Three Essays in Monetary Policy

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

This thesis examines critical and timely issues in monetary policy, focusing on balance sheet strategies, forward guidance, and commodity price dynamics. The first essay employs a New Keynesian Dynamic Stochastic General Equilibrium (NK-DSGE) model calibrated to Canadian data to evaluate central bank balance sheet policies during crises marked by simultaneous adverse shocks. Comparing five policy scenarios—including corridor/floor systems, quantitative easing (QE), tightening (QT), and tapering—the findings show that QE during crises followed by QT in recovery optimizes outcomes under pre-crisis corridor systems, while maintaining a floor during crises with post-crisis bond sales is superior under pre-crisis floor systems. Both strategies enhance macroeconomic stability, inflation control, and welfare.

The second essay addresses the qualitative dimension of monetary policy, particularly forward guidance, by proposing a novel identification strategy using sentiment analysis of news articles around Federal Open Market Committee (FOMC) meetings. Quantifying sentiment shifts related to interest rate guidance, balance sheet policies, and economic outlooks, it demonstrates that media-driven sentiment aligns with actual policy impacts, offering insights into expectation formation and financial market transmission. This approach mitigates endogeneity concerns in existing literature while disentangling forward guidance into its distinct components.

The third essay investigates the underexplored link between U.S. unconventional monetary policy and commodity price surges post-pandemic. Combining vector error correction models (VECM), structural VARs (SVAR), and event studies, it shows that a 1 percentage point (pp) rise in the effective federal funds rate (EFFR) reduces commodity prices by 3.66%, while a 1 pp cut in the proxy funds rate (PFR, representing unconventional policies) increases them by 47.65%. Short-term effects are pronounced: contractionary EFFR shocks drive a 5% decline, while expansionary unconventional shocks yield a 20% rise within six months. Hawkish forward guidance sentiment further amplifies speculative behavior, underscoring unconventional policy's role in commodity market volatility.

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Table of Contents

List of Figures

List of Tables

General Introduction

Monetary policy is a cornerstone of economic stability, shaping the course of inflation, employment, and economic growth. Central banks, through their policy decisions, play a critical role in moderating economic cycles, maintaining financial stability, and fostering an environment for sustainable growth. This importance has led to substantial research dedicated to unraveling the complex impacts of monetary policy across diverse economic arenas, from broad macroeconomic indicators to the subtle behavior of asset prices and financial markets. This thesis contributes to this rich body of knowledge by examining how monetary policy influences economic fundamentals and financial markets, offering new insights into the mechanisms through which policy decisions reverberate through the economy.

In the recent COVID-19 pandemic, central banks faced the unprecedented challenge of managing both demand and supply shocks. These dual shocks have emphasized the need for central banks to adopt flexible and robust frameworks, particularly in using balance sheet tools to maintain stability. In Chapter 1, titled **"Central Bank Balance Sheet Policies Amidst Simultaneous Demand and Supply Shocks,"** I address this challenge by employing a NK-DSGE model to evaluate the effectiveness of various central bank strategies in managing inflation and stabilizing output under dual-shock conditions. This analysis compares corridor and floor systems and considers different balance sheet policies, including quantitative easing (QE) and quantitative tightening (QT), to determine the optimal policy responses during crises. The results show that the most effective approach varies by pre-crisis framework: for a pre-crisis corridor system, QE during the crisis followed by QT in recovery yields the best outcomes, while for a floor system, maintaining ample reserves during the crisis and reducing the balance sheet afterward is optimal. These findings offer guidance for policymakers managing economic disruptions and contribute to the debate on the optimal monetary policy framework for resilience and stability.

As central bank transparency becomes a foundational aspect of monetary policy, understanding the public's interpretation of these communications is essential for assessing policy impacts. Traditional methods struggle to capture the qualitative nuances of these communications as filtered through media. In Chapter 2, **"News Sentiments and the Identification of Monetary Policy Shocks,"** I bridge this gap by evaluating how media sentiment surrounding FOMC meetings reflects and shapes public and market perceptions of the Federal Reserve's actions. This chapter introduces a refined dictionary-based sentiment analysis, focusing on key policy dimensions—interest rate guidance (IRG), balance sheet policies (BSP), and economic outlook (EOA)—to capture sentiment shifts and their alignment with actual policy impacts. This approach uncovers how media-driven sentiment shapes financial market dynamics, offering a new method to trace and identify sentiment shocks as they develop through media narratives, while providing insights into the Fed's role in steering public and market expectations.

The reach of U.S. monetary policy extends beyond traditional financial markets, impacting global commodity prices, especially in periods of economic upheaval. Chapter 3, titled **"U.S. Monetary Policy and Commodity Prices: An Empirical Analysis,"** examines the relatively underexplored relationship between U.S. unconventional monetary policy and commodity prices. Using a structural vector autoregressive model, a vector error correction model, and an event study approach, the results show significant long-run relationships: conventional monetary policy, represented by a 1 percentage point (pp) increase in the effective federal funds rate (EFFR), is associated with a 3.66 percent drop in commodity prices, while unconventional monetary policy, represented by a 1 pp decrease in the proxy funds rate (PFR), is linked to a 47.65 percent rise in commodity prices. The results also indicate that a contractionary conventional monetary policy shock (a 1 pp increase in the EFFR) leads to a persistent 5 percent decline in commodity prices in the short term, while an expansionary unconventional monetary policy shock (a 1 pp decrease in the PFR) results in a 20 percent increase in commodity prices within six months. Additionally, the findings reveal that unconventional monetary policy was a key driver behind the surge in commodity prices during the pandemic. The event study underscores the significant impact of monetary policy sentiment shocks, particularly hawkish interest rate guidance, on market expectations and speculative behavior.

