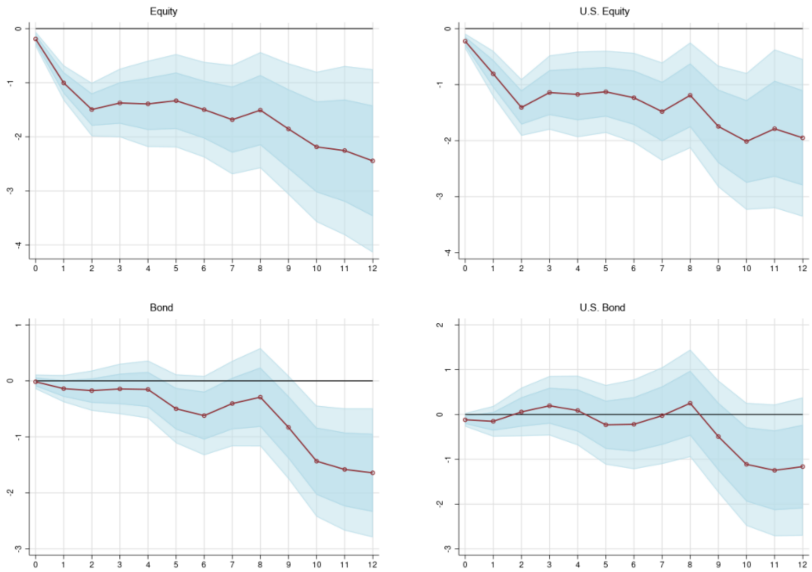


Figure 2.16. Impact of Surprise on U.S. domicile mutual fund flows towards performing funds. The figure shows the impact of monetary surprise on fund flows identified by Kroencke et al. (2021) obtained from linear projections. From the top-left of each row: equity, U.S. equity and U.S. bond. Confidence bands at 68% and 90%.

Identification Another important consideration is the extent to which our results depend on the specific identification of monetary surprises proposed by Kroencke et al. (2021). To address this, we replicate the analysis using the monetary shock series estimated by Jarociński and Karadi (2020). In Figure 2.5, Kroencke et al. (2021) shows that the risk-shift surprise is an extension of the information shock, and thus the short-run and long-run shocks can be seen as a pure monetary policy shock and a central bank information shock, respectively. In this regard, we assume that if the results for the short-run (pure monetary shock) and long-run shocks (central bank information shock) hold, so too will the risk shift. The results are shown in Figure 2.17, which adopts the same layout of previous specifications (see Figure 2.16 for example).

The tests confirm that a shock to the short-end part of the yield curve induces outflows from equity and bond funds driven by domestic markets. The effects of the information shock are more straightforward for the bond market. As we discussed earlier, the effect of the shock on the long-term part of the yield curve influences securities with high duration, which are thus more sensitive to price reductions and capital losses, prompting investors to redeem their shares. The effect on equity is more complex in our interpretation. Given that the information shock, as defined by Jarociński and Karadi (2020), positively co-moves with stock prices, flows follow prices (Kroencke et al., 2021). In terms of the effect on stock prices, given the positive information about the economy's future, investors are more willing to bear risk in search of returns. As a final step, we also check for different threshold values in the definition of the asset class (above the median instead of the 75th percentile) in panel (a) of Figure 2.18 and in panel (b) for the main indicators of fund management and performance we have seen in Section 2.4.4. The results are consistent with those in the baseline estimations.

Monetary Policy Shock



Information Shock

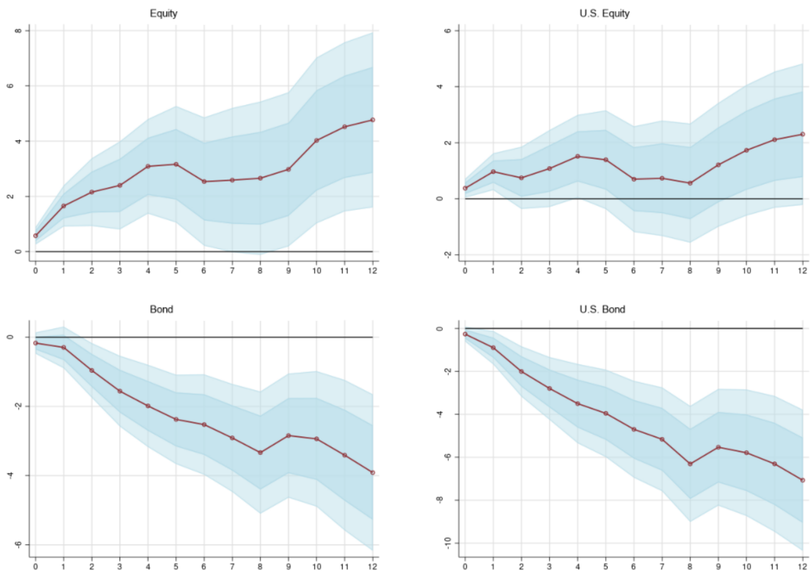
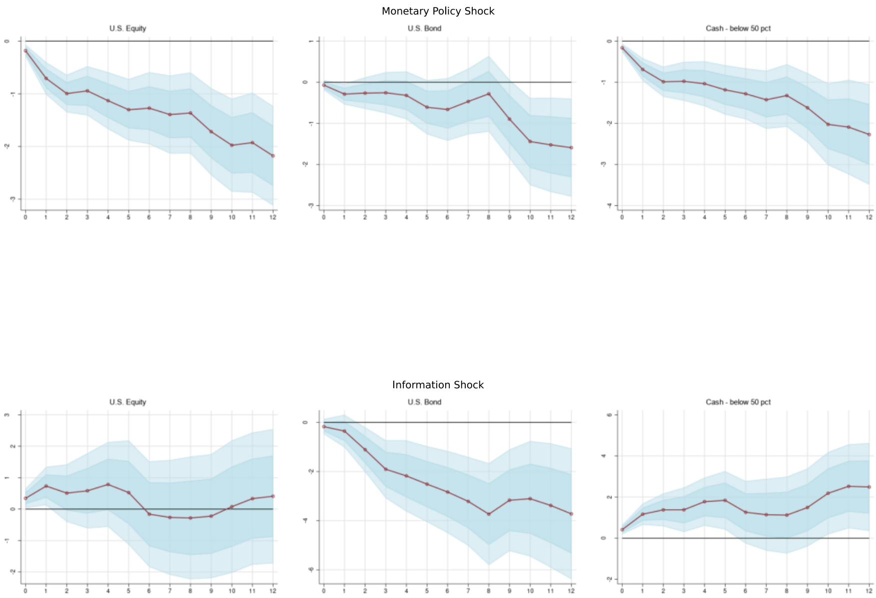


Figure 2.17. Impact of monetary shocks on U.S. domestic mutual fund flows towards different asset classes. The figure shows the impact of pure monetary surprise (upper panel), and information shock (bottom panel) on fund flows identified by Jarociński and Karadi (2020) obtained from linear projections. From the top-left of each row: equity, U.S. equity, bond and U.S. bond. Confidence bands at 68% and 90%.

(a) Median threshold



(b) Performance

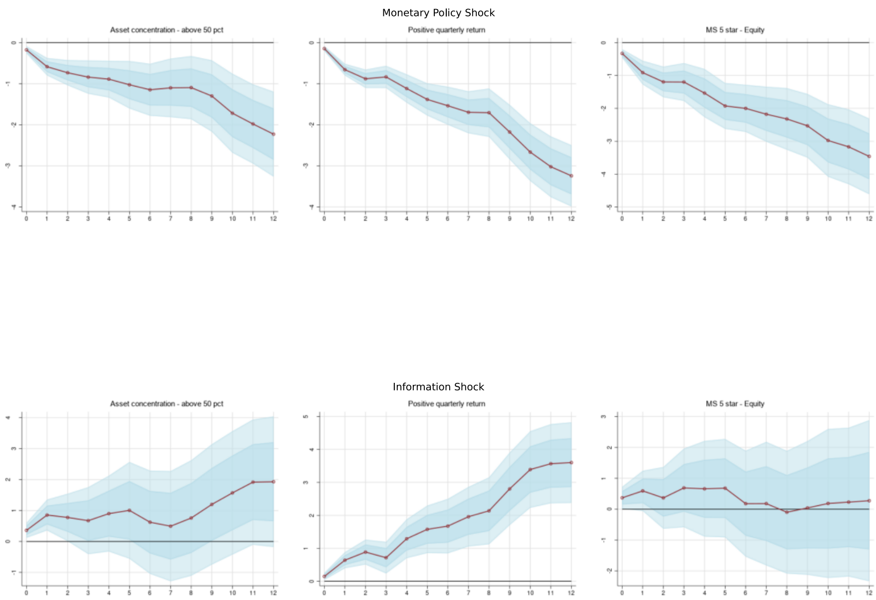


Figure 2.18. Impact of monetary shocks on U.S. domicile mutual fund flows. The figure shows the impact of pure monetary surprise (first row) and information shock (second row) on fund flows identified by Jarociński and Karadi (2020) obtained from linear projections. In panel (a): U.S. equity, U.S. bond and Cash. In panel (b): asset concentration, positive return over the last quarter, a high rating in equity funds. Confidence bands at 68% and 90%.

2.6 Conclusion

The significant growth of the mutual fund industry in the U.S. is crucial when discussing monetary policy transmission. Therefore, understanding how mutual funds react to monetary policy shocks and the implications for transmission and potential unintended consequences for financial stability is vital.

Focusing on the U.S. market, this chapter demonstrates that investment funds actively respond to monetary policy shocks, representing a significant channel for monetary policy transmission. The focus on the impact of monetary policy on international capital flows has often overshadowed this aspect. More specifically, utilizing the shocks identified by Kroencke et al. (2021), we have been able to discuss the effects of three types of monetary shocks: short-run and long-run shocks, which are mainstream, and a novel one, the risk-shift surprise, which captures variations in investors' risk attitudes. We provide evidence of consistent portfolio rebalancing in response to monetary policy shocks. For policy targeting the short-term and long-term parts of the yield curve, we observe consistent outflows from risky positions. However, this is not the case following a positive risk-shift surprise, which leads investors to flow into riskier positions, actively searching for yield. This finding contributes to our understanding of how monetary policy can influence the risk-taking behaviour of investors and the allocation decisions of mutual funds, which is a significant vehicle for the transmission of monetary policy, especially via the risk-taking channel.

As the fund sector continues to grow in importance, so too will the significance of the risk-taking channel. On the one hand, this will enhance the transmission of monetary policy, but on the other hand, it may undermine financial stability. As we have shown, with less liquid funds, risk-taking behaviour may result in a build-up of liquidity risk that can reduce the capacity to face abrupt redemptions in times of financial turmoil. Hence, these results have important policy implications. Monetary policy transmission through the investment funds sector can only occur with adequate macroprudential policy (e.g., countercyclical measures regarding redemptions) to avoid unintended consequences.

Appendix B

Additional material

B.1 Further extensions

B.1.1 Below the median

As a further check, we estimate the baseline specification for funds below the median regarding shares invested in a given asset class. Again, we consider equity, U.S. equity, and U.S. bonds. We find consistent results in the magnitude and sign of the responses as shown in Figure B.1.

B.1.2 Focus on Government bond

In this Section, we focus exclusively on funds that fall within the top decile of the distribution based on their investment proportions in government bonds. Figure B.2 illustrates how funds with allocations in the government bond asset category respond to short-term shocks, long-term shocks, and risk-shifting, in that order from left to right. We observe no substantial reactions following short-term shocks and risk shifts. The most significant impact comes from the long-term shock, a result consistent with the idea that bonds with extended durations are more vulnerable to changes in the long-term segment of the yield curve. Due to their typically long maturities, government bonds are linked with extended durations.

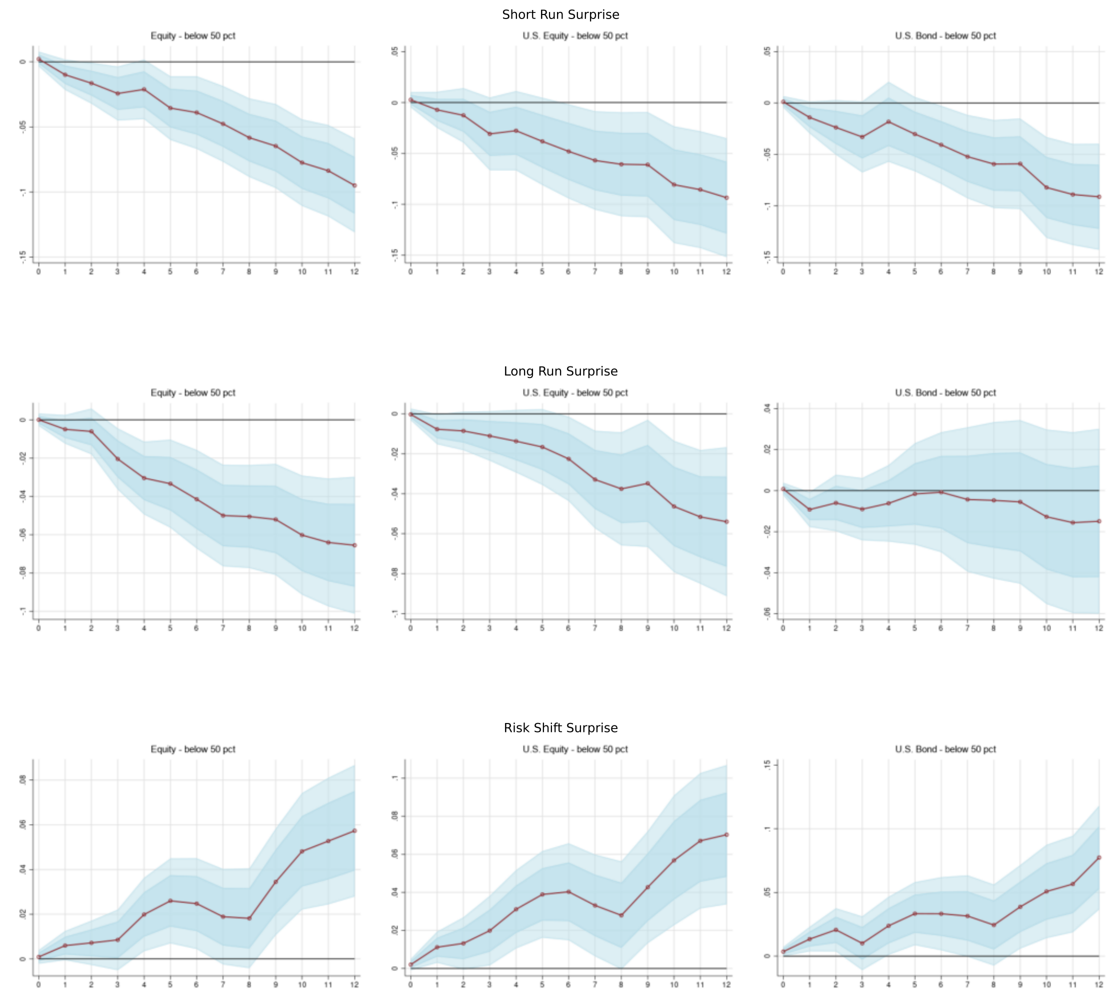


Figure B.1. Impact of Surprises on U.S. domicile mutual fund flows across a different asset class. The figure shows the impact of the surprises on fund flows identified by Kroencke et al. (2021) obtained from linear projections. From the top-left corner, the responses refer to the short-run, long-run and risk-shift surprise on flows towards funds that are below the median for shares invested in equity and bonds. Confidence bands at 68% and 90%.

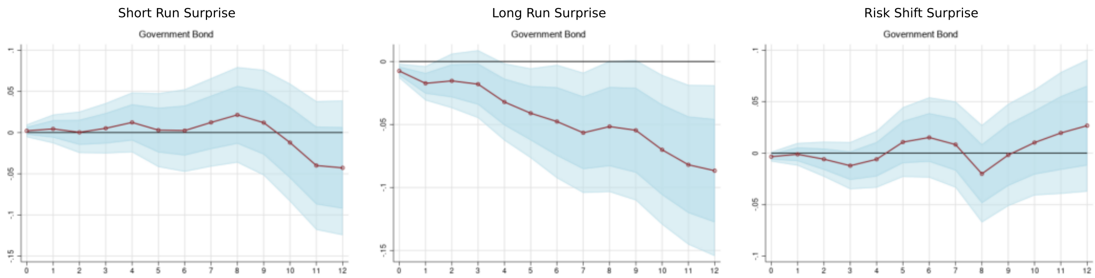


Figure B.2. Impact of Surprises on U.S. domicile mutual fund flows across a government bond asset class. The figure shows the impact of the surprises on fund flows identified by Kroencke et al. (2021) obtained from linear projections. From the top-left corner, the responses refer to the short-run, long-run and risk-shift surprise on flows towards government bond class. Confidence bands at 68% and 90%.