These chapters provide a thorough examination of central bank monetary policy impacts, combining theoretical modeling, empirical analysis, and the perspective of media sentiment. The research demonstrates how monetary policy influences the economy, including its effects on financial markets, public perception, and commodity prices, particularly during crises. By exploring these impacts from multiple angles, this thesis enhances understanding of the mechanisms underlying monetary policy effectiveness. It emphasizes the importance of adaptable strategies in response to changing economic conditions and the role of media in shaping market perceptions of policy actions.

Chapter 1

Central Bank Balance Sheet Policies Amidst Simultaneous Demand and Supply Shocks: A DSGE Analysis

1.1 Introduction

Following the global financial crisis and more recently, the COVID-19 pandemic, the resilience of economies to adverse shocks has become a topic of great interest and concern. Central banks worldwide have been tasked with implementing effective policies to cushion the impact of simultaneous demand and supply shocks on key macroeconomic indicators. Among these measures, balance sheet policies have proven essential, with central banks employing unconventional tools such as large-scale asset purchases (LSAPs) to stabilize financial markets, ensure credit availability, and support the broader economy. This approach has led several central banks—including the Reserve Bank of New Zealand, the Reserve Bank of Australia, and the Bank of Canada (BoC)—to adopt a floor system for managing interest rates.

The floor system, introduced by the Federal Reserve after the financial crisis, sets interest rates by maintaining abundant reserves and a fixed floor rate, contrasting with the corridor system, which actively manages rates within a target range. The corridor system offers precise control over short-term rates and fosters interbank lending, enhancing market competitiveness, but requires intensive liquidity management, making it less flexible during economic stress. In contrast, the floor system simplifies operations by anchoring rates through reserves, reducing the need for constant interventions and proving effective during periods of quantitative easing (QE). However, its reliance on excess reserves can weaken interbank activity and distort market pricing. Central banks weigh these trade-offs based on their operational priorities and economic objectives.[1]

As inflationary pressures rise alongside economic recovery, central banks are reassessing their monetary policy frameworks, with some considering a shift back to the corridor system for finer control over short-term interest rates. The BoC, for example, initially implemented the floor system during the financial crisis but later reverted to the corridor by withdrawing reserves. Following the extensive reserve injections of the pandemic, however, the BoC has chosen to maintain the floor system, appreciating its operational simplicity. In contrast, central banks like Sveriges Riksbank continue to favor the corridor system for its closer alignment with market rates, while the Bank of England (BoE), currently using the floor system, has begun reducing reserves as it contemplates a gradual transition back to the corridor. This range of approaches underscores an ongoing debate about the ideal framework for long-term stability, balancing the simplicity of the floor system with the more precise rate control offered by the corridor.

The discussion underscores a critical question: Which central bank balance sheet strategy optimally stabilizes inflation, maximizes economic welfare, and fosters post-crisis recovery under simultaneous demand and supply shocks? This question remains unresolved, as central banks grapple with choosing the most effective post-crisis strategy to foster resilience and economic stability. Despite ongoing debates, there is limited formal analysis using rigorous theoretical models to evaluate the effectiveness of these frameworks under post-crisis conditions. Identifying the optimal monetary policy approach is crucial for guiding future responses to economic shocks and ensuring long-term financial stability.

To my knowledge, no prior research has evaluated the effectiveness of different central bank balance sheet (CBBS) strategies in addressing simultaneous demand and supply shocks. This study is the first to examine and compare various CBBS policies specifically in the context of the COVID-19 pandemic using a DSGE model. I build upon recent developments in the DSGE modeling literature focused on monetary policy frameworks (e.g., Gertler and Kiyotaki, 2010; Curdia and Woodford, 2011; Gertler and Karadi, 2011; Chen et al., 2016; Gertler and Karadi, 2018; Arce et al., 2020).

This research advances traditional comparisons of corridor and floor systems by examining both central banks' initial and follow-up responses to shocks, offering a comprehensive view of policy behavior through crisis phases. Unlike studies focused solely on demand shocks (e.g., Arce et al. (2020)), I model the dual-shock nature of the COVID-19 pan-

[1] A detailed explanation of monetary policy implementation can be found in Appendix A.

demic by incorporating both demand and supply disruptions.[2] This approach reflects the pandemic's complex economic impact, where reduced consumer spending and significant production constraints, such as labor shortages and supply chain breakdowns, interact, providing a more thorough assessment of central bank adaptability under multifaceted pressures.

Building on Arce et al. (2020), I enhance the model by introducing a total factor productivity (TFP) shock to represent the pandemic's supply-side disruptions and by integrating household deposits into the utility function to capture liquidity benefits that influence consumption and savings choices. This addition reflects the increased liquidity preference observed during the crisis, crucial for understanding monetary transmission under severe constraints.[3] Additionally, I modify the Taylor rule to include output deviations, aligning the model with central banks' focus on stabilizing output during COVID-19.[4] By targeting Canada—a unique case transitioning between a corridor and floor system—this study provides insights within a distinct monetary policy context while contributing a robust framework adaptable to central bank strategies globally.

I analyze five scenarios, each representing a distinct central bank approach to managing monetary policy. The first scenario considers a traditional response without unconventional policies, operating as a pure corridor system. The second scenario explores a pure floor system, where a large initial balance sheet is maintained without using unconventional tools. The third examines outcomes under a floor system framework that incorporates quantitative tightening (QT) through bond sales to reduce the balance sheet. In the fourth scenario, a temporary bond purchase program is implemented within a corridor system, with reinvestments to sustain an expanded balance sheet (QE with tapering). The fifth scenario begins with QE under a corridor system, transitioning to QT through bond sales. These scenarios provide policymakers with insights into the impacts of various balance sheet strategies during crises characterized by simultaneous demand and supply shocks.

The results show that the best outcomes—minimal inflation rise, higher welfare, and greater post-shock output—depend on the central bank's pre-crisis framework. For a pre-

[2]Several papers propose simulating the COVID-19 shock as a combination of demand and supply shocks. See: Primiceri and Tambalotti (2020), Gomme (2020), Cesa-Bianchi and Ferrero (2021), Ruch and Taskin (2022), Bartocci et al. (2022), and Garcia et al. (2023).

[3]This addition enables the model to more accurately reflect the transmission of both conventional and unconventional monetary policies, including the impact of interest rate changes on household savings and consumption decisions, and the broader macroeconomic effects of QE policies, as supported by the empirical literature (Airaudo, 2023).

[4]This adjustment aligns with the Federal Reserve's 'balanced approach' to accommodative policy, as seen in its response to the economic impact of the pandemic, where output stabilization was prioritized over inflation stabilization (Eggertsson et al., 2021).

crisis corridor system, the optimal response is to apply QE during the crisis and QT in recovery. For a pre-crisis floor system, maintaining the floor during the crisis and selling bonds afterward is most effective. This research also cautions against using a corridor system in crises, aligning with Arce et al. (2020). Overall, QT proves more beneficial than other strategies, such as tapering.

The paper is organized as follows: Section 2 reviews literature on monetary policy and shocks. Section 3 outlines Canada's monetary policy framework. Section 4 presents the New Keynesian DSGE model, adapted for simultaneous shocks. Section 5 examines transmission effects of central bank bond transactions. Section 6 offers a quantitative analysis of balance sheet policies. Section 7 concludes with findings and implications.

1.2 Literature Review

Studies provide valuable insights into the mechanisms and implications of corridor and floor systems in monetary policy. Berentsen and Monnet (2008) offers foundational analysis on the corridor system through a general equilibrium model, demonstrating that central banks can manage policy by shifting the corridor or adjusting its spread, making specific interest-rate rules unnecessary. Leveraging New Keynesian DSGE models, such as Christiano et al. (2005) and Gertler and Karadi (2011), Berentsen et al. (2014) compare the two systems, identifying fiscal challenges within the floor system, especially when central banks face financing constraints. Arce et al. (2020) further assess these frameworks during demand shocks, showing that both systems can achieve stability, with the corridor system benefiting from temporary QE.

The floor system is widely regarded as effective during crises (Berentsen et al., 2014, 2018; Armenter and Lester, 2017), though its post-crisis role is debated. Some studies warn that prolonged use may encourage excessive leverage and pose risks to financial stability (e.g., Acharya and Viswanathan (2011)), while others, such as Grossmann-Wirth, 2019; Saxegaard, 2006; Lebedinski, 2007; Agénor and El Aynaoui, 2010, argue that, despite its simplicity, the floor system requires careful monitoring due to its potential to weaken monetary policy transmission and complicate contractionary efforts. Williamson (2019) highlights welfare losses associated with expanded central bank balance sheets, while Martin et al. (2018) notes potential lending instability in the floor system. However, tools like central bank bills have been shown to effectively manage interest rates within the floor framework (Berentsen et al., 2015), underscoring the need for a balanced approach to liquidity and stability.

Recent literature underscores that models incorporating both demand and supply shocks offer a more accurate view of economic dynamics in complex crises like the COVID-19 pandemic (Baqaee and Farhi, 2022; del Rio-Chanona et al., 2020; Pichler and Farmer, 2021; Brinca et al., 2020). Unlike typical recessions, the pandemic involved both reduced consumer demand and severe supply chain disruptions, exposing the limitations of single-shock models in capturing these effects and guiding optimal policy responses (Cochrane, 2020; Triggs and Kharas, 2020). Studies find that dual-shock models better represent these dynamics, helping policymakers to understand crisis impacts more fully and to craft effective responses (DiCecio, 2004; Altig et al., 2005; Elbourne et al., 2008; Abo-Zaid and Sheng, 2020; Sinamo and Hanggraeni, 2021; Pichler and Farmer, 2021).

The financial crisis highlighted challenges for financial institutions in securing funding during market stress, with interbank tensions often signaling crises. Gertler and Kiyotaki (2010) address these challenges by introducing "liquidity" shocks that create institutional surpluses and deficits, showing how credit market frictions raise credit costs. Building on this, Gertler and Karadi (2011) develop a DSGE model with financial intermediaries to analyze unconventional policies like central bank credit intermediation during crises, while Gertler and Karadi (2018) extend it to LSAPs, demonstrating how these measures reduce credit costs and stimulate the economy. Arce et al. (2020) incorporate the interbank market explicitly, examining how corridor and floor systems respond to demand shocks in the Euro area, offering insights into the effectiveness of these systems under specific shock conditions. This study builds on prior research by modeling the COVID-19 pandemic as simultaneous demand and supply shocks in a DSGE framework.

1.3 Stylized Facts about Monetary Policy Implementation in Canada

The corridor system was first introduced by the BoC and Sweden's Riksbank in June 1994, later adopted by other central banks, including the ECB, the Fed, and the BoE, until the 2007 global financial crisis (Lee, 2016). In response to the crisis, central banks, including the BoC, transitioned to the floor system to accommodate unconventional monetary measures. As shown in Figure 1.1, the BoC implemented the floor system from May 2009 to May 2010, increasing its balance sheet by nearly 50 percent in late 2008 (see Figure 1.4 in Appendix C).

By June 2010, the BoC had reduced its balance sheet nearly to pre-crisis levels, with bank reserves at central banks also falling sharply, as depicted in Figure 1.5 in Appendix C. At this point, the BoC officially returned to the corridor system, which it maintained effectively until the COVID-19 pandemic. This shift is illustrated in the bottom left panel of Figure 1.1.