B.2 Geographical breakdown

B.3 Implications for capital flows

Our investigation into fund flow levels emphasizes the U.S. market and its associated implications. However, it is also interesting to consider the global spillover of U.S. monetary policy. As demonstrated in Figure B.3, approximately 20% of U.S.-domiciled equity funds engage in foreign market investment, making an analysis of their operations noteworthy. The proportion of bonds oriented towards international markets is lower, standing around 10% as depicted in Figure B.4. In this Section, we initially utilize the Morningstar category to segregate the primary geographical domains: the U.S., Advanced Economies (AE), and Emerging Market Economies (EME). Subsequently, we generate narrower indicators based on the distribution of investment shares, specifically targeting the Euro Area, Asia, and Latin America.

B.3.1 The effect of Short-Run surprise

Figure B.5 and Figure B.6 display the reactions to short-term shocks for the three primary groups - U.S., AE, and EME - as well as for the detailed breakdown, for both equity and bonds. We note that a short-term shock results in a decrease in foreign investment in equity, whereas the responses of flows directed towards bonds do not show significant changes (Figure B.5). Moving forward, we leverage the regional geographical breakdown to enhance our understanding of the reactions of U.S. domiciled funds investing in foreign securities. Regarding equity, we observe persistent and uniform outflows unaffected by whether the relative region is an Advanced Economy (AE) or an Emerging Market Economy (EME). The Euro Area experiences substantial outflows, along with Asian EMEs and

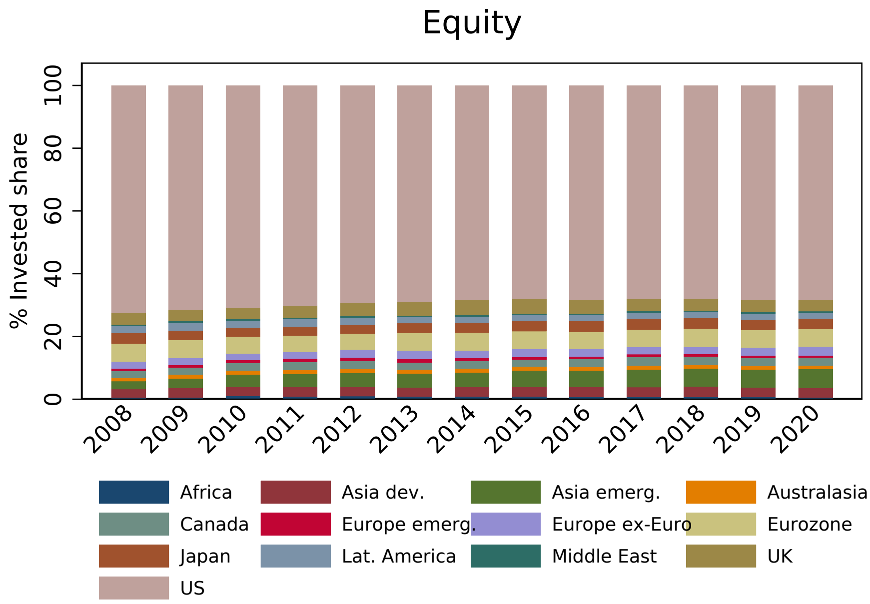


Figure B.3. Geographical breakdown of equity funds. Geographical breakdown of investment funds domiciled in the U.S. Most shares are invested in the U.S., and the non-U.S. 's more important areas are the U.K., the Eurozone, and Asia.

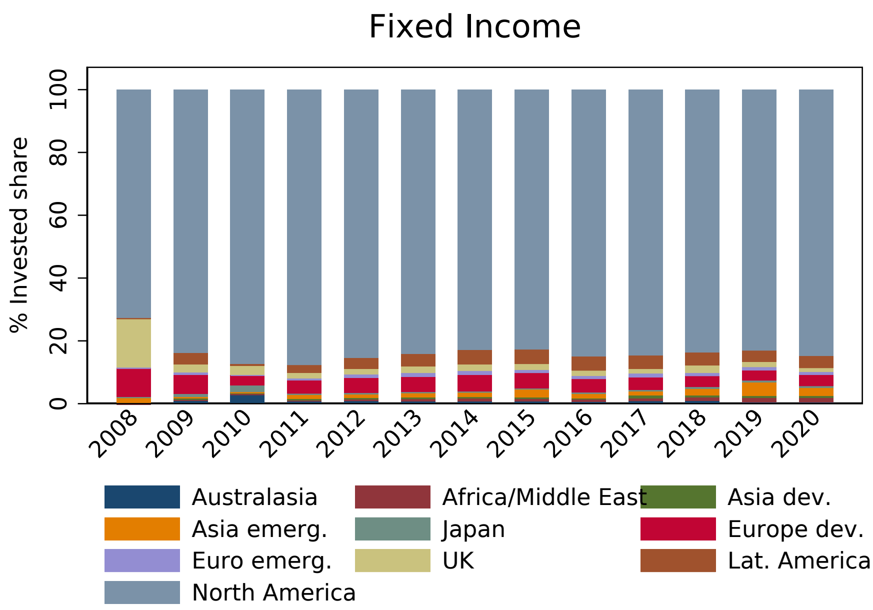


Figure B.4. Geographical breakdown of equity funds. Geographical breakdown of investment funds domiciled in the U.S. Most shares are invested in the U.S., and the non-U.S. 's more important areas are Latin America, the Eurozone, and Asia.

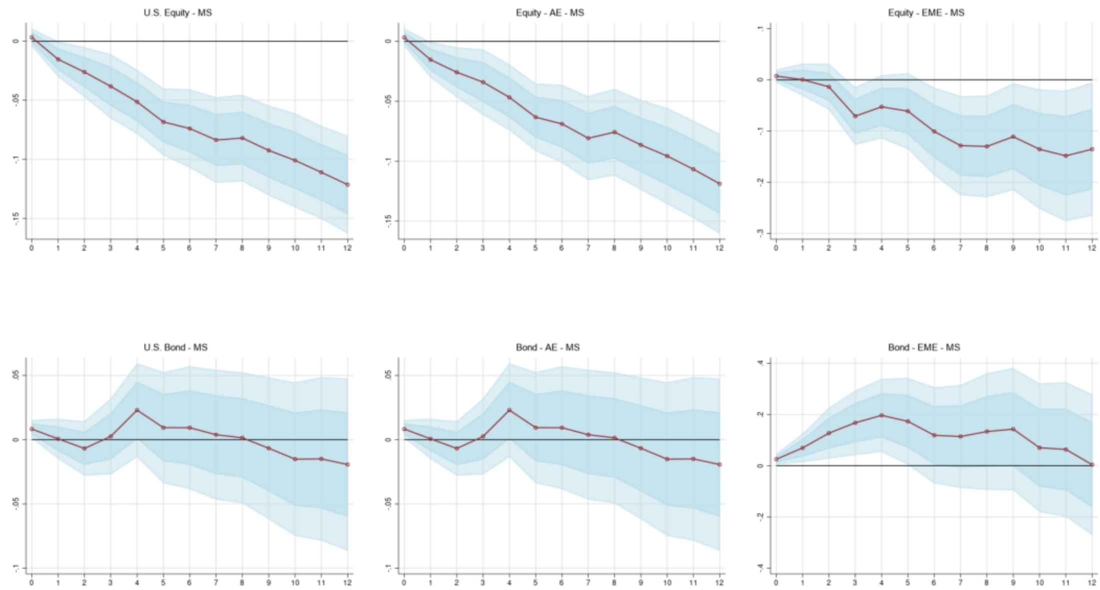


Figure B.5. Impact of Short-Run surprise on U.S. domicile mutual fund flows across a range of asset class. The figure shows the impact of Short-Run surprise on fund flows identified by Kroencke et al. (2021) obtained from linear projections. From the top-left corner, the responses refer to flows towards asset class defined by Morningstar: U.S. equity, equity AE and equity EME. From the bottom-left corner, the responses refer to flows towards asset class defined by Morningstar: U.S. bond, bond AE and bond EME. Confidence bands at 68% and 90%.

Latin American equities (roughly -0.13% after 12 business days). However, the dynamics for bond funds differ. As evidenced in Figure B.5, there are net positive inflows towards EME regions, notably with increases observed in Asian EMEs (+0.2%) and Latin America (+0.1%). This behaviour suggests that Asian EMEs largely influence the wider category of EME bonds. Conversely, the neutral reaction of funds with bonds invested in the AE region implies that the U.S. market predominantly drives the fund flows in this category. Given the geographical distribution, this conclusion is hardly unexpected. Building upon our observations, an analysis of why a pure tightening monetary policy shock - affecting the short-end part of the yield curve in the U.S. - should induce positive inflows in Emerging Market Economies (EMEs) is warranted.

A critical factor that determines cross-border capital flows is the interest rate differential. Changes in the U.S. short-term rate do not affect EME rates; thus, the interest rate differential contracts potentially make EME assets less attractive to investors. However, investors' portfolio rebalancing towards riskier assets due to higher U.S. interest rates can counteract this, thereby resulting in increased capital flows to EMEs in the short-run period we observe. Additionally, the risk-taking channel becomes relevant. Tightened U.S. monetary policy can also prompt investors to pursue higher yields in other markets, thus driving capital towards EMEs in the short term, while this is different for longer horizons.

B.3.2 The effect of Long-Run surprise

In this Section, we explore the impact of long-run surprises, referring specifically to a shock affecting the long-end segment of the yield curve. Similar to our baseline specification, bond outflows are more pronounced than equity. Nonetheless, it is evident that the main driver of the Advanced Economy (AE) sector remains the U.S. market, as illustrated in Figure B.7. Figure B.8 showcases the responses across various regions. Notably, in terms of outflows, the effects are most acute for Asia's Emerging Market Economies (EMEs), with decreases of -0.06% and -0.15% observed in equity and bonds, respectively. This suggests that Asia EMEs largely influence the overall responses of the EME category. A similar trend appears in the Latin American region, albeit to a lesser degree, where equity and bond outflows register at -0.03% and -0.05%, respectively. The effects on the Euro Area appear to follow a similar trajectory to the U.S. market, albeit to a lower extent. These findings are coherent with the empirical studies such as those by Bruno and Shin (2015), Rey (2015), Kroencke et al. (2015) and Miranda-Agrippino and Rey (2022) suggest the existence of the "global financial cycle" perspective, whereby a tightening U.S. monetary policy, by escalating global risk premiums and bolstering the U.S. dollar, can provoke a contraction of global liquidity. A reversal of capital flows away from EMEs.

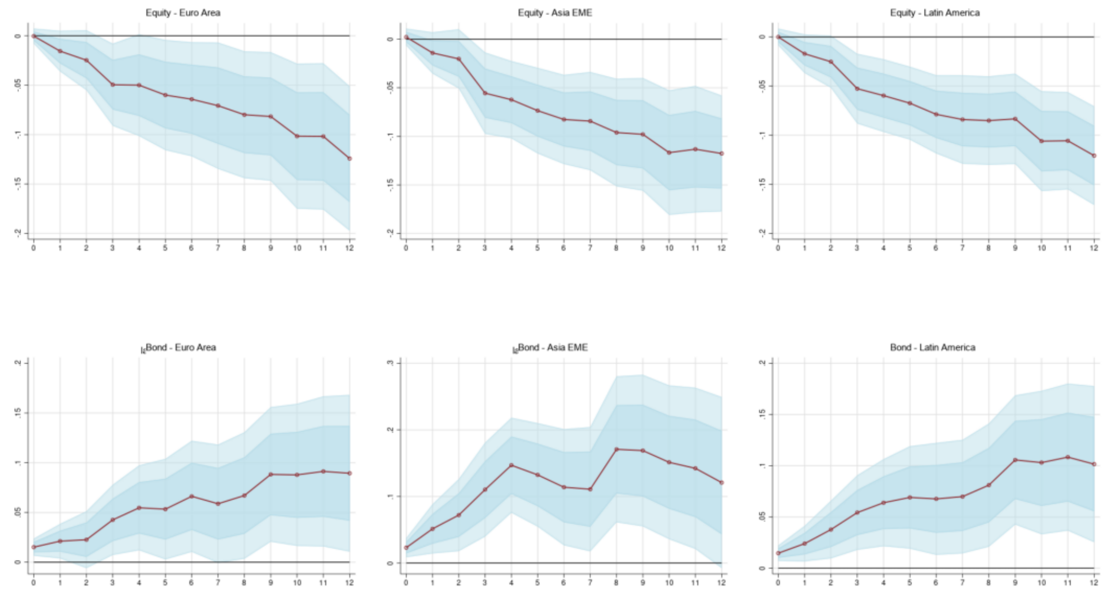


Figure B.6. Impact of Short-Run surprise on U.S. domicile mutual fund flows across a range of asset class. The figure shows the impact of Short-Run surprise on fund flows identified by Kroencke et al. (2021) obtained from linear projections. From the top-left corner, the responses refer to flows towards asset class defined by Morningstar: equity Euro Area, equity Asia EME and equity Latin America. From the bottom-left corner, the responses refer to flows towards asset class defined by Morningstar: bond Euro Area, bond Asia EME and bond Latin America. Confidence bands at 68% and 90%.

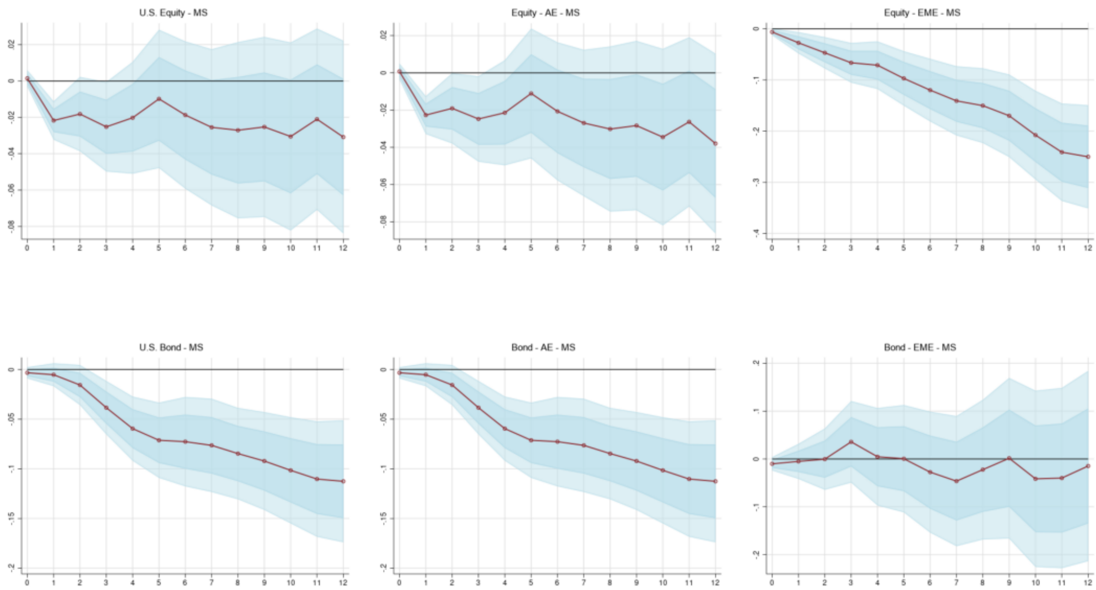


Figure B.7. Impact of Long-Run surprise on U.S. domicile mutual fund flows across a range of asset class. The figure shows the impact of Long-Run surprise on fund flows identified by Kroencke et al. (2021) obtained from linear projections. From the top-left corner, the responses refer to flows towards asset class defined by Morningstar: U.S. equity, equity AE and equity EME. From the bottom-left corner, the responses refer to flows towards asset class defined by Morningstar: U.S. bond, bond AE and bond EME. Confidence bands at 68% and 90%.

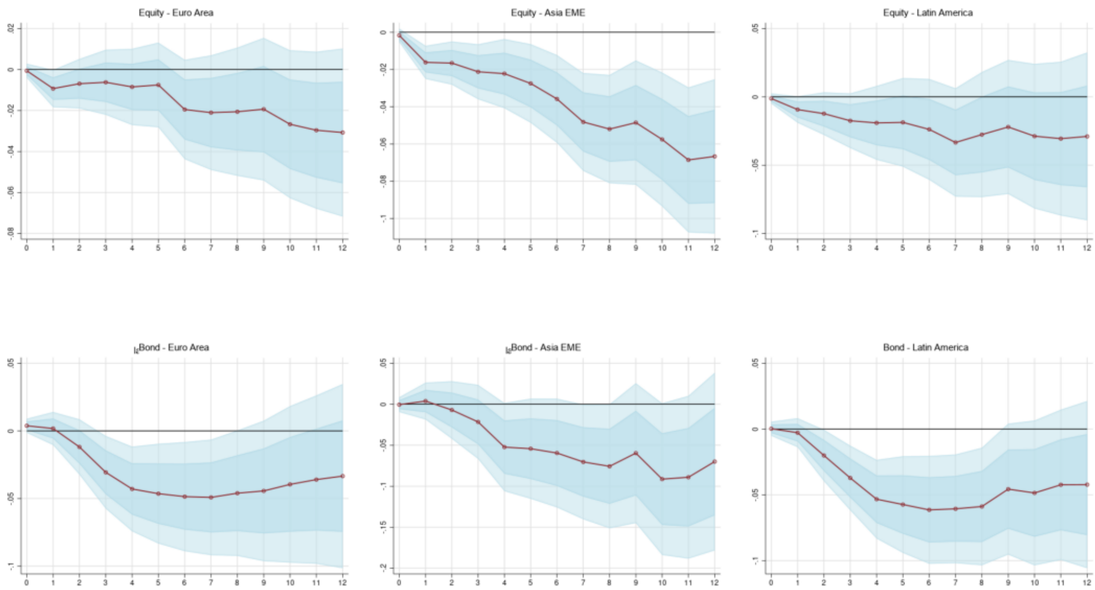


Figure B.8. Impact of Long-Run surprise on U.S. domicile mutual fund flows across a range of asset class. The figure shows the impact of Long-Run surprise on fund flows identified by Kroencke et al. (2021) obtained from linear projections. From the top-left corner, the responses refer to flows towards asset class defined by Morningstar: equity Euro Area, equity Asia EME and equity Latin America. From the bottom-left corner, the responses refer to flows towards asset class defined by Morningstar: bond Euro Area, bond Asia EME and bond Latin America. Confidence bands at 68% and 90%.

B.3.3 The effect of Risk-Shift surprise

We wrap up our examination of the global spillover effects of U.S. monetary policy shocks by studying the impact of risk-shift surprises. Consistent with the concept of the risk-taking channel, a positive surprise in investor risk appetite results in inflows into riskier positions. In this context, emerging markets are considered the riskiest and experience the most substantial inflows (+0.15 Figure B.10 portrays the geographical breakdown. We

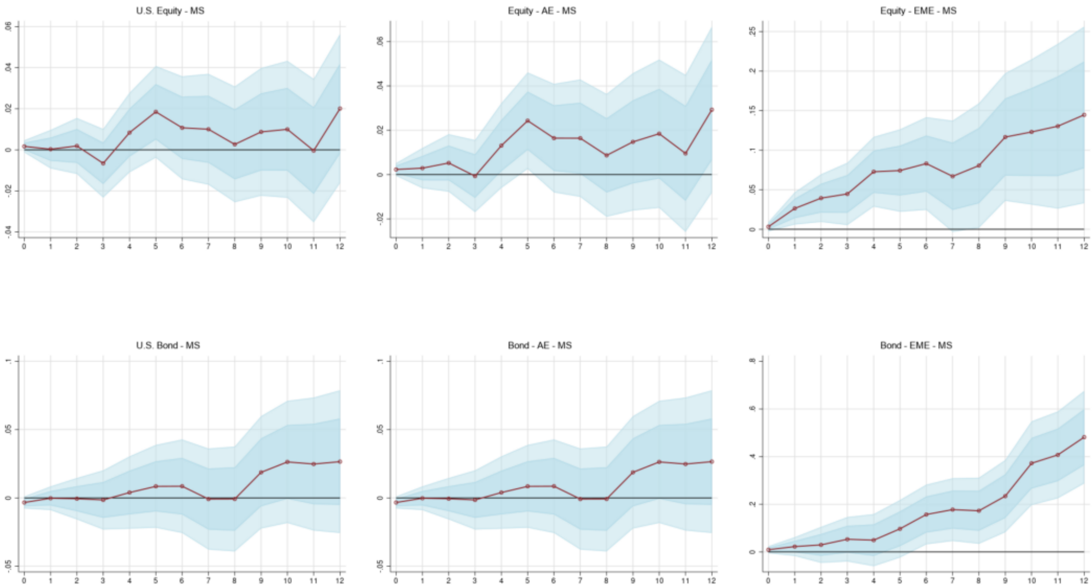


Figure B.9. Impact of Risk-Shift surprise on U.S. domicile mutual fund flows across a range of asset class. The figure shows the impact of Risk-Shift surprise on fund flows identified by Kroencke et al. (2021) obtained from linear projections. From the top-left corner, the responses refer to flows towards asset class defined by Morningstar: U.S. equity, equity AE and equity EME. From the bottom-left corner, the responses refer to flows towards asset class defined by Morningstar: U.S. bond, bond AE and bond EME. Confidence bands at 68% and 90%.

do not observe significant responses in Asia EME and Latin America when examining individual regions. This output suggests that the regions driving the inflows into the EMEs Morningstar category may not be represented here. Conversely, we observe a robust response for bond funds across all regions, with the most substantial flows directed towards Asia EME (+0.3

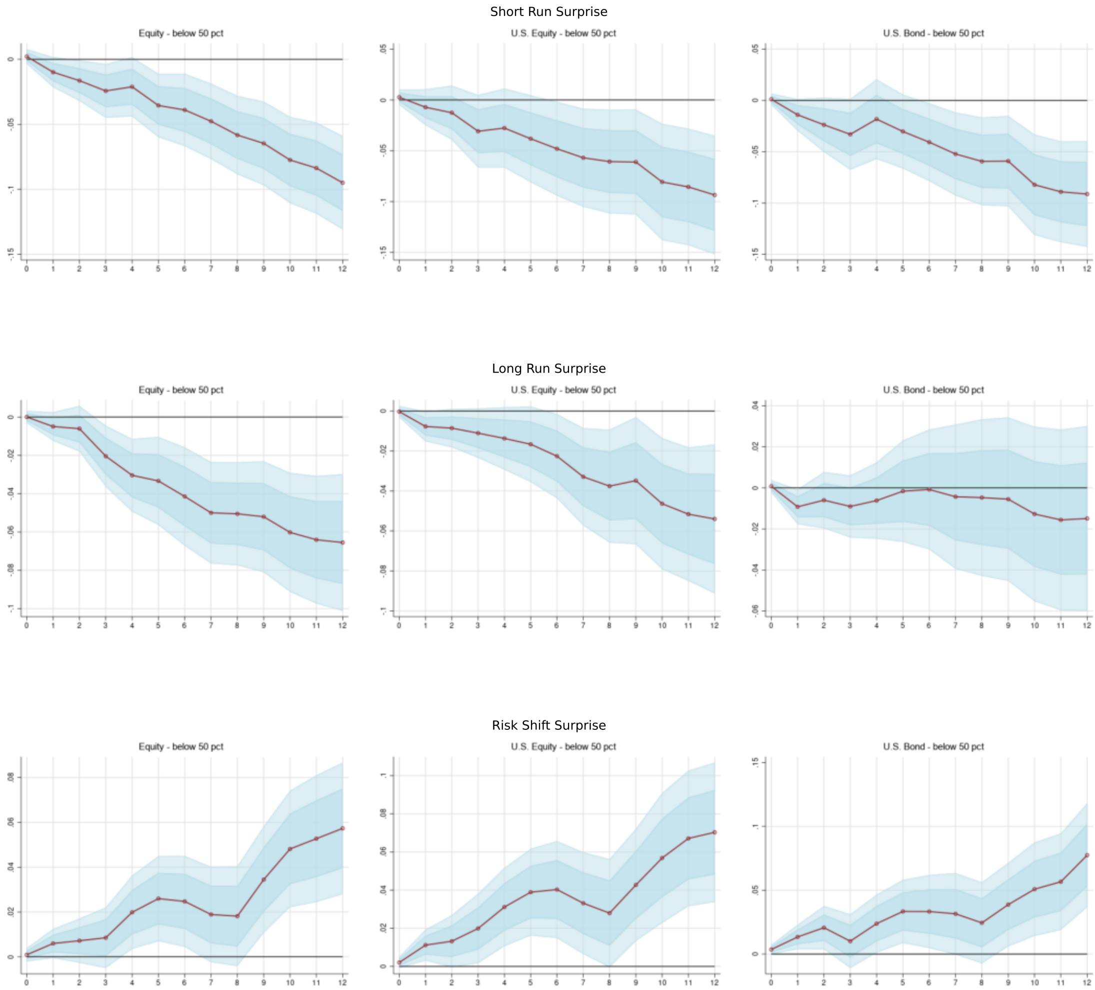


Figure B.10. Impact of Risk-Shift surprise on U.S. domicile mutual fund flows across a range of asset class. The figure shows the impact of Risk-Shift surprise on fund flows identified by Kroencke et al. (2021) obtained from linear projections. From the top-left corner, the responses refer to flows towards asset class defined by Morningstar: equity Euro Area, equity Asia EME and equity Latin America. From the bottom-left corner, the responses refer to flows towards asset class defined by Morningstar: bond Euro Area, bond Asia EME and bond Latin America. Confidence bands at 68% and 90%.

B.4 List of asset class and Morningstar indicators

Below, we enumerate all the indicators that we have devised for our study based on the distribution of invested shares:

- **Equity**
  - Equity - above the 50^{th} percentile
  - Equity - above the 75^{th} percentile
  - U.S. Equity - above the 50^{th} percentile
  - U.S. Equity - above the 75^{th} percentile
  - Non-U.S. Equity - above the 75^{th} percentile
  - Equity - AE - above the 50^{th} percentile
  - Equity - Euro Area - above the 50^{th} percentile
  - Equity - EME - above the 75^{th} percentile
  - Equity - Asia EME - above the 75^{th} percentile
  - Equity - Latin America - above the 75^{th} percentile
  - Equity - below the 50^{th} percentile
  - U.S. Equity - below the 50^{th} percentile
- **Bond**
  - Bond - above the 75^{th} percentile
  - U.S. Bond - above the 50^{th} percentile
  - U.S. Bond - above the 75^{th} percentile
  - Non-U.S. Bond - above the 90^{th} percentile
  - Government Bond - above the 90^{th} percentile
  - Bond - below the 50^{th} percentile
  - Bond - Euro Area - above the 90^{th} percentile
  - Bond - Asia EME - above the 90^{th} percentile
  - Bond - Latin America - above the 90^{th} percentile
- **Cash**
  - Cash - below the 50^{th} percentile
  - Cash - above the 50^{th} percentile
- **Asset concentration**
  - Asset concentration - above the 50^{th} percentile
  - Asset concentration - below the 50^{th} percentile
  - Asset concentration - 1^{st} quartile

- Asset concentration - 2^{nd} quartile
- Asset concentration - 3^{rd} quartile
- Asset concentration - 4^{th} quartile

In the list below, we outline all the Morningstar indicators that we use for our analysis:

- **Asset class**
  - Equity U.S.
  - Equity AE
  - Equity EME
  - U.S. Bond
  - Bond AE
  - Bond EME
- **Performance**
  - Positive return over the last quarter
  - Positive return over the last month
  - Alpha positive - overperform the market
  - Mornigstar 1 star
  - Mornigstar 2 star
  - Mornigstar 3 star
  - Mornigstar 4 star
  - Mornigstar 5 star

Chapter 3

Decomposing the Transmission Channel of Monetary Policy

JEL Codes: E4, E5, G1, G2
Keywords: Banks, Transmission channel of monetary policy, Monetary policy, Euro Area.

Notes and Acknowledgements

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3.1 Introduction

> *We brought interest rates down to zero virtually. At this point, it is necessary for banks to transfer these conditions to companies, entrepreneurs, and households. (...) monetary policy can improve conditions for the financing of the economy, but other conditions must exist so that people go to the bank and borrow money. They have to be confident in the future.*
>
> Mario Draghi, President of the ECB, Naples, 2 October 2014

In the Introductory to the press conference, the former ECB president underscores the significance of the banking sector in transferring the stimulus to the real economy, along with confidence in the future. Banking institutions play a pivotal role in the monetary policy transmission mechanism within the Euro Area, as it typically addresses the implications of interest rates on households and firms (Altavilla et al. 2019b, Altavilla et al. 2020, Albertazzi et al. 2021b, Ciccarelli et al. 2015, Carpinelli and Crosignani 2017). Traditionally, central banks have influenced the economy through conventional monetary policy tools, such as policy rates that work with the standard transmission mechanisms through the financial and banking system, such as the "interest rate channel", the "bank-lending channel", the "balance sheet channel", and "the risk-taking channel". However, during a financial crisis, the disruption of the financial and banking systems hampers the transmission of monetary policy impulses across the full spectrum of financial assets. The Global Financial Crisis began with a frozen interbank market due to a lack of confidence in the banking system. Thus, under these circumstances, unconventional policy is needed to rectify the malfunctioning of the standard transmission mechanism and restore confidence. Following the Global Financial Crisis, the ECB, like other central banks, has adopted unconventional monetary policy measures to restore confidence in the banking sector and push the Euro Area economy out of the crisis. The ECB implemented several of these measures, including the Negative Interest Rate Policy (NIRP), Forward Guidance (FG), Quantitative Easing (QE), and Targeted Long-Term Refinancing Operations (TLTROs). FG and QE are the policies with the most significant impact on the yield curve's medium- and long-term ends. The QE program fosters the transmission of monetary policy via the "portfolio-balance channel", i.e. the substitution of money with more profitable assets. It is often credited with restoring confidence in the Euro Area (Rostagno et al., 2021). FG about the monetary policy stance is crucial for managing expectations when hitting the Effective Lower Bound. These policies helped reduce fragmentation and encouraged risk-taking in the Euro Area, thereby improving lending conditions and supporting economic recovery (Bubeck et al. 2020, Altavilla et al. 2021c, Rostagno et al. 2021).

But what about the role of bank confidence? A crucial factor in the transmission mechanism is that standard models do not typically capture (Rostagno et al., 2021). Also, despite the significance of the banking sector in the Euro Area, the discussions often overlook the quantitative aspects of lending and the management of banks' balance sheets, precisely the volume of new loans issued and net investments, despite the significant role these factors play in determining the effectiveness of the transmission mechanism (Altavilla et al., 2020). Thus, in this chapter, we revisit the monetary policy transmission mechanism by incorporating the level of confidence held by the banking sector and the varied outcomes of conventional and unconventional monetary policy. Drawing on the literature on financial sentiment analysis (Loughran and McDonald 2020; Araci 2019), we construct a confidence index for banks based on banks' earnings call transcripts. We then interact this index with monetary policy shocks to quantify the extent to which banks' confidence influences the pass-through of the quantity channel of monetary policy. We empirically demonstrate that banks' confidence can either attenuate or amplify the effects of monetary policy, thereby creating differences between the impacts of conventional and unconventional monetary policies on the bank lending and portfolio-balance channels.

The empirical analysis employed in this chapter leverages the benefits of innovative econometric methodologies. Firstly, for defining bank confidence, we compute an index of banks' sentiment based on state-of-the-art machine learning techniques by carrying out a sentiment analysis on transcripts of earnings conference calls for significant European institutions (from now on, referred to as SIs). Secondly, to accommodate potential asymmetries, we deconstruct the responses of balance sheet flows using the Kitagawa-Oaxaca-Blinder (Kitagawa 1955, Oaxaca 1973, Blinder 1973) decomposition, a microeconometric tool recently incorporated into macro analysis (Cloyne et al. 2020 and Alessandri et al. 2023). Monetary policy shocks are the monetary surprises derived by the high frequency identification by Altavilla et al. (2019a), that basically quantify the different segment of the yield curve reaction on the days of central bank communication of policy decisions. We observe that the confidence levels of banks positively respond to conventional and unconventional monetary policy easing. This finding confirm that confidence, business sentiment, and investors' assessments of risks would have been even more impaired in the absence of QE and FG (Rostagno et al., 2021). Secondly, in line with existing literature, we find that easing both conventional and unconventional monetary policies has divergent effects on banks (see Albertazzi et al. 2021b, Altavilla et al. 2018). Loosening conventional monetary policy typically affects the short end of the yield curve, often leading to a steepening of the curve and increased interest margins for banks. Conversely, unconventional easing, which tends to flatten the yield curve, can decrease banks' profitability (Brunnermeier and Koby, 2018).

Our main finding is that the interplay between monetary shocks and the confidence index of banks proves pivotal in the pass-through analysis. Banks' confidence enhances the transmission of unconventional monetary policy, particularly concerning newly generated loans and towards riskier investments, such as equity and shares of investment funds. This analysis contributes to the existing literature in two primary ways. First, we illustrate the different effects of conventional and unconventional monetary policy on banks' balance sheets in terms of volume intermediated, both towards the real economy (loans to households and firms) and the financial sector (holdings in government bonds, corporate bonds, and equity shares and investment funds). Consistent with monetary policy theory, unconventional shocks substantially impact the balance sheet through the portfolio-substitution channel. Second, we demonstrate that banks' confidence significantly influences portfolio decisions, such as the issuance of new loans.

Related literature This work is related to two broad strands of literature. The first and broadest one relates to monetary policy transmission, especially via bank institutions under conventional and unconventional monetary policy. The second strand of literature related to our chapter studies sentiment analysis in finance.