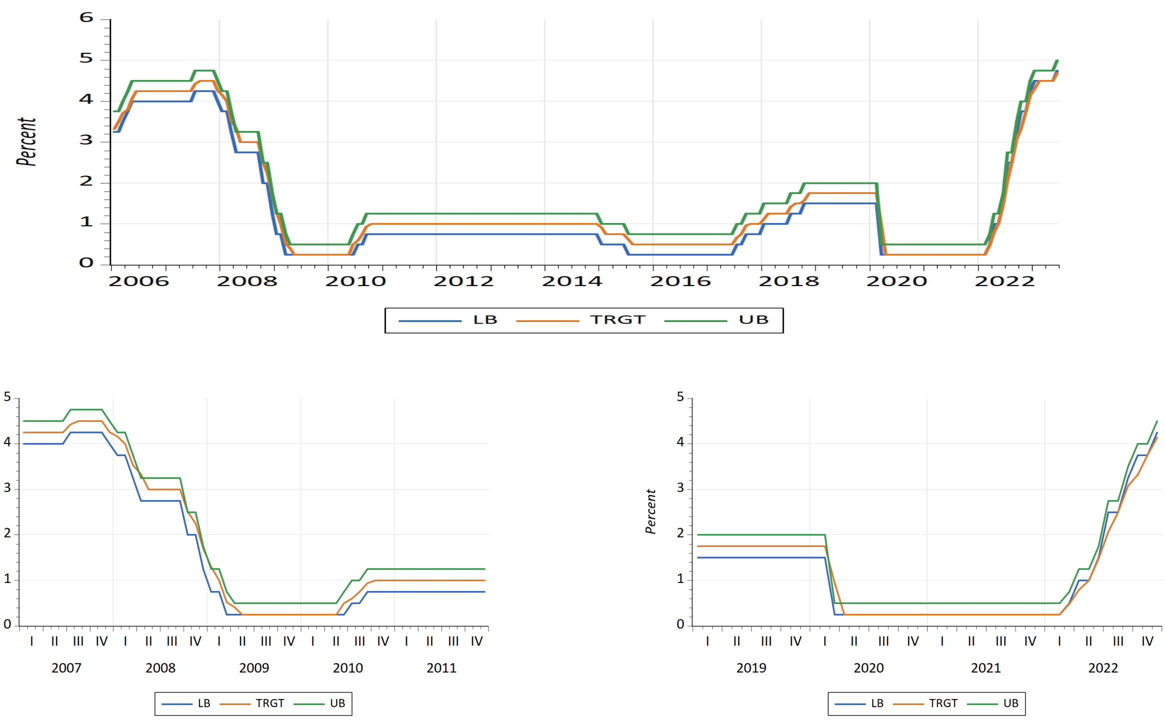

Figure 1.1: The figure illustrates the overnight interest rate corridor diagram for Canada, where (LB) denotes the lower bound and (UB) the upper bound of the corridor, which represent the central bank deposit facility rate and lending facility rate, respectively. The target interbank rate ($TRGT$) is also depicted.

Source: Bank of Canada, Haver analytics.

Many central banks, including the BoC, implemented QE during the COVID-19 pandemic, prompting a transition from the corridor to the floor system.[5] This shift is illustrated in the bottom right panel of Figure 1.1. From March to July 2020, the BoC's balance sheet more than tripled (Figure 1.4 in Appendix C), while settlement balances surged between CAD 175 billion and CAD 400 billion (Figure 1.5 in Appendix C), vastly exceeding pre-pandemic levels by over 1,000 times. For comparison, during the 2008 crisis, settlement balances under the floor system were around CAD 3 billion.

[5]Notably, some central banks, like the Fed, maintained the floor system post-crisis and continue to operate under it.

In contrast to its post-financial crisis approach, the BoC opted to maintain the floor system for the foreseeable future. On April 13, 2022, it announced the end of its asset purchase reinvestment phase, confirming no plans to sell bonds. Consequently, maturing government bonds will no longer be replaced, allowing the balance sheet to gradually shrink. Between August 2020 and May 2023, the BoC's balance sheet consistently declined by an average of 1.1% per month, remaining more than twice its pre-crisis size, as shown in the bottom right panel of Figure 1.4 in Appendix C. Similarly, Figure 1.5 in Appendix C highlights the persistently high settlement balances post-crisis, contrasting sharply with near depletion after the financial crisis.

In comparison, the BoE began reducing its asset holdings in February 2022, halting the reinvestment of maturing bonds and launching a corporate bond sales initiative. By August 2022, the BoE planned to sell UK government bonds, aiming to reduce its holdings by £80 billion within twelve months. While the corporate bond sales program concluded in June 2023, a few short-term bonds will remain in the portfolio until April 2024.

The BoE noted that, initially, its floor system goals would be maintained with ample reserves; however, as reserves near the minimum level required for liquidity needs, short-term market rates could rise and become more volatile. Eventually, the BoE anticipates a shift from the floor to a corridor system, supported by a new open market operation—the short-term repurchase agreements—allowing unlimited reserve borrowing at Bank Rate.[6] This hints at a gradual transition back to a corridor system through bond sales.

These developments raise a key question: Is the strategy of gradually reducing the balance sheet while retaining the floor system (as in the COVID-19 response) more effective, in terms of macroeconomic impacts, than the approach of reducing the balance sheet to return fully to a corridor system (as during the financial crisis)?

1.4 Model

The NK-DSGE framework of Arce et al. (2020) is extended with modifications to analyze monetary policy in Canada. The model incorporates households, firms (intermediate, retail, and final goods), banks, the monetary authority, and the government. Key adjustments include the addition of a TFP shock to capture supply disruptions, the incorporation of household deposits into the utility function to reflect increased liquidity preferences and better capture the effects of QE on consumption and savings, and a modification of the

[6] See: https://www.bankofengland.co.uk/markets/bank-of-england-market-operations-guide/our-objectives

Taylor rule to account for output deviations from its steady state, consistent with interest rate reductions during the COVID-19 pandemic. Calibrated specifically to the Canadian economy, the model adopts the consumption equivalent variation (CEV) for welfare measurement, replacing the traditional utility-based approach. This provides a more intuitive and comparable welfare metric, expressed as a percentage change in consumption, enhancing clarity in policy impact communication and supporting cost-benefit analyses.