Overall, the literature suggests that both conventional and unconventional monetary policies play a critical role in the banking sector of the Euro area. However, the effectiveness of these policies often depends on the specific economic conditions and characteristics of individual banks and country idiosyncrasies (e.g. Kashyap and Stein 2000, Maddaloni and Peydró 2011, Ciccarelli et al. 2013). Bubeck et al. (2020) and Altavilla et al. (2021c) offered a comprehensive view of the effectiveness of UMPs, such as QE, Forward Guidance, and Long-Term Refinancing Operations (LTROs). They argued that these policies reduced fragmentation and increased risk-taking in the Euro area, improving lending conditions and boosting economic recovery. Other works study the effect of liquidity provision on credit supply by exploiting the Bank Lending Surveys (BLS) by the ECB, which contain reliable quarterly information on changes in loan conditions due to bank, firm and household balance sheet strength and on changes in loan demand (Ciccarelli et al. 2013, Carpinelli and Crosignani 2017, Altavilla et al. 2019b and Carpinelli and Crosignani 2021). Concerning the role of QE policy, Andrade et al. (2016) found that these UMPs significantly affected banks' lending behaviour. They concluded that QE had effectively improved bank lending, lowering interest rates and increasing asset prices as Altavilla et al. (2021b). These results regarding the bank lending channel cope with Albertazzi et al. (2021a), who also highlights the role of QE in fostering the portfolio-balancing channel. However, the too-low-for-too-long interest rate environment can harm banks profitability (Alessandri and Nelson 2015 and Altavilla et al. 2018). Brunnermeier and Koby (2018) and Adrian et al. (2019) presented a "reversal interest rate" concept, implying a point where lowering policy rates (NIRP) becomes counterproductive, harming banks' net interest margin and, consequently, their willingness to lend. Other findings corroborate these results concerning unconventional monetary policy, while conventional measures may have opposite outcomes working through the steepening of the short part of the yield curve (Albertazzi et al., 2021b), despite other studies consider the NIRP as one of the most effective UMP (Rostagno et al., 2021).

The second strand of the literature relates to a relatively recent trend in financial research: sentiment analysis on earnings conference call transcripts to gauge the tone of communication. This methodology helps uncover hidden signals about a company's financial health, future outlook, or management effectiveness that may not be captured in traditional financial statements. Early work on textual analysis in finance, such as Angela K. et al. (2006) and Tetlock (2007), used simple word-count methods to demonstrate that the tone of news articles can predict stock market movements. Concerning earnings conference calls, the milestone work is the paper by Loughran and McDonald (2011) (LM from now on), who proposed a financial dictionary for textual analysis specifically designed for financial context. Prior to this work, the literature (e.g. Huang et al. 2014, Price et al. 2012) typically used sentiment dictionaries created by the psychology and sociology fields (i.e. the Harvard IV-4 Psychosocial lexicon) to measure the tone of business documents However, the use of general purpose word list has significant limitations when applied to business disclosures (Loughran and McDonald, 2011). The LM Dictionary became a cornerstone for most of the subsequent studies in the field (Fei et al. 2023, Aryal et al. 2022 and De Amicis et al. 2021 among others) and it is the most prominent textual tone measure in financial literature (Luo and Zhou 2020 and Loughran and McDonald 2020). Matsumoto et al. (2011) and Price et al. (2012) improved the methodology by demonstrating that the Questions and Answers segment of the call could provide more valuable insights and the effective tone of the management (also Chen et al. 2018 and De Amicis et al. 2021). Managers have the incentive to be ambiguous in disclosing negative information and usually use an abnormally positive tone in the presentation part, which does not reveal more information than the financial statement (Huang et al., 2014). The LM financial lexicon has long served as the cornerstone for financial text analysis; nevertheless, with cutting-edge machine learning algorithms and the augmenting computational power, pioneering methodologies have been unveiled (Loughran and McDonald, 2020). An illustration of such innovation is exhibited in the work of Shapiro et al. (2022), where the author amalgamates the synthesis of existing dictionaries with freshly trained algorithms for discerning economic news sentiment. Nonetheless, among the recently introduced methodologies in sentiment analysis, Bidirectional Encoder Representations from Transformers (Devlin et al., 2018), commonly known as BERT, holds a prominent position. BERT is a language model that employs a layered structure of bidirectional Transformers. The Transformer is an encoder-decoder deep neural network architecture designed to manage sequential information (Vaswani et al., 2017). The BERT framework consists of two steps: pre-training and fine-tuning. During pre-training, the model is trained on unlabeled data across various tasks. For fine-tuning, the BERT model is initialized with the pre-trained parameters, and all of them are fine-tuned using labelled data. The visual representation of the architecture in Figure 3.1 may assist in elucidating the process. BERT excels in tasks such as sentiment analysis and named entity recognition (Li et al., 2020). Araci (2019) pre-trained BERT on a financial corpus (Reuters TRC2, nearly 2 million pieces of economic news) and fine-tuned it on Financial Phrasebank (Malo et al., 2014), resulting in FinBERT, a specialized variant of BERT for financial sentiment classification. FinBERT achieves a 97% test-set accuracy in manually tagged text and 86% in plain text. To the best of our knowledge, our research is the first to use FinBERT on transcripts from banks' earnings conference calls. This innovative approach aims to accurately gauge the overall confidence

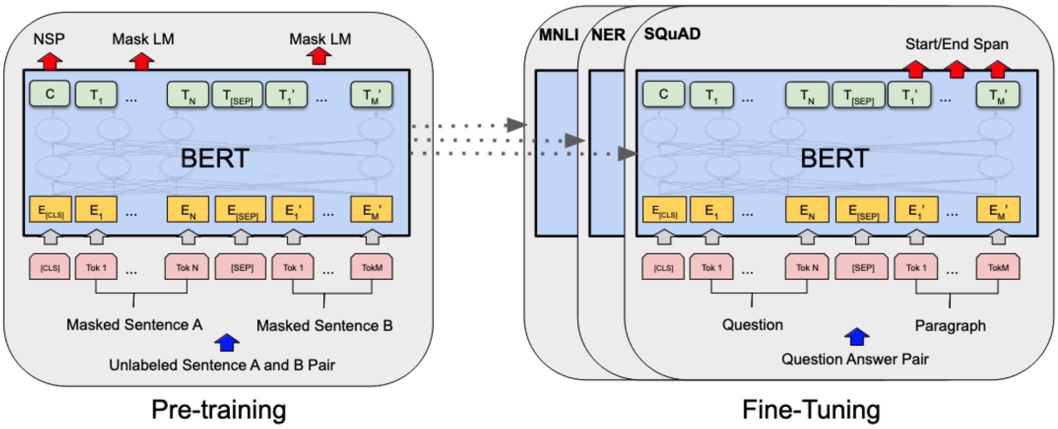

Figure 3.1. Overall pre-training and fine-tuning procedures for BERT (Devlin et al., 2018). The model is pre-trained to comprehend language through two simultaneous unsupervised tasks: *Hidden word prediction* (BERT learns to predict hidden words) and *Next sentence prediction* (the model is given two sentences and learns whether the second sentence logically follows the first sentence or is random). BERT can be fine-tuned to solve various downstream tasks that require language understanding. For additional details about the BERT architecture, see the Appendix C.1.

in the banking sector, representing a significant advancement in financial sentiment analysis.

In this study, we make two contributions to the existing literature. Firstly, we expand the literature on earnings call conferences by employing FinBERT to analyze bank transcripts. This approach allows us to gain insights into the communication dynamics of banks during these conferences. Secondly, we enlarge the literature on the transmission of monetary policy through the banking system by introducing a novel methodology based on the Kitagawa-Oaxaca-Blinder decomposition (Kitagawa 1955; Oaxaca 1973; Blinder 1973). Our approach builds upon the work of Cloyne et al. (2020) and Alessandri et al. (2023), who have also utilized this decomposition technique in their studies. This methodology enables us to examine the non-linear effects of banks' confidence on the transmission mechanism of both conventional and unconventional monetary policy shocks.

The remainder of the chapter is organized as follows: Section 3.2 motivates the analysis. Section 3.3 illustrates the empirical framework, and Section 3.4 discusses the main findings. Section 3.5 provides robustness checks and alternative specifications while Section 3.6 concludes.

3.2 Data and descriptive evidence

This work investigates the transmission of monetary policy stimulus via the banks' balance sheet decisions subject to their confidence. We focus both on the bank lending channel and the portfolio-balancing channel. The analysis is conducted over the period from the beginning of 2003 to the end of 2021 in the Euro Area.[1] We use quarterly data collected from different sources at the country level. Country-level data about the banks' balance sheets, such as bank loan volumes, securities held, and total assets, come from the ECB - Balance Sheet Item (BSI) dataset. Based on-balance-sheet items, we construct the following indicators for banks at the country level: newly generated loans to households, non-financial corporations; net acquisition of corporate bonds, government bonds and shares in equity instruments and investment funds. All indicators are in percentage of total assets. Also, we define sovereign exposure as the ratio of domestic sovereign bonds to total assets. Table 3.2 provides summary statistics for the country bank-specific variables considered. We further collect three other sets of variables from the ECB Statistical Data Warehouse (SDW). Financial variables include the yield curve slope, country-specific index for financial distress, 3-month Euribor, EONIA and MRO rates. Macroeconomic variables include the quarterly year-on-year GDP growth, Inflation rate (HICP yearly change) and the forecast from the Survey of Professional Forecasters for GDP and Inflation at 1-year horizon. We also consider other banks specific variables from the ECB - BLS dataset. BLS convey information in the form of an aggregate diffusion index about variations in credit standards applied to the customers and variations in demand. We consider the variation in the demand for households[2] and non-financial firms. From Alam et al. (2019), we get the indicators at the country level in the form of dummy variables for macroprudential policy. The regulatory measures implemented after the Global Financial Crisis have imposed constraints on the portfolio allocation of commercial banks, explicitly advocating for a reduction in the size and risk associated with their balance sheets. Table 3.2 provides the summary statistics. In a specific paragraph, we will discuss variables for monetary policy shocks and banks' confidence index in more detail.

3.2.1 Banking sector and monetary policy

Monetary policy In the overall analysis, we exploit the monetary policy surprise series by Altavilla et al. (2019a). There are three surprises (factors) that capture most of the variation in the yield curve:

- Policy Target: This factor captures the market's perception of the ECB's policy

[1] Due to the availability of data, the countries considered are Austria, Belgium, Finland, France, Ireland, Germany, Greece, Italy, Portugal, Spain and The Netherlands

[2] Variation in the demand for households is obtained as the sum of variation in demand for mortgage and consumer credit

Table 3.1. Descriptive statistics for banks balance sheet

	Mean	SD	25p	Median	75p	N
STOCK						
Loans						
Loans from MFI to Households	17.56	7.38	12.68	18.01	23.73	912
Loans from MFI to NFC	15.28	6.32	10.73	14.78	19.95	912
Securities						
MFI holdings in corporate bond	8.59	3.81	5.75	8.52	10.93	912
MFI holdings in Gov. Bonds	5.67	3.34	3.31	4.90	7.06	912
MFI holdings in IF and non-MFI shares	3.19	1.70	1.82	3.32	4.63	912
FLOW						
Loans						
Loans from MFI to Households	0.00	0.10	-0.02	0.00	0.02	911
Loans from MFI to NFC	-0.00	0.10	-0.02	-0.00	0.01	911
Securities						
MFI holdings in corporate bond	-0.00	0.14	-0.03	-0.00	0.03	911
MFI holdings in Gov. Bonds in pct of total assets	0.00	0.16	-0.05	-0.01	0.04	911
MFI holdings in IF and non-MFI shares	-0.00	0.15	-0.03	-0.00	0.03	911

Note: Data are at quarterly frequency covering the period 2003Q1-2021Q4. Variables in percentage.

Table 3.2. Descriptive statistics for control variables

	Mean	SD	25p	Median	75p	N
Finance						
Euribor 3M	-0.55	1.39	-1.58	-0.44	0.15	912
Yield Curve Slope 10Y-2Y	1.17	0.70	0.52	1.14	1.75	912
Financial Stress Index	0.13	0.11	0.05	0.09	0.16	912
EONIA	0.88	1.45	-0.35	0.26	2.06	912
Shadow Rate Lemcke	-0.09	2.22	-1.98	-0.68	1.85	912
MRO	-0.09	0.22	-0.25	-0.05	0.00	840
Shadow Rate Wu-Xia	-1.49	3.67	-5.26	-0.69	1.62	840
Macroeconomic						
GDP YoY	1.06	3.11	0.47	1.68	2.26	912
GDP forecast YoY	1.43	8.55	0.02	1.82	2.53	912
Inflation EA YoY	1.63	1.08	0.80	1.70	2.25	912
Expected Inflation EA	1.56	0.33	1.30	1.60	1.80	912
Banks						
Δ demand for loans from NFC	-0.65	18.64	-10.00	0.00	10.00	912
Δ in the demand for loans from Households	0.76	20.88	-8.33	3.71	12.50	912
Capital requirements	0.01	0.20	0.00	0.00	0.00	912
Liquidity requirements	0.03	0.24	0.00	0.00	0.00	912
Sum of the 17 policy-action dummy-type indicators	0.15	0.80	0.00	0.00	0.00	912
MFI sovereign exposure	3.43	3.08	1.10	2.30	5.31	912
Loan to Deposit Spread	2.70	0.28	2.53	2.65	2.80	912

Note: Data are at quarterly frequency covering the period 2003Q1-2021Q4. Variables in percentage.

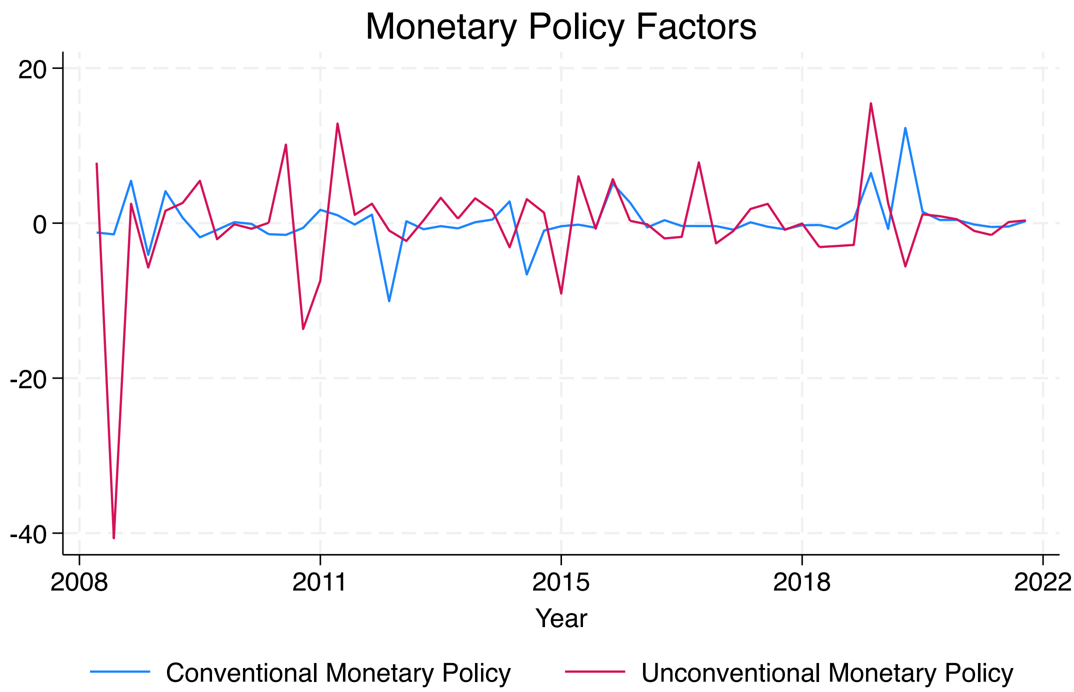

Figure 3.2. Monetary policy shocks series from Altavilla et al. (2019a). The data is gathered at a quarterly frequency, spanning the period from the first quarter of 2003 to the fourth quarter of 2021. The surprises are orthogonal by construction and scaled to produce a one-unit effect on the rate referring to different yield curve segments. Given the orthogonal nature of the factors by design, each factor is summed within the same quarter to yield quarterly data.

changes, and it targets the short-end part of the yield curve;

- Forward Guidance (FG): This involves the market's interpretation of the ECB's forward-looking statements and guidance about future policy actions. It targets the medium-end part of the yield curve.
- Quantitative Easing (QE): This factor represents the market's response to the ECB's QE measures, which involve large-scale asset purchases that affect the long-end part of the yield curve.

The Target factor is a proxy for conventional monetary policy and the sum of FG and QE factors for unconventional monetary policy[3] (see Figure 3.2). Indeed, we state that banks' confidence also matters in the transmission via the banking system.

Banks confidence Now, we dive into the importance of banks' confidence for monetary policy transmission. To get a confidence index for banks, we construct a sentiment index

[3]Given that FG and QE are orthogonal by construction and affect different segment of the yield curve, we can sum them up to obtain a unique measure of unconventional surprise

for the SIs in the Euro Area. We acquire the transcripts of earnings conference calls of the major Euro Area SIs[4] from Refinitiv Eikon. Listed companies conduct earnings conference calls to disseminate information to all stakeholders, including institutional and individual investors and buy- and sell-side analysts. Conference calls enable companies to underscore successes during prosperous periods and relieve concerns during adverse ones. Companies conduct conference calls following the release of financial results, typically at the end of each quarter. Consequently, the transcripts are available at a quarterly frequency. We commence by distinguishing management and analyst dialogue from the transcripts of approximately 1,040 earnings calls from 2003 to 2021. We separate managers' remarks from analysts' remarks in a remark-by-remark manner and retain only the management speeches in the Questions and Answers (Q&A) session. Numerous studies suggest that the true management tone emerges in the Q&A sessions (Matsumoto et al. 2011, Chen et al. 2018 among others). We utilize the FinBERT algorithm and the LM Dictionary for each transcript to calculate the managers' tone.

The FinBERT algorithm yields a set of scores (positive, negative, and neutral). We assign equal weights to the positive and negative scores (0.4 each) and a lower weight to the neutral score (0.2) to derive a singular index. We reverse the sign of the negative score to ensure the index falls within the range of -1 to 1, and we obtain the unique index as the weighted sum of the three scores.[5] With the LM Dictionary, the tone is computed as the number of positive (i.e. optimistic) words minus negative (i.e. pessimistic) words for all managers' answers on the call, scaled by the sum of positive and negative managers' words.

To derive the confidence index at the country level, we rescale the individual bank index by the market share in terms of total assets and aggregate them.[6] Table 3.4 provides a general overview of the average sentiment index, which is slightly negative across almost all countries. Embracing a prolonged period of financial crisis (2008-2012) followed by economic stagnation, this is not surprising. Figure 3.3 provides a graphical index inspection. The indexes built upon the FinBERT algorithm seem more variable than those obtained with the LM Dictionary. We now focus on estimating a local projections equation (Jordà, 2005) using the confidence index as the dependent variable and monetary policy shocks as independents. We observe the effect of monetary policy shocks at the impact. Loosening conventional and unconventionally monetary policy shocks positively affects banks' confidence (see Table 3.2.1). This finding confirm that confidence, business

[4]See the Appendix C.3 for the full list

[5]To validate manually assigned weights, we extract the first component in the Principal Component Analysis. The results hold.

[6]For countries like Finland, Ireland and Luxembourg, no earning calls transcripts were available. We build the index as the weighted average of the index for other countries

Table 3.4. Average sentiment index in the period 2003-2021 for European SIs

	AT	BE	DE	ES	FI	FR	GR	IE	IT	LU	NL	PT
LM Dictionary score	-0.01	-0.08	-0.04	0.00	-0.10	-0.03	-0.05	-0.10	0.02	-0.10	-0.04	-0.02
	(0.06)	(0.05)	(0.05)	(0.13)	(0.10)	(0.05)	(0.05)	(0.10)	(0.06)	(0.10)	(0.11)	(0.16)
FinBERT score	-0.06	-0.06	-0.07	-0.13	-0.23	-0.12	-0.08	-0.23	-0.06	-0.23	-0.08	-0.21
	(0.11)	(0.11)	(0.11)	(0.17)	(0.20)	(0.14)	(0.08)	(0.20)	(0.11)	(0.20)	(0.25)	(0.24)

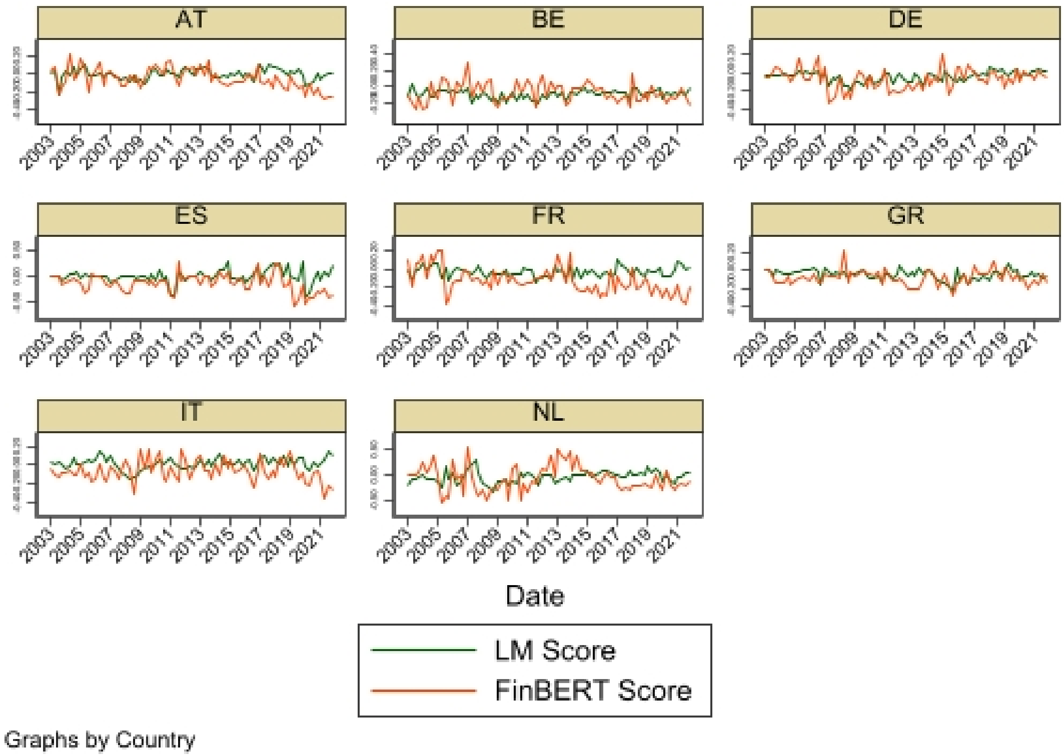

Figure 3.3. Sentiment index for Euro Area countries. The blue line corresponds to the index computed using the LM Dictionary, while the red line corresponds to the index derived from the FinBERT scores. We rescale the individual bank index by the market share of total assets and aggregate to obtain the country index.

sentiment, and investors' assessments of risks would have been even more impaired in the absence of QE and FG (Rostagno et al., 2021). To delve more in depth the analysis of the

Table 3.5. Response of banks' confidence to monetary shocks.

	FinBert score$_t$	LM Dictionary score$_t$
Conventional MP	0.000	0.002**
	(0.004)	(0.001)
Unconventional MP	0.003**	0.002***
	(0.001)	(0.000)

Note: *** p<0.01, ** p<0.05, * p<0.10.
All regressions include as additional controls the lagged values of the variable of interest, GDP forecast for the Euro Area, EONIA rate and a dummy for macroprudential policy.

effect of monetary policy shocks on banks' confidence, we focus on the two key components of UMP: FG and QE (see Table 3.2.1). FG is designed to manage expectations, while QE aims to lower interest rates on the long-term segment of the yield curve and stimulate the portfolio substitution channel. QE boosts confidence by 0.4 basis points, which is twice the effect of FG. Our analysis confirms that QE effectively restores confidence in the banking sector. In contrast, we interpret the positive impact of FG as a response to a negative Odyssean shock, specifically an announced future interest rate decrease that is coupled with a general expectation of increased economic activity (Andrade and Ferroni, 2021). We find that that monetary policy influences banks' confidence, but it does not

Table 3.6. Response of banks' confidence to monetary shocks.

	FinBert score_t	LM Dictionary score_t
Forward Guidance	0.002*	0.002***
	(0.001)	(0.000)
Quantitative Easing	0.004**	0.000
	(0.002)	(0.001)

Note: *** p<0.01, ** p<0.05, * p<0.10.
All regressions include as additional controls the lagged values of the variable of interest, GDP forecast for the Euro Area, EONIA rate and a dummy for macroprudential policy.

Granger-cause it at 1% confidence (see Appendix C.2). Thus, we can continue with the empirical strategy as outlined in Section 3.3.

3.3 Methodology

This chapter aims to isolate the role of banks' confidence within the bank lending and portfolio-balance channels and examine whether it accounts for heterogeneous effects. The empirical framework necessitates handling non-linear regressors and employing a stratagem to dissect the role of banks' confidence in transmitting the shocks. In broad terms, the monetary shock should interact with an exogenous shift in the banks' confidence to isolate the role played by banks' confidence in influencing balance sheet management decisions. For this purpose, we refer to the new extensions of the local projections method (Jordà, 2005), augmented with the Kitagawa-Oaxaca-Blinder (KOB from now on) decomposition (Kitagawa 1955, Oaxaca 1973, Blinder 1973) formalized by Cloyne et al. (2020) and adapted to monetary policy by Alessandri et al. (2023). The KOB decomposition is commonly used in applied microeconometrics to decompose the average treatment effect and explore the importance of various characteristics. Cloyne et al. (2020) bring this method to the macroeconomic analysis to retrieve state-dependent impulse response function. The KOB decomposition is crucial for disentangling the *direct* effect of a shock on the dependent variables from the *indirect* effect, that is, any state dependencies that may influence the outcome. The third effect is the *composition* effect that quantifies the potential bias due to imperfect identification. In formal terms, the linear projections model in $i = 1, ..., N; t = 1, ..., T$ and augmented with the KOB decomposition can be written as follows:

$$y_{t+h} = \mu_0^h + (x_t - \bar{x})\gamma_0^h + f_t\beta^h + f_t(x_{it} - \bar{x})\theta^h + \omega_{t+h} \tag{3.1}$$

where f_t is the shock. Thus, $\hat{\beta}^h = \hat{\mu}_1^h - \hat{\mu}_0$ is the estimate of the direct effect, $(\bar{x}_1 - \bar{x})\hat{\theta}^h$, where $\hat{\theta}^h = \hat{\gamma}_1^h - \hat{\gamma}_0^h$, reflects changes in how the covariates affect the outcome due to the intervention. This gives the estimate of the indirect effect. It is important to note that the x_t is expressed in deviation from its mean to ensure the direct effect captures the average impact, and the indirect effect captures heterogeneity around the average. Finally, the term $(\bar{x}_1 - \bar{x}_0)\gamma_0^h$ represents any potential effect driven by the difference in the average value, and it is an estimate for the composition effect. Given a value of x^* and noting that the composition effect is zero,[7] the estimate of the impulse response value from equation 3.3 becomes:

$$IRF_{h,\delta}^{LP-KOB} = \delta\hat{\beta}^h + \delta(x^* - \bar{x})\hat{\theta}^h \tag{3.2}$$

[7]This happens because $(x^* - \bar{x})$ is the same for the treatment and control group from the following equation:

$$E(y_1|x^*, \delta) - E(y_0|x^*, \delta = 0) = \delta\mu_1 + \delta[x^* - E(x)]\gamma_1 - \{\mu_0 + [x * -E(x)]\gamma_0\}$$

In our framework, the KOB decomposition is crucial for disentangling the *direct* a monetary policy shock on the dependent variables from the *indirect* effects transmitted by the change in banks' confidence. The model in a panel setup is given by:

$$\Delta_h y_{t-h,i} = \alpha_h MP_t^k + \beta_{h,i} MP_t^k CI_{t,i} + \Gamma_{h,i}(L) X_{t-1,i} + \epsilon_{t,h,i} \tag{3.3}$$

Where the left-hand-side variable is represented alternatively by the net percentage variation in terms of total assets of new loans issued to households, non-financial firms, and of new holdings in government bonds, corporate bonds, equity, and investment funds share for each i-th Euro Area country. MP_t^k is the monetary shocks identified with the monetary factors by Altavilla et al. (2018) that could be of conventional or unconventional according to k. $CI_{t,i}$ is the confidence index introduced in the regression in its plain form and interacted with monetary policy shocks. The interaction term allows the impact of the monetary shock to vary according to the degree of confidence. The $\Delta_h y_{t-h,i}$ prefix deserves special mention. After checking for the stationarity of the series, we decided to run a reverse local projection to better capture all the unconventional shocks, concentrated in the period 2014-2021. Changes in demand for loans may also be relevant for the supply of new loans; thus, following Albertazzi et al. (2021b), we control for the demand factor with a $country \times time$ variable and fixed effect. We also adopt the same control for financial side balance sheet variables to include exogenous effects that the Financial Stress Index may not capture. X_{t-1} is the set of lagged controls in which we include three lags of the dependent variable, the 10-year to 2-year Euro Area Government bond spread as a proxy for the slope of the yield curve, GDP and inflation forecast for the Euro Area, the dummy indicator for the implementations of macroprudential policy,he country-specific Financial Stress Index, and the sovereign exposure (only for marketable assets). The set of controls is also interacted with the monetary shock in contemporaneous value, omitted for simplicity in Equation 3.3, to control for the potential indirect effect of monetary shocks that do not depend on CI. Among the controls, we also include the confidence index as the contemporaneous and lagged variable to identify the confidence shock as in a VAR model (Plagborg-Møller and Wolf, 2021). All the variables are in deviation from their mean. The linear projections are estimated with fixed effects, and standard errors are robust in the sense of Driscoll and Kraay (1998). The estimation sample runs from 2003Q1 to 2021Q4.

In the linear projections in equation 3.3, the coefficients of interest are α_h and β_h. The following equation gives the IRF estimator:

$$IRF^{LP} h, \delta = \alpha^h \delta + \bar{C}I_{t,i} \beta^h \delta \tag{3.4}$$

where there is an element of non-linearity. The coefficient α_t represents the direct effect of the monetary policy shock, while the coefficient β_h, the non-linear element, represents the indirect effect or the state-dependent form. This coefficient captures the response of the balance sheet variable to the monetary shock generated by a concurrent variation on average of the banks' confidence.

3.4 The effect of confidence

In this Section, we assess the influence of monetary shocks on banks' balance sheet variables, emphasizing the differential effects of conventional and unconventional policy. This analysis enhances the existing literature in two primary ways. First, we illustrate the disparate effects of conventional and unconventional monetary policy on banks' balance sheets in terms of volume intermediated, both towards the real economy (loans to households and firms) and the financial sector (holdings in government bonds, corporate bonds, and equity shares and investment funds). Consistent with monetary policy theory, unconventional shocks substantially impact the balance sheet through the portfolio-substitution channel. Second, we demonstrate that banks' confidence significantly influences portfolio decisions, such as the issuance of new loans.

3.4.1 Linear model

Our analysis commences with a linear version of the model in Equation 3.3, where we exclude the interaction terms. The banking system within the Euro Area is pivotal in transmitting monetary stimulus, with bank loans constituting more than 50% of external financing, a stark contrast to the mere 25% in the US (Altavilla et al., 2020). Total loans comprise approximately 60%[8] of total assets on banks' balance sheets. At the same time, securities held account for 15-20% of the balance sheet. Government securities constitute 60% of the securities held, whereas equity instruments represent only 10%. We concentrate on a loosening monetary shock where a one-standard-deviation variation corresponds to a one-unit effect in the conventional and unconventional surprises. In the linear model, a conventional monetary easing results in a 0.5% decrease in net new loans issued to households and Non-Financial Corporations at a one-year horizon (4 quarters). Conversely, an unconventional shock reverses this effect, causing a increase of about 0.05% at the same one-year horizon. These responses align well with the existing literature. For instance, Albertazzi et al. (2021b) found a heterogeneous effect of conventional and unconventional monetary policy on the bank lending channel. Specifically, a decrease in the short-term rate leads to a steepening of the yield curve, boosting bank net interest income. On the other hand, an unconventional monetary easing is associated with a flattening of the yield curve, which erodes profitability (Brunnermeier and Koby, 2018). These opposing effects on the yield curve slope (Altavilla et al., 2021c) result in the heterogeneous effects observed

[8]34% of total assets if we consider only loans to households and firms

in Figure 3.4. Beyond the bank lending channel, our focus also extends to the portfolio-

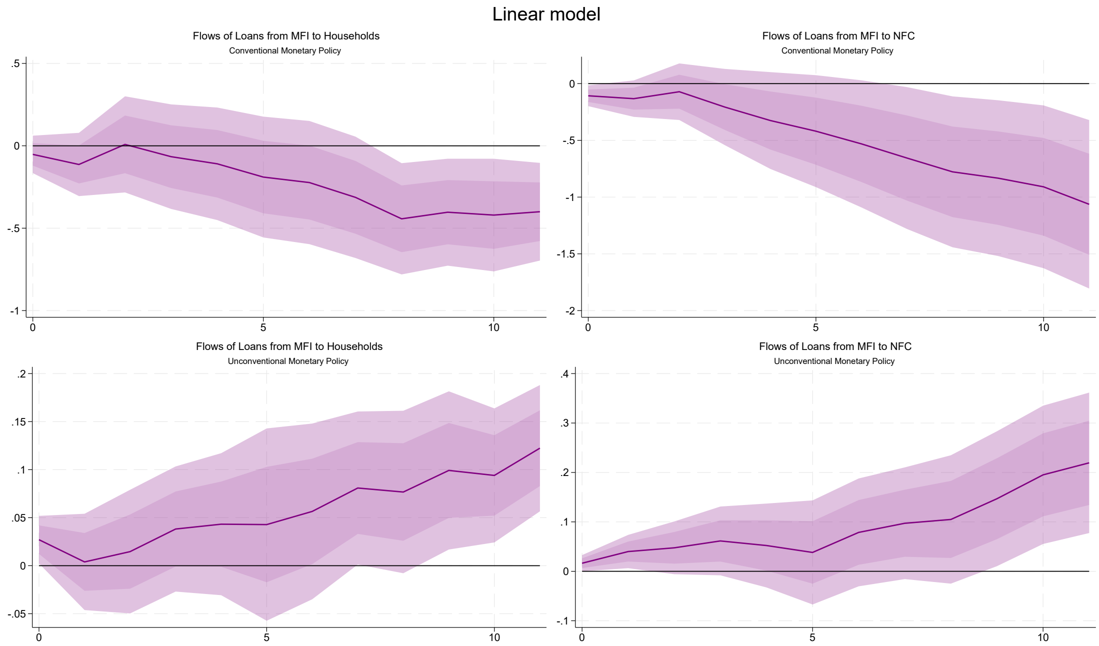

Figure 3.4. Impact of monetary policy shocks in the linear model. The figure shows the impact of both loosening conventional and unconventional monetary policy shocks identified by Altavilla et al. (2018) obtained from linear projections. The top-left and top-right panels refer to average quarterly change in newly issued loans to households following a conventional and an unconventional shock. The bottom-left and bottom-right panels refer to average quarterly change in newly issued loans to Non-Financial Corporations following a conventional and an unconventional shock. Confidence bands at 68% and 90% for 12 quarters (3 years) horizon.