In the rest of this section, I summarize the key aspects of the model, which include households, intermediate-good firms, banks, the interbank market, the central bank, and the treasury. For the remaining parts of the model, transitional dynamics, and steady state system, please refer to Appendix B.

1.4.1 Households

There is a continuum of measure one of homogeneous households that live infinite periods in the economy. The representative household's utility is:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t U\left(C_t, D_t^H, L_t\right) \tag{1.1}$$

where C_t is (real) consumption, L_t is labor supply, D_t^H is (real) deposits, and β^t is the household's discount factor. Households can acquire deposits, which are highly liquid assets. I assume that individuals derive satisfaction from the liquidity services this asset provides.

The utility function is a monotone increasing function in consumption and deposits, a monotone decreasing function in labor, and satisfies Inada conditions on all variables. The functional form assumed in the numerical exercise for the households' utility function is the CRRA utility function:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \frac{[C_t^{1-\iota}(D_t^H)^{\iota}]^{1-\gamma}}{1-\gamma} - \frac{L_t^{1+\psi}}{1+\psi} \tag{1.2}$$

where ι is a preference parameter that determines the relative utility weight of deposit holdings compared to consumption, γ is the inverse intertemporal elasticity (risk aversion), and ψ is the inverse Frisch elasticity.

In addition to the choice of acquiring deposits, households also have the choice to invest in capital goods. Households build new capital goods K_t using technology:

$$K_t = \left[1 - S\left(\frac{I_t}{I_{t-1}}\right)\right] I_t + (1-\delta)\Omega_{t-1}K_{t-1} \tag{1.3}$$

The variable I_t represents the final goods utilized for investment purposes, while $(1-\delta)\Omega_{t-1}K_{t-1}$ refers to the repurchased depreciated effective capital from firms after production in period t. In the latter expression, δ denotes the depreciation rate, and Ω_{t-1} represents an effective capital index, which the household considers as a given parameter. The function S fulfills the conditions $S(1) = S'(1) = 0$ and $S''(1) \equiv \zeta > 0$.

To specify the investment adjustment costs, I adopt a standard quadratic form:

$$S(x) = \frac{\varepsilon}{2}(x-1)^2 \tag{1.4}$$

Here, ε is commonly referred to as the investment adjustment cost parameter.

The budget constraint (in real term) is:

$$C_t + I_t + D_t^H = W_t L_t + \frac{R_{t-1}^D}{1+\pi_t} D_{t-1}^H + Q_t^K \left[1 - S\left(\frac{I_t}{I_{t-1}}\right)\right] I_t + \sum_{s=R,B} \Pi_t^s - T_t \tag{1.5}$$

where $1 + \pi_t = \frac{P_t}{P_{t-1}}$, P_t is the aggregate price level, R_{t-1}^D is the riskless gross deposit rate, W_t is the real wage, Q_t^K is the real price of capital goods, $\{\Pi_t^s\}_{s=R,B}$ are lump-sum real dividend payments from the household's ownership of retailers ($s = R$) and banks ($s = B$), and T_t are lump-sum taxes.

The budget constraint balances the household's total uses of resources (LHS) with its total available resources (RHS). The household must allocate its income from labor, returns on savings, and returns on investment in capital between consumption, new capital investment, and saving in the form of deposits, while also accounting for taxes and adjustment costs in investment.

1.4.2 Firms

There are three types of firms: intermediate-good firms, retail-good firms, and final-good firms, so that the production takes place in three steps. In the first step, a continuum of intermediate-good producers indexed by $j \in [0,1]$ produces a homogeneous good by hiring labor and purchasing a pre-determined stock of capital supplied by households, taking the wage rate and the price of capital as given. Second, the retail-good firms purchase units of the intermediate-good firms, transfer them one-for-one into retail good varieties, and sell them to final good producers. These retailers operate in a monopolistically competitive environment where they set prices of differentiated goods à la Calvo. The final-good producer aggregates a continuum of differentiated retail goods to produce a homogeneous final good and sell it to buyers in a perfectly competitive market. Below I present the intermediate-good firms. Retail-good firms and final-good firms are explained in Appendix B.

Intermediate Good Firms

The intermediate-good firms, together with banks, are dispersed across different "islands" indexed by $j \in [0, 1]$, with each island representing a distinct market segment. Within each segment, a representative firm operates under perfect competition and produces an intermediate good, denoted as Y_t^j, using a Cobb-Douglas production technology. The production function for each firm is given by:

$$Y_t^j = Z_t(\omega_{t-1}^j K_{t-1}^j)^\alpha (L_t^j)^{1-\alpha}, \tag{1.6}$$

where α is the capital share, Z_t represents an AR(1) aggregate total factor productivity (TFP) process, L_t^j is the labor input, K_{t-1}^j is the predetermined stock of installed capital, and ω_{t-1}^j is an island-specific shock to effective capital. This production process indicates that output depends not only on labor and capital but also on the productivity of capital, which is subject to the island-specific shock ω_{t-1}^j. After production, the capital stock depreciates to $(1-\delta)\omega_{t-1}^j K_{t-1}^j$, where δ is the depreciation rate. The shock ω_{t-1}^j, known as a capital quality shock, affects both the output produced and the remaining value of the capital stock, distinguishing it from a total factor productivity (TFP) shock.

The firm's decision-making process begins at the end of period $t-1$, when it learns the specific capital quality shock ω_{t-1}^j that will influence its effective capital in the next period. These shocks are independently and identically distributed (iid) across time and market segments, with a cumulative distribution function $F(\omega)$. At this stage, the firm must acquire capital for its operations in the upcoming period, purchasing it from the household at the prevailing unit price Q_{t-1}^K. To finance this acquisition, the firm seeks funding from its local bank. The firm issues one unit of equity A_{t-1}^j for each unit of capital acquired, so that $A_{t-1}^j = K_{t-1}^j$. This equity represents a state-contingent claim on the future returns from the capital and is traded at the price $Q_{t-1}^{A,j}$. Given the perfect competition in the market, the prices of capital goods and equity are identical, leading to the equality $Q^K_{t-1}K^j_{t-1} = Q^K_{t-1}A^j_{t-1}$. At the start of period t, the firm hires labor and commences production.