balance channel. This channel operates on the principle that when investors encounter lower yields on secure assets, they shift their portfolio towards riskier assets. This shift reduces risk premiums and boosts real investment (Rajan, 2006). Consequently, portfolio rebalancing indirectly transmits the effects of safe asset purchases to broader financial market conditions. We investigate the efficacy of the portfolio rebalancing mechanism by investigating net new asset holdings of Euro Area banks. In Figure 3.5, we present the responses of net new asset holdings to conventional and unconventional easing shocks. Both shocks exert a significant, nearly symmetrical, influence on government and corporate bond holdings. However, net acquisition in equity and investment funds share appears to be more affected by unconventional easing monetary policy, which triggers a quite significant drop in the short-run (-0.5%) but tends to revert sing in the longer horizon. The effect of the unconventional shocks is not significant and it may depend on the fact that if the asset purchases have the desired effect of accelerating economic recovery and keep interest rate low, investors tend to react by bringing forward the date on which they expect the central bank to start raising its policy rates, thus postponing investment in equity shares when their price is inflated. Conversely, the significant response of holdings in corporate bonds (+0.25% at the one-year horizon) may reflect banks' intent to acquire assets eligible as collateral for monetary policy operations. If we narrow our focus to only QE shocks,

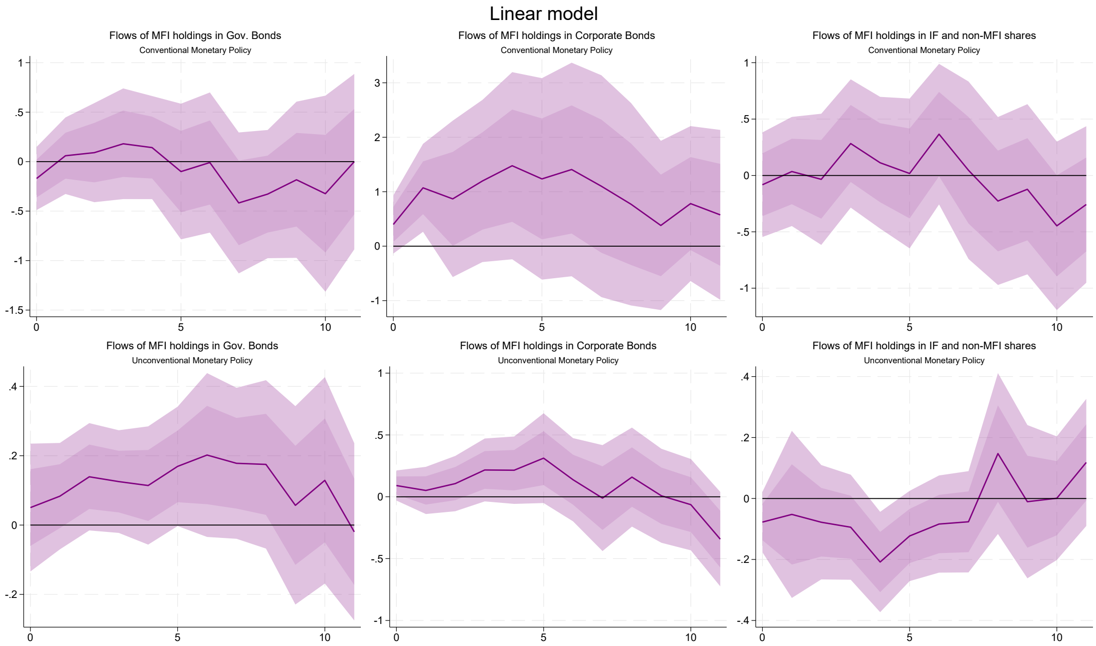

Figure 3.5. Impact of monetary policy shocks in the linear model. The figure shows the impact of both loosening conventional and unconventional monetary policy shocks identified by Altavilla et al. (2018) obtained from linear projections. From the top-left panel, average quarterly change in holdings in government bonds, corporate bonds, and equity shares and investment funds following a conventional shock. From the bottom-left panel average quarterly change in holdings in government bonds, corporate bonds, and equity follow an unconventional shock. Confidence bands at 68% and 90% for 12 quarters (3 years) horizon.

the results align with expectations and existing literature (see Figure 3.6). QE – working through suppression of long-term sovereign yields – explains the strong expansionary effect of QE on loan volumes. At the impact, we observe an increase in the issuance of new loans to households (+0.1%) that tends to increase over time. As documented in an important literature, the bank capital channel is a critical driver of loan creation (Kashyap and Stein 1995, Kishan and Opiela 2000 and Van den Heuvel et al. 2002). However, we observe a decline in government and in corporate bonds. This may depend on two factors: one is the scarcity effect triggered by the Corporate Sector Purchase Programme (CSPP) and the other one the sell-off in the euro area bond market was strengthened and made more protracted in time by the way the purchasing pattern under APP varied in response to market yields. Due to the stipulation that the ECB could not purchase securities whose yield to maturity fell below the DFR, duration extraction under the programme was self-reinforcing, with the average maturity of the purchased bonds becoming longer as market yields declined, thus amplifying market changes (Rostagno et al., 2021). The effect on equity shares and investment funds remain ambiguous.

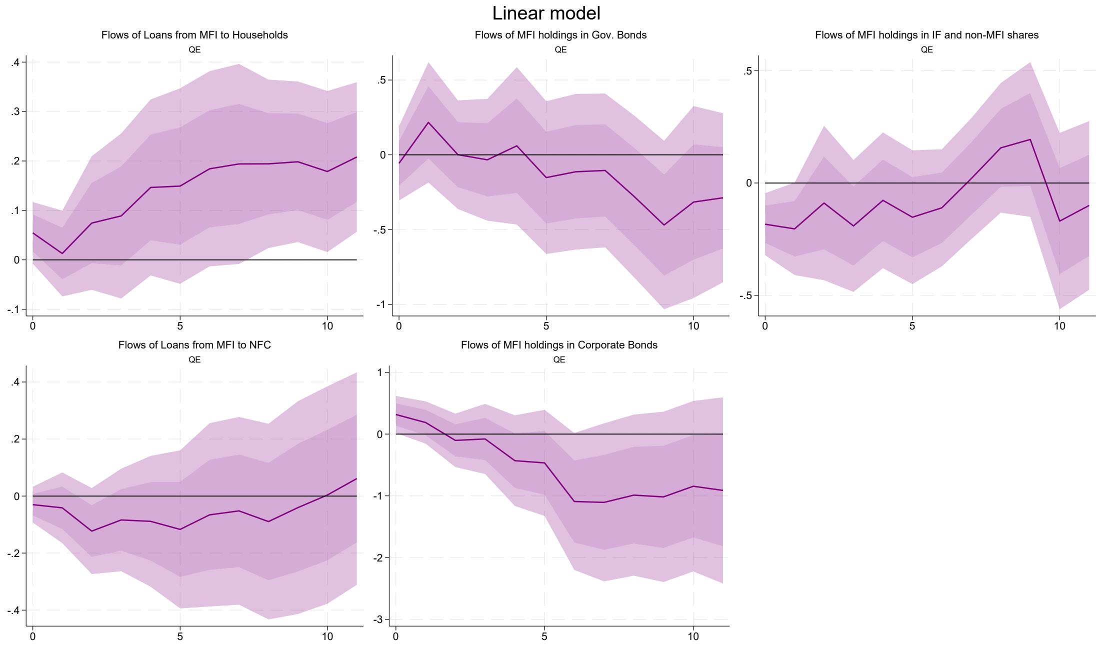

Figure 3.6. Impact of QE shock in the linear model. The figure shows the impact of QE monetary policy shock identified by Altavilla et al. (2018) obtained from linear projections. From the top-left corner, the responses refer to the average quarterly change in holdings in government and corporate bonds, equity shares and investment funds. Confidence bands at 68% and 90% for 12 quarters (3 years) horizon.

3.4.2 KOB augmented model

In the subsequent analysis, we focus on the model incorporating the KOB decomposition as outlined in Equation 3.3. For comparison, we present the IRF, as defined in Equation 3.3, alongside those derived from the linear model. We focus primarily on the effects of conventional and unconventional monetary easing and dissect these effects channel by channel. We initiate our discussion of the non-linear model by exploring the bank lending channel (Figure 3.7). The responses to new loans issued to households and Non-Financial Corporations exhibit a strikingly similar pattern. In the context of the conventional shock, the confidence index seems to amplify the fluctuations observed in the linear responses, leading to an additional increase of almost 1% in the issuance of new loans after one year. When considering the unconventional shock, the banks' confidence appears to mute the effect on new loans issued to households, but to really sustain the loans to Non-Financial Corporations (+0.75% at one-year horizon). Let us turn our attention to the portfolio-balance channel. Here, we observe a split in behaviour: in some cases, confidence amplifies

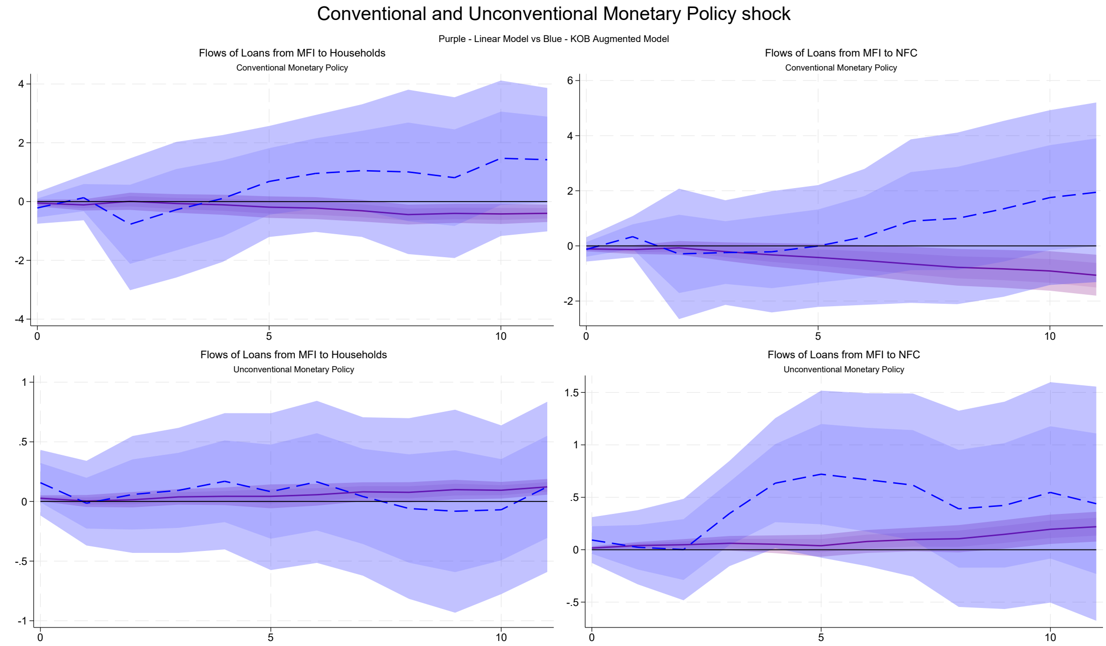

Figure 3.7. Impact of monetary policy shocks in the non-linear model. The figure shows the impact of loosening conventional and unconventional monetary policy shock identified by Altavilla et al. (2018) obtained from non-linear projections. The top-left and the bottom-left panels refer to newly issued loans to households in percentage of total assets following a conventional and an unconventional shock. The top-right and the bottom-right panels refer to newly issued loans to Non-Financial Corporations in the percentage of total assets following a conventional and an unconventional shock. Confidence bands at 68% and 90% for 12 quarters (3 years) horizon.

the effects of the shock, while in others, it dampens them. The left panels of Figure 3.8 show the responses of net government bond acquisitions. When considering confidence, the impact of a conventional shock is more pronounced, but it is less significant in the case of an unconventional shock. Given the dominant role of government bonds under the asset purchase program, confidence does not appear to play a significant role.

The central panels of Figure 3.8 show the responses of net corporate bond acquisitions. When confidence is considered, a conventional shock initially stimulates new acquisitions, easing financial conditions, but this effect turns negative over time due to the previously described sell-off. For unconventional shocks, the results remain muted when considering banks' confidence.

Finally, the right panels present the results for equity shares and investment fund holdings. Banks' confidence amplifies the effects of both conventional and, particularly, unconventional monetary policy shocks, highlighting the expected shift towards riskier assets under the portfolio-balance channel.

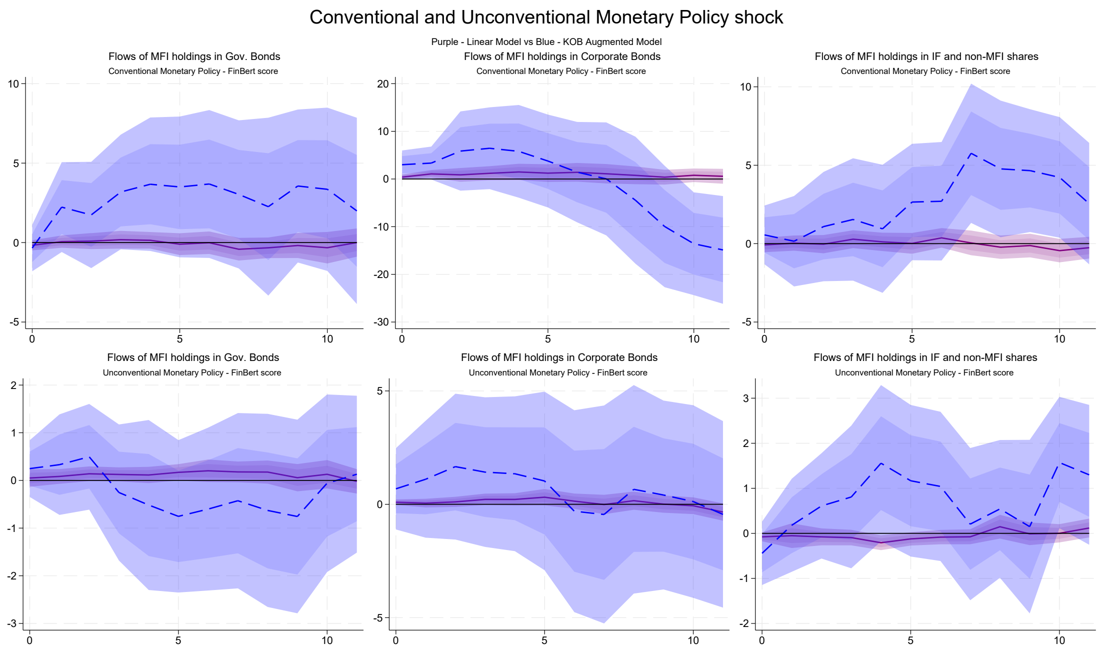

Figure 3.8. Impact of monetary policy shocks in the non-linear model. The figure shows the impact of loosening conventional and unconventional monetary policy shock identified by Altavilla et al. (2018) obtained from non-linear projections. The responses of government bond holdings, corporate bond holdings, equity shares, and investment funds to a conventional shock are from the top left-corner. The responses of government bond holdings, corporate bond holdings, equity shares, and investment funds to an unconventional shock are from the bottom-left corner. Confidence bands at 68% and 90% for 12 quarters (3 years) horizon.

3.4.3 Does bank sentiment play a role in the transmission mechanism?

Utilizing Equation 3.3, we can further investigate the state-dependent impact of the shock. Specifically, we calculate the responses for a grid of 10 evenly spaced values of the confidence index within the interval of -1 and 0 and between 0 and 1, representing the range of the confidence index. Darker lines correspond to higher confidence values. Figure 3.9 displays what we might term the standard effect in the transmission mechanism of both the bank lending channel and the portfolio channel.[9] When SI's confidence is high, the expansionary effect of the conventional loosening shock is approximately 4% for the bank lending channel. It is interesting to note that in the portfolio balance channel the conventional monetary policy is more effective when confidence is low, while a strong negative effect is observed when confidence is high. When confidence is already high a further reduction in interest rate may induce banks to search for yield in non-EU assets (Fratzscher et al., 2018), thus implying more itnernational spillover rather than domestic effects. The subsequent step is to concentrate on the unconventional monetary shock.