The firm j then optimizes its labor input to maximize operating profits, given by the difference between revenue from the sale of the intermediate good and the wage bill. The optimization problem is expressed as:

$$\max_{L^j_t} \quad P^Y_t Y^j_t - P_t W_t L^j_t \quad \text{subject to} \quad Y^j_t = Z_t(\omega^j_{t-1}K^j_{t-1})^{\alpha}(L^j_t)^{1-\alpha}, \tag{1.7}$$

where P^Y_t is the price of the intermediate good, P_t is the aggregate price level, and W_t is the real wage. The first-order condition for profit maximization ensures that the effective capital-labor ratio is uniform across all islands:

$$\frac{\omega^j_{t-1}K^j_{t-1}}{L^j_t} = \left(\frac{W_t}{MC_t(1-\alpha)Z_t}\right)^{\frac{1}{\alpha}}, \tag{1.8}$$

where $MC_t \equiv \frac{P^Y_t}{P_t}$ represents the inverse of the average gross markup of final goods prices over the intermediate good price. This equation implies that firms adjust their capital-labor ratio in response to changes in wages, markups, and productivity, ensuring efficient allocation of resources across islands.

The firm's nominal profits, after labor costs, are given by:

$$P^Y_t Y^j_t - P_t W_t L^j_t = P_t R^k_t \omega^j_{t-1}K^j_{t-1}, \tag{1.9}$$

where $R^k_t \equiv \alpha MC_t Z_t \left[\frac{(1-\alpha)MC_t Z_t}{W_t}\right]^{\frac{1-\alpha}{\alpha}}$ is the common real return on effective capital. This return depends on the productivity of capital, the markup in the goods market, and the wage level.

After production, the firm sells the depreciated effective capital $(1-\delta)\omega^j_{t-1}K^j_{t-1}$ to households at the current unit price Q^K_t. The total real cash flow from the firm's investment project includes both the operating profits and the proceeds from the sale of the depreciated capital:

$$R^k_t \omega^j_{t-1}K^j_{t-1} + (1-\delta)Q^K_t \omega^j_{t-1}K^j_{t-1}. \tag{1.10}$$

Since the firm's capital acquisition is entirely financed by equity, this entire cash flow is paid out to the lending bank.

1.4.3 Banks

Each island has a designated bank, with only the bank on island j possessing the necessary tools to effectively monitor, track, and enforce contractual obligations of the operating firms. Consequently, firms are effectively restricted from obtaining financial support from alternative sources, such as individuals or other banks. The isolation of each island's financial system makes the local bank's performance closely tied to the specific shocks affecting its local firms. This increases the relevance of idiosyncratic risk within the model, as the bank cannot diversify its portfolio across multiple regions or industries. The financial health of the bank becomes more sensitive to the success or failure of the firms it finances.

In this model, banks generate earnings through three primary channels: (i) profits from investments in local firms, (ii) income from lending in the interbank market, and (iii) returns from investing in government bonds. At the same time, banks face two main types of costs: (i) interest payments on funds borrowed from the interbank market and (ii) interest payments on deposits received from households. The details of these revenue sources and costs are outlined in Appendix B. The following subsection focuses on the bank's net earnings.

Bank's Net Earnings

Bank's real net earnings at the start of the following period, denoted by E^j_{t+1}:

$$E^j_{t+1} = R^A_{t+1} Q^K_t \omega^j_t A^j_t + \tfrac{R^L_t}{1+\pi_{t+1}} B^{-,j}_t - \tfrac{R^B_t}{1+\pi_{t+1}} B^{+,j}_t + \tfrac{R^G_{t+1}}{1+\pi_{t+1}} b^{j,G}_t - \tfrac{R^D_t}{1+\pi_{t+1}} D^{j,B}_t \tag{1.11}$$

During each time period t, the following events occur in a sequence. The bank initiates the period with net earnings E^j_t. It is assumed that a portion $1-\varsigma \in (0,1)$ of the earnings is distributed to households as dividends. The remaining fraction ς is kept as post-dividend equity, represented by $N^j_t = \varsigma E^j_t$. After the dividend payment, but before learning about the upcoming shock to the local firm's capital productivity in the next period (ω^j_t), the bank accepts deposits $D^{j,B}_t$ from households. The deposits market then closes, followed by the realization of the island-specific shock ω^j_t. Upon observing the shock, the bank determines the amount to invest in the local firm ($Q^K_t A^j_t$) and in government bonds ($b^{j,G}_t$), as well as how much to borrow or lend in the interbank market ($B^{+,j}_t, B^{-,j}_t$), while adhering to its balance sheet constraint.

$$Q_t^K A_t^j + B_t^{-,j} + b_t^{j,G} = N_t^j + D_t^{j,B} + B_t^{+,j} \tag{1.12}$$

Additionally, banks are subject to an exogenous leverage constraint, expressed as:

$$Q_t^K A_t^j \leq \phi N_t^j \tag{1.13}$$

They are not allowed to engage in short selling of assets ($A_t^j, B_t^{+,j}, b_t^{j,G} \geq 0$) or lend negative amounts $B_t^{-,j} \geq 0$.