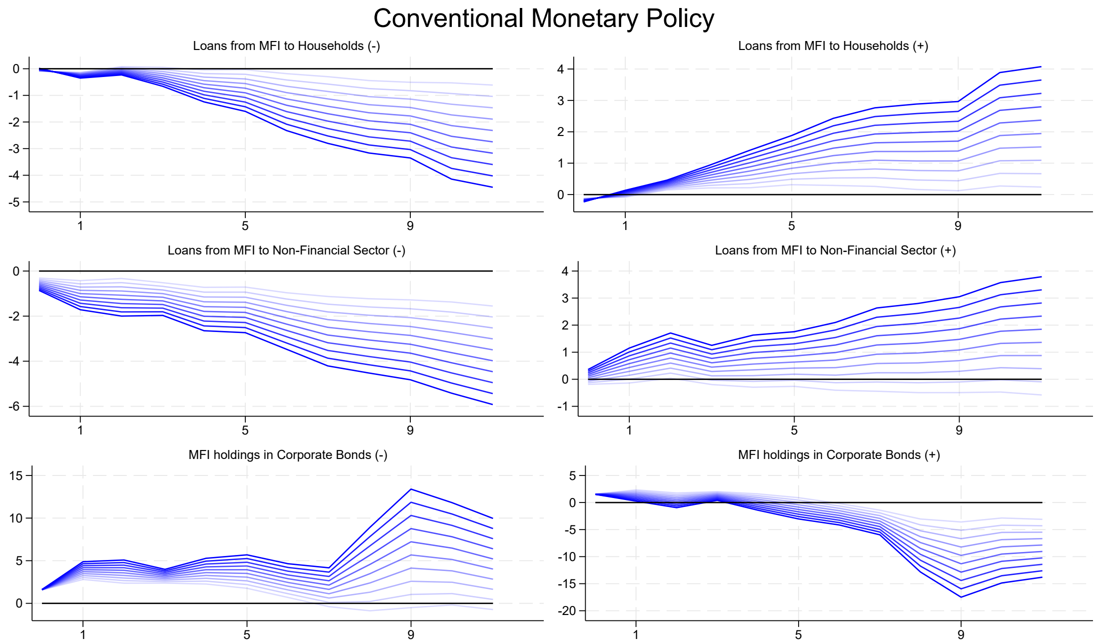

Figure 3.9. Influence of banks confidence in transmission mechanism. The figure illustrates how the impact of a conventional monetary shock on banks' balance sheet positions varies depending on the banks' confidence response to it. The responses are obtained by conditioning on different SIs responses in the KOB decomposition.

In this case, the magnitude of the responses is lower by about 100 basis points, and we reverse the sign of the response. Considering the bank lending channel, unconventional monetary policy supports issuing new loans to household and Non-Financial Corporations

[9] We consider only corporate bonds since they are directly targeted in the APP

when banks' confidence is high. Also the magnitude of the portfolio channel is lower, but in this case positive when confidence is high. The hump-shaped response cope with the above described mechanism of the sell-off of corporate bonds. Another valuable candidate

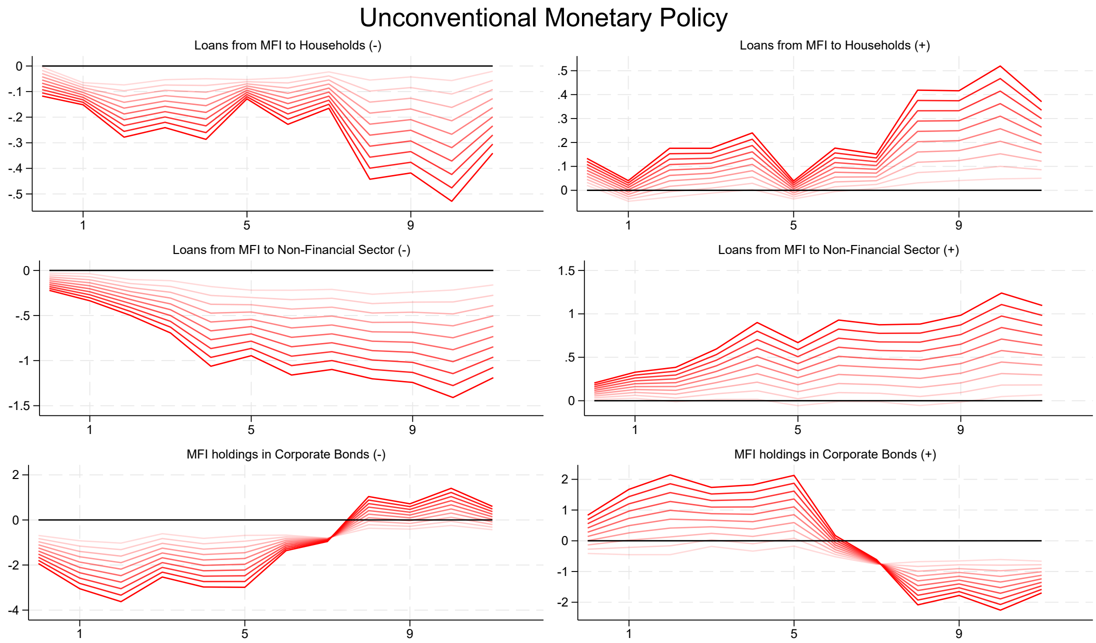

Figure 3.10. Influence of banks confidence in transmission mechanism. The figure shows how the impact of an unconventional monetary shock on banks' balance sheet positions varies depending on the bank's confidence response to it. The responses are obtained by conditioning on different SIs responses in the KOB decomposition.

methodology for this analysis would have been the one proposed by McKay and Wolf (2023). McKay and Wolf propose a methodology that constructs policy counterfactuals using empirical evidence on multiple distinct policy shocks, aiming to predict the consequences of changes in policy rules within a dynamic macroeconomic environment. Their approach is designed to address the limitations posed by the Lucas critique, which suggests that policy evaluation based on historical data may not be valid if the policy change alters the behavior of economic agents. However, the McKay's methodology offers a robust framework for evaluating dynamic policy counterfactuals, but it is not a direct substitute of the KOB decomposition, rather a complement. Our research question is that the banks' confidence levels in which a monetary policy intervention occurs will influence the transmission channel. That is, the level of banks' confidence modulates the response of the bank lending and portfolio channel in monetary policy. The KOB decomposition in a time-series context leads to a very natural empirical framework for studying monetary-banks confidence interactions and allows us to decompose the typical macro impulse response function to quantify how the transmission mechanism of monetary policy may vary with banks confidence.

3.5 Robustness and extensions

Sentiment Index Our findings may depend on computing the bank's confidence index with FinBERT. As discussed in Section 3.2, we also compute the Sentiment Index with the mainstream word counting technique based on the Loughran and McDonald (2011) Dictionary. Figure 3.11 presents the estimates for the conventional shock using the confidence index derived from the LM Dictionary. These estimations corroborate the findings of the baseline model for both the banking and the portfolio channel. Figure 3.12

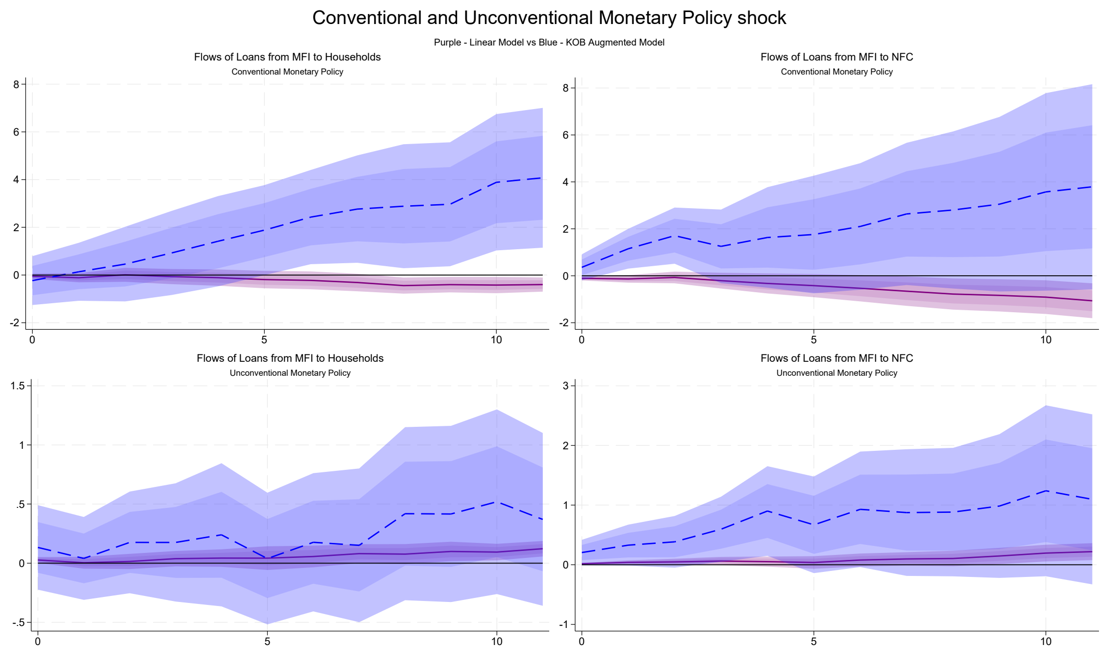

Figure 3.11. Impact of conventional and unconventional monetary shock in the non-linear model. Alternative specification. The figure illustrates the impact of loosening conventional and unconventional monetary policy shock identified by Altavilla et al. (2018) obtained from non-linear projections. The CI is derived using the LM Dictionary. Confidence bands at 68% and 90% for 12 quarters (3 years) horizon.

displays the estimates for the unconventional shock using the confidence index derived from the LM Dictionary. The results remain robust in terms of both direction and magnitude.

Monetary policy Another important point in the analysis is to what extent the results depend on the monetary policy factors identified by Altavilla et al. (2019a). We replicate the analysis using the methodology by Inoue and Rossi (2021) to investigate this issue. Inoue and Rossi (2021) propose a new method called functional forms that identify monetary policy shocks in the shift of the entire function that defines the yield curve.

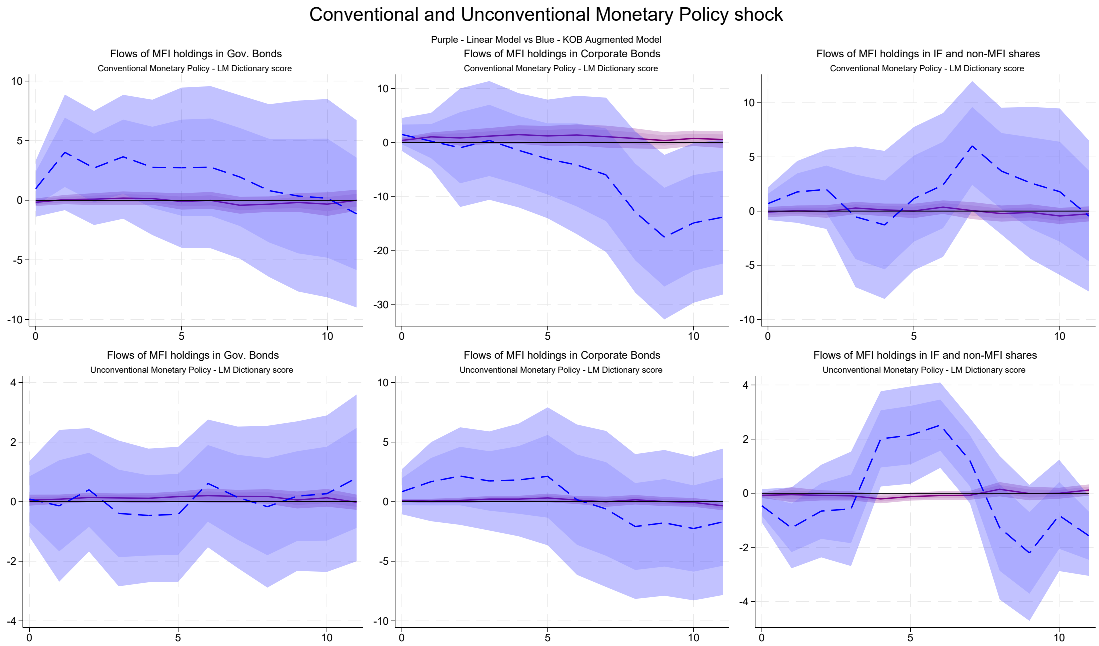

Figure 3.12. Impact of conventional monetary shock in the non-linear model. Alternative specification. The figure shows the impact of loosening unconventional monetary policy shock identified by Altavilla et al. (2018) obtained from non-linear projections. The CI is derived using the LM Dictionary. Confidence bands at 68% and 90% for 12 quarters (3 years) horizon.

The conventional and unconventional shocks with a time-varying high-frequency event study rely on the coefficients on the yield curve based on the Nelson and Siegel (1987) model. We get the Euro Area yield curve coefficients for all rated bonds from the ECB SDW. We instrument the coefficient β_0[10] with high-frequency changes in the one-month, three-month, six-month, one-year and two-year bonds for conventional monetary policy and the coefficient β_2 with three-year, five-year, ten-year OIS for unconventional monetary policy. In order to accurately characterize both conventional and unconventional monetary policy shocks, we establish an indicator variable for the state of monetary policy. This variable is set to 1 when the policy rate (EONIA) exceeds 0.75. The high-frequency data comes from the Altavilla et al. (2019a) dataset. The results are shown in Figure 3.13 for

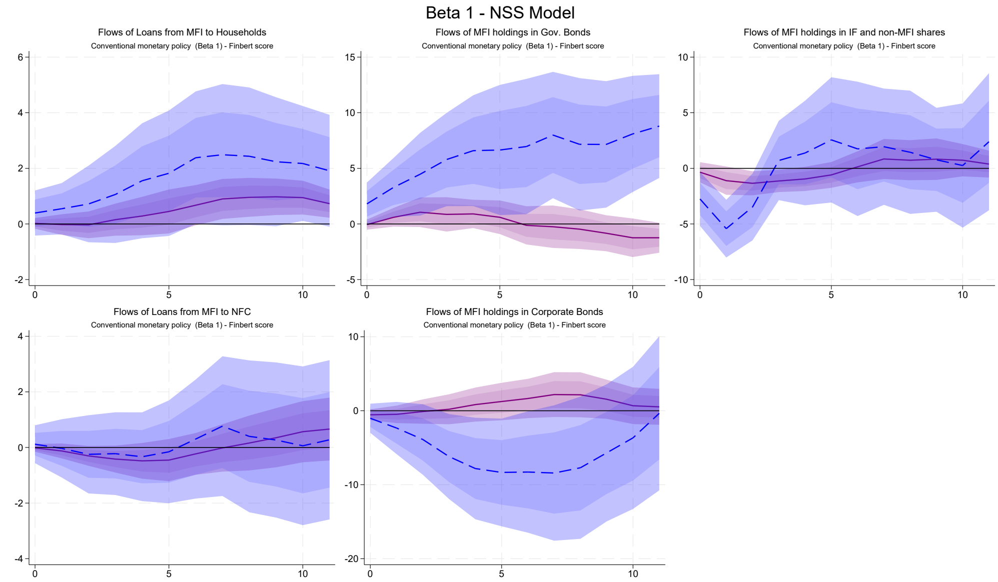

Figure 3.13. Impact of conventional monetary shock in the non-linear model. Alternative specification. The figure shows the impact of loosening conventional monetary policy shock identified as in Inoue and Rossi (2021) obtained from non-linear projections. Confidence bands at 68% and 90% for 12 quarters (3 years) horizon.

conventional shocks and in Figure 3.14 where we plot only the KOB augmented IRF for the sake of clarity. The results hold either with an alternative monetary policy shock identification.

BLS A third conceptual extension we would like to discuss is limited to issuing new loans. In the baseline specification, we control for variation in the loan demand with the *country* $\times$ *time* interaction as in Albertazzi et al. (2021b). In this alternative specification, we drop the *country* $\times$ *time* and employ the variation in the demand for loans by households

[10] β_0 and β_1 both represent the short-term part of the yield curve and are strictly correlated. The regression is sufficient to use one of the two (Inoue and Rossi, 2021). See Section C.4 for further details.

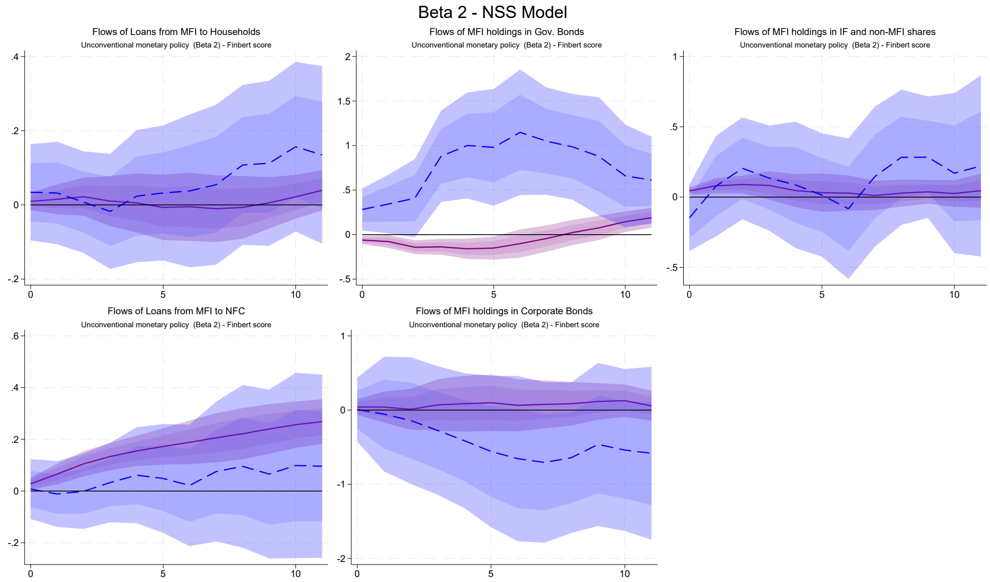

Figure 3.14. Impact of unconventional monetary shock in the non-linear model. Alternative specification. The figure shows the impact of loosening unconventional monetary policy shock identified as in Inoue and Rossi (2021) obtained from non-linear projections. Confidence bands at 68% and 90% for 12 quarters (3 years) horizon.

and firms obtained from the ECB BLS dataset (e.g. Altavilla et al. (2019b) and Altavilla et al. (2021a)). Results are depicted in Figure 3.15.