Banks' Problem

The bank maximizes the expected stream of dividends,

$$E_t \sum_{s=1}^{\infty} \Lambda_{t,t+s}(1-\varsigma)E_{t+s}^j \tag{1.14}$$

$\Lambda_{t,t+s}$ represents the stochastic discount factor. The problem can be expressed recursively as a two-stage problem within each period, whereby the bank first chooses deposits and then, after the realization of the idiosyncratic shock, the remaining balance-sheet items,

$$V_t(N_t^j) = \max_{D_t^{j,B}} \int \bar{V}_t(N_t^j, D_t^{j,B}, \omega)\, dF(\omega) \tag{1.15}$$

where:

$$\bar{V}_t(N_t^j, D_t^{j,B}, \omega) = \max_{A_t^j \geq 0,\, b_t^{j,G} \geq 0,\, B_t^{+,j} \geq 0,\, B_t^{-,j} \geq 0,} E_t \Lambda_{t,t+1} \left[(1-\varsigma)E_{t+1}^j + V_{t+1}(\varsigma E_{t+1}^j)\right] \tag{1.16}$$

subject to equations (1.11), (1.12), and (1.13).

Heterogeneous Shocks to Banks

The uncertainty faced by banks in this model arises from the idiosyncratic shocks to the productivity of local firms, denoted by ω_t^j. These shocks affect the return on investments that banks make in local firms, which in turn influence the banks' overall profitability and financial decisions.

In each period t, the sequence of events unfolds as follows. Banks begin period t with initial net earnings, denoted by E_t^j. A fixed share $(1-\beta_b)$ of these earnings is distributed as dividends to shareholders, while the remaining portion $(\beta_b E_t^j)$ is retained as equity. After dividends are paid but before the realization of the island-specific productivity shock ω_t^j, banks collect deposits D_t^j from households. Once deposits are secured and this market closes, banks observe the shock ω_t^j. Banks then decide on asset allocation—specifically, investment in local firms' capital $Q_t K_t^j$, and participation in interbank $(B_t^{+,j}, B_t^{-,j})$ and government bond markets (b_t^j)—under the constraint of their balance sheets. The uncertainty is further compounded by the heterogeneity of shocks across different islands, which categorizes banks into three distinct groups:

1. **Banks with high productivity shocks** $(\omega_t^j \geq \omega_t^B)$ are likely to borrow from the interbank market to finance additional investments in their local firms. These banks are constrained by their leverage, meaning the productivity of their investment significantly affects their ability to expand or maintain their operations. The borrowing threshold is defined as:

$$\omega_t^B \equiv \frac{E_t\left[\tilde{\Lambda}_{t,t+1}\frac{R_t^B}{1+\pi_{t+1}}\right]}{E_t\left[\tilde{\Lambda}_{t,t+1}R_{t+1}^A\right]} \tag{1.17}$$

2. **Banks with low productivity shocks** $(\omega_t^j \leq \omega_t^L)$ are more likely to lend their available resources (equity and deposits) in the interbank market and to the government, with both investments offering the same expected return. The lending threshold is defined as:

$$\omega_t^L \equiv \frac{E_t\left[\tilde{\Lambda}_{t,t+1}\frac{R_t^L}{1+\pi_{t+1}}\right]}{E_t\left[\tilde{\Lambda}_{t,t+1}R_{t+1}^A\right]} \tag{1.18}$$

3. **Banks with intermediate productivity shocks** $(\omega_t^L \leq \omega_t^j \leq \omega_t^B)$ neither borrow nor lend in the interbank market. Instead, they invest their equity and deposits directly in the local firm.

As a result, the leverage constraint is always binding for the more productive banks, while it remains relaxed for the less productive ones. This observation is further detailed in lemma 1 in Appendix B.

Furthermore, the deposit rate (R_t^D) that banks offer to households is also influenced by these uncertainties. The deposit rate depends on the distribution of productivity shocks across islands, meaning banks must set a rate that balances the expected costs and benefits across different potential outcomes.

lemma 1 demonstrates that the deposit rate R_t^D, which represents the marginal cost of accepting deposits at the beginning of the period, is equivalent to the expected benefit across different realizations of ω_t^j:

$$R_t^D = \left[1 - F(\omega_t^B)\right] R_t^B + F(\omega_t^L) R_t^L + [F(\omega_t^B) - F(\omega_t^L)] \frac{E(\omega|\omega_t^L \leq \omega \leq \omega_t^B) E_t[\tilde{\Lambda}_{t,t+1} R_{t+1}^A]}{E_t[\frac{\tilde{\Lambda}_{t,t+1}}{1+\pi_{t+1}}]} \tag{1.19}$$

For banks with high productivity shocks ($\omega_t^j \geq \omega_t^B$) constrained by leverage, each additional unit of deposits enables them to reduce interbank borrowing and save $\frac{R_t^B}{1+\pi_{t+1}}$. In contrast, for banks with low productivity shocks ($\omega_t^j \leq \omega_t^L$), each additional unit of deposits is invested in interbank lending or government bonds, resulting in a return of $\frac{R_t^L}{1+\pi_{t+1}}$. For banks with intermediate productivity shocks ($\omega_t^L \leq \omega_t^j \leq \omega_t^B$), each additional unit of deposits is invested in the local firm, providing an average idiosyncratic return of $E(\omega \mid \omega_t^L \leq \omega \leq \omega_t^B)$.

1.4.4 Interbank Market

The interbank market is modeled as a decentralized, over-the-counter market. Banks that wish to lend place lending orders, whereas banks that wish to borrow place borrowing orders. Lending and borrowing orders are placed on a per-unit basis. Borrowing and lending orders then search for each other in an interbank market characterized by search and matching frictions.

Determining the Volume of Borrowing and Lending Orders

We know from subsection (1.4.3) that banks with $\omega_t^j \geq \omega_t^B$ borrow from other banks in the interbank market. Given their balance sheet (1.12) and the leverage constraint (1.13), and knowing that $b_t^{j,G} = B_t^{-,j} = 0$, this implies that each bank borrow the amount:

$$B_t^{+,j} = (\phi - 1) N_t^j - D_t^{j,B} \tag{1.20}$$

Then the mass of borrowing is:

$$\Phi_t^B \equiv \int_0^1 B_t^{+,j}\, dj = \int_{j=\omega_t^j > \omega_t^B} [(\phi - 1)N_t^j - D_t^{j,B}]\, dj = [1 - F(\omega_t^B)][(\phi - 1)N_t - D_t^B] \quad (1.21)$$

where $N_t \equiv \int_0^1 N_t^j\, dj$ is aggregate bank equity, and $D_t^B \equiv \int_0^1 D_t^{j,B}\, dj$ is aggregate deposits.