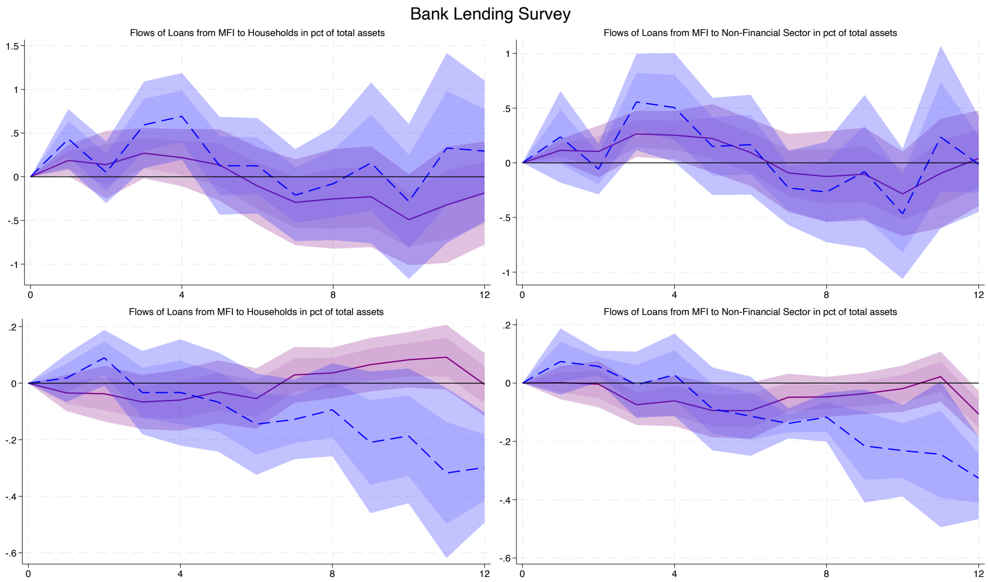

Figure 3.15. Impact of conventional monetary shock in the non-linear model. Alternative specification. The figure shows the impact of loosening unconventional monetary policy shock identified by Altavilla et al. (2018) obtained from non-linear projections. We employ BLS data to control for the demand for loans. Confidence bands at 68% and 90% for 12 quarters (3 years) horizon.

3.6 Conclusion

This chapter studies the role of banks' confidence in transmitting monetary policy. In the initial phase, we demonstrate that conventional and unconventional monetary policies have heterogeneous impacts on banks' intermediated volumes. Specifically, conventional shocks trigger an expansionary effect on the volume of new loans issued, following a steep yield curve that enhances profitability. However, unconventional shocks tend to increase more the volume of new loans to Non-Financial Corporations. The portfolio balance channel also exhibits more pronounced effects following unconventional shocks, as predicted by existing literature.

However, we employ KOB augmented LP where monetary shocks interact with a bank's confidence index to explore the mechanisms underlying banks' portfolio decisions. We derive the confidence index through sentiment analysis of banks' earnings conference call transcripts. Utilizing the KOB decomposition, we examine how the level of banks' confidence influences the propagation of a shock. The analysis suggests that when confidence is low, unconventional monetary operations can foster the issuing of new loans and a search for yield behaviour.

Our findings underscore that the limitations in the pass-through of monetary policy are, to a certain extent, dependent on banks' confidence, which may undermine the effectiveness of the portfolio-balance channel if not correctly considered.

Appendix C

Additional material

C.1 BERT Architecture

Following Devlin et al. (2018), we outline the primary features of BERT and describe its structure. BERT is a language model that employs a layered configuration of bidirectional Transformers. The Transformer (Vaswani et al., 2017) is a deep neural network architecture designed for encoding-decoding that handles sequential information. Transformers avoid locality bias as their self-attention architecture takes the entire sentence as input. Additionally, Transformers are efficient during training due to their suitability for parallelization. BERT utilizes the Transformer's encoder to process the input sequence and generate word embeddings encapsulating contextual information. BERT's key innovation lies in its profoundly bidirectional pre-training instead of unidirectional training.

Input/Output Representations To equip BERT to handle a range of downstream tasks, the input representation is designed to unambiguously represent both a single sentence and a pair of sentences (e.g., a Question and Answer pair) in one token sequence. Therefore, a "sequence" is the input token for BERT, which could be a single or two combined sentences. We employ WordPiece embeddings with a 30,000-token vocabulary. The first token of every sequence is always a unique classification token (`[CLS]`). The final hidden state corresponding to this token is the aggregate sequence representation for classification tasks. Sentence pairs are combined into a single sequence. We differentiate the sentences in two ways. Firstly, we separate them with a unique token (`[SEP]`). Secondly, we add a learned embedding to every token indicating whether it belongs to sentence `A` or sentence `B`. As depicted in Figure 3.1, E denotes input embedding, the final hidden vector of the special `[CLS]` token as $C \in R^H$, and the final hidden vector for the $i-th$ input token as $T_i \in R^H$. The input representation is constructed by summing the corresponding token, segment, and position embeddings, as shown in Figure C.1.

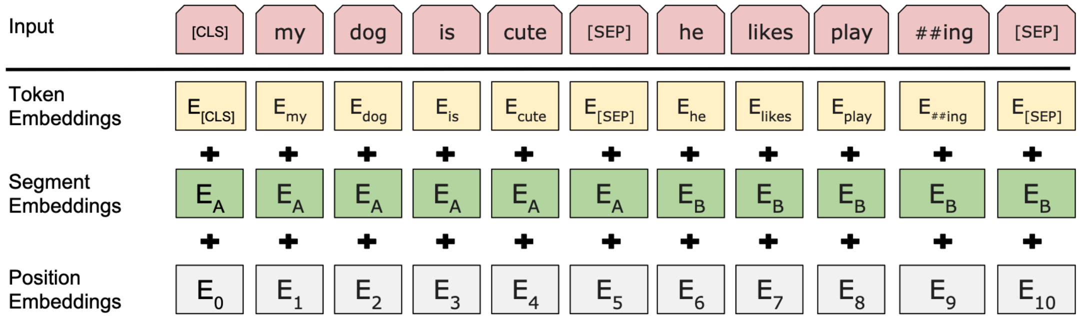

Figure C.1. BERT input representation. The figure represents the architecture of BERT when detecting input. Devlin et al. (2018).

Pre-training The model is pre-trained to understand language through two simultaneous unsupervised tasks:

- Hidden word prediction: BERT learns to predict hidden words by taking sentences with 15% of the words masked by `[MASK]`-tags and training to complete sentences based on the remaining words. The "masked language model" (MLM) randomly masks some of the tokens from the input, and the objective is to predict the original vocabulary ID of the masked word based only on its context.
- Next sentence prediction: The model is given two sentences and learns whether the second sentence logically follows the first sentence or if it is a random sentence.

BERT is trained on articles in English Wikipedia (2,500M words) and BookCorpus (800M words).

Fine-tuning BERT can be fine-tuned to solve various downstream tasks that require language understanding. For each task, the task-specific inputs and outputs are integrated into BERT and all the parameters are fine-tuned end-to-end. Apart from output layers, the same architecture is used in pre-training and fine-tuning, with the difference that the fine-tuning phase is less computationally demanding. In this regard, BERT can be used for translation, named entity recognition, and sentiment classification tasks.

FinBERT Given BERT's architecture, the model can be conveniently fine-tuned for domain-specific tasks, such as financial text, to enhance its performance on financial sequence classification tasks. This is achieved by further training the BERT language model in the finance domain, using a large financial corpus, and fine-tuning it for financial sentiment classification. The Financial PhraseBank by Malo et al. (2014) is utilized for fine-tuning. Please refer to the paper by Araci (2019) for more comprehensive details.

C.2 Granger causality test

By exploiting the Stata package `xtgcause`, that test for Granger non causality in a panel set-up, we observe that neither conventional (Table C.1) or unconventional monetary policy (Table C.2) Granger-cause banks confidence at 1%.

Hypotheses:

H0: *Conventional MP* does not Granger-cause *FinBERT score*.

H1: *Conventional MP* does Granger-cause *FinBERT score* for at least one panel (EUA country).

Table C.1. Dumitrescu & Hurlin (2012) Granger non-causality test results

Test Statistic	**Value**
Lag order	4
W-bar	4.2028
Z-bar	0.2028
Z-bar tilde	0.0357
P-value (Z-bar)	0.8393
P-value (Z-bar tilde)	0.9715

Hypotheses:
H0: *Unconventional MP* does not Granger-cause *FinBERT score*.
H1: *Unconventional MP* does Granger-cause *FinBERT score* for at least one panel (EUA country).

Table C.2. Dumitrescu & Hurlin (2012) Granger non-causality test results

Test Statistic	**Value**
Lag order	4
W-bar	4.4385
Z-bar	0.4385
Z-bar tilde	0.2490
P-value (Z-bar)	0.6610
P-value (Z-bar tilde)	0.8033

C.3 List of SIs

The subsequent list enumerates the banks classified as Significant Institutions along with their ISIN identifier, for which we have obtained the earnings call transcripts from Refinitiv Eikon to conduct the sentiment analysis:

- Austria
  - Erste Group Bank AG - AT0000652011
- Belgium
  - KBC Group NV - BE0003565737
- Germany
  - Commerz Bank - DE000CBK1001
  - Deutsche Bank - DE0005140008
- Spain
  - Santander - ES0113900J37
  - BBVA - ES0113211835
- France
  - BNP Paribas - FR0000131104
  - Crédit Agricole - FR0000045072
- Greece
  - National Bank of Greece SA - GRS003003035
- Italy
  - Intesa San Paolo - IT0000072618
  - Unicredit - IT0005239360
- The Nederlands
  - ING - NL0011821202
- Portugal
  - Millennium BCP - PTBCP0AM0015

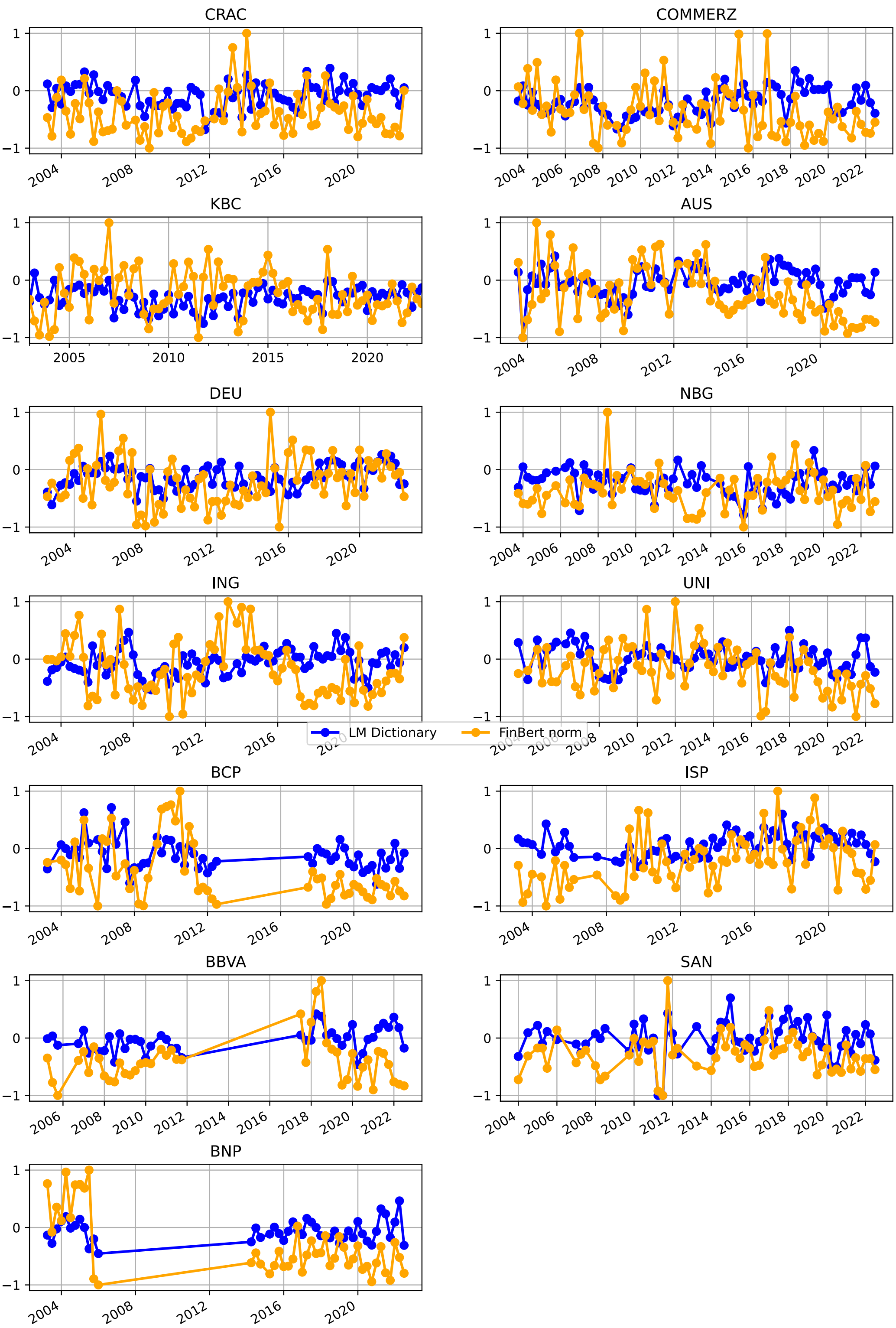

Figure C.2. Sentiment scores. Sentiment scores computed via LM Dictionary - orange line and FinBERT - blue line.

C.4 The Nelson-Siegel Model

In the model proposed by Nelson and Siegel (1987), a function of three time-varying parameters characterizes the yield curve at any given time. The model is as follows:

$$y_t(\tau) = \beta_{0,t} + \beta_{1,t}\left(\frac{1 - e^{-\lambda\tau}}{\lambda\tau}\right) + \beta_{2,t}\left(\frac{1 - e^{\lambda\tau}}{\lambda\tau} - e^{-\lambda\tau}\right) \tag{C.1}$$

Here, $y_t(\tau)$ represents the yield to maturity at time t for maturity τ, $\beta_{0,t}$ is the latent level, $\beta_{1,t}$ is the slope, and $\beta_{2,t}$ is the curvature factor. As is customary in the literature, the conventional shock impacts the short-term portion of the yield curve, leaving the medium-long run unaffected. The opposite is true for unconventional shocks. The functional monetary policy shocks can be defined as:

$$\epsilon_{f,t}(\tau) \equiv \Delta y_t(\tau) \cdot d_t \tag{C.2}$$

In this equation, d_t is a dummy variable identifying the days when monetary shocks occur, and Δ denotes time differences.

Regarding economic interpretation, $\beta_{0,t}$ can be viewed as a level factor as it uniformly increases at all maturities. $\beta_{1,t}$ can be interpreted as the short-term factor (or the slope) since it equals unity when $\tau = 0$ and decays as $\tau \to \infty$. Lastly, $\beta_{2,t}$ is the medium-term factor as it equals zero when $\tau = 0$ and then increases and decreases as a function of τ. Therefore, $\beta_{1,t}$ describes conventional monetary policy and $\beta_{2,t}$ the unconventional shock. However, given that $\beta_{0,t}$ and $\beta_{1,t}$ are serially correlated, only one can be used.

The methodology employed at the ECB for the estimation of the yield curve is an extension by Svensson (1994):

$$y_t(\tau) = \beta_{0,t} + \beta_{1,t}\left(\frac{1 - e^{-\lambda\tau_1}}{\lambda\tau_1}\right) + \beta_{2,t}\left(\frac{1 - e^{\lambda\tau_1}}{\lambda\tau_1} - e^{-\lambda\tau_1}\right) + \beta_{3,t}\left(\frac{1 - e^{\lambda\tau_2}}{\lambda\tau_2} - e^{-\lambda\tau_2}\right) \tag{C.3}$$

This model is the same as the one by Nelson and Siegel (1987) but augmented with the $\beta_{3,t}$ coefficient. Thus, the interpretation of the first three coefficients remains the same.

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