For lending banks with ($\omega_t^j \leq \omega_t^L$), they invest their equity and deposits in the interbank market and government bond market. Given their balance sheet (1.12) and the leverage constraint (1.13), and knowing that $A_t^j = B^{+,j} = 0$, this implies that each bank lend the amount:

$$B_t^{-,j} = N_t^j + D_t^{j,B} - b^{j,G} \quad (1.22)$$

Then the mass of lending is:

$$\Phi_t^L \equiv \int_0^1 B_t^{-,j}\, dj = \int_{j=\omega_t^j < \omega_t^L} [N_t^j + D_t^{j,B} - b^{j,G}]\, dj = F(\omega_t^L)[N_t + D_t^B] - b_t^G \quad (1.23)$$

where $b_t^G \equiv \int_0^1 b_t^G\, dj$ is aggregate bank holdings of government bonds.

Foe each equality I have used the fact that ω_t^j is distributed independently from N_t^j and $D_t^{j,B}$.

Competitive Search Environment

Matching Process

The interbank market comprises various submarkets (s) where lenders and borrowers seek to find suitable matches for their lending and borrowing needs. In each of these submarkets, there are orders for lending ($\Phi_{s,t}^L$) and borrowing ($\Phi_{s,t}^B$). These orders are matched using a common matching function denoted as $\Upsilon(\Phi_{s,t}^L, \Phi_{s,t}^B)$ which describes the total number of successful matches between lending and borrowing orders in a given submarket.[7] Given the assumed constant returns to scale, the probability of each lending (borrowing) order in the interbank market finding a corresponding borrowing (lending) order can be expressed as follows, respectively:

[7] The function Υ is assumed to be C^1, weakly increasing, and concave in both of its arguments. It satisfies the natural conditions $0 \leq \Upsilon(x, y) \leq \min(x, y)$, ensuring that the number of matches cannot exceed the minimum of borrowing and lending orders. Furthermore, Υ exhibits constant returns to scale, meaning that doubling both borrowing and lending orders results in a doubling of the number of matches.

$$\frac{\Upsilon(\Phi_{s,t}^L, \Phi_{s,t}^B)}{\Phi_{s,t}^L} = \Upsilon\left(1, \frac{\Phi_{s,t}^B}{\Phi_{s,t}^L}\right) \equiv \Gamma^L\left(\frac{\Phi_{s,t}^B}{\Phi_{s,t}^L}\right) \tag{1.24}$$

$$\frac{\Upsilon(\Phi_{s,t}^L, \Phi_{s,t}^B)}{\Phi_{s,t}^B} = \Upsilon\left(\frac{1}{\frac{\Phi_{s,t}^B}{\Phi_{s,t}^L}}, 1\right) \equiv \Gamma^B\left(\frac{\Phi_{s,t}^L}{\Phi_{s,t}^B}\right) \tag{1.25}$$

When a lending order finds a match in the interbank market, it earns the interest rate $R_{s,t}^{IB}$. However, if a lending order does not find a match, the funds are instead deposited at the central bank, and the deposited funds earn the deposit facility rate, R_t^{DF}. On the other hand, if a borrowing order finds a match, it pays the interest rate $R_{s,t}^{IB}$. In case a borrowing order fails to find a match, the funds must be borrowed from the central bank, but this transaction incurs the lending facility rate, R_t^{LF}, which is higher than R_t^{DF}.

Let $\theta_{s,t} \equiv \frac{\Phi_{s,t}^B}{\Phi_{s,t}^L}$ represent the ratio of borrowing to lending orders in submarket s, commonly referred to as the interbank (sub)market tightness. Consequently, the matching probability for lending orders (Γ^L) increases with market tightness, while the matching probability for borrowing orders (Γ^B) decreases. In essence, as market tightness rises (indicating more borrowers relative to lenders), lending orders are more likely to secure a match.

The matching function used in calibration is as in Den Haan et al. (2000),

$$\Upsilon(\Phi_t^L, \Phi_t^B) = \frac{\Phi_t^L \Phi_t^B}{((\Phi_t^L)^\lambda + (\Phi_t^B)^\lambda)^{\frac{1}{\lambda}}} \tag{1.26}$$

The parameter $\lambda > 0$ controls how lending and borrowing orders work together to form matches in the market. If λ is small, it means that having more of either lending or borrowing orders makes it much easier to create matches. As λ gets larger, the number of matches becomes more limited by whichever side (lenders or borrowers) has fewer orders. This helps the model adjust to different types of markets, from highly flexible ones to those with stricter matching rules.

Optimization Problems of Borrowers and Lenders

Lenders (borrowers) send their respective orders to the submarkets that maximize (minimize) their lending return (borrowing cost). For lenders, there are two options: lending their excess funds to borrowing banks in the interbank market and obtaining a return of

$R^{IB}_{s,t}$, or deposit these excess funds at the central bank's deposit facility and obtaining a return of R^{DF}_t:

$$\Gamma^L(\theta_{s,t})R^{IB}_{s,t} + (1 - \Gamma^L(\theta_{s,t}))R^{DF}_t \equiv R^L_{s,t} \tag{1.27}$$

Likewise, borrowers have two options: borrowing from lending banks in the interbank market and paying an interest rate of $R^{IB}_{s,t}$, or borrowing from the central bank using its loan facility and paying an interest rate of R^{LF}_t:[8]

$$\Gamma^B(\theta_{s,t})R^{IB}_{s,t} + (1 - \Gamma^B(\theta_{s,t}))R^{LF}_t \equiv R^B_{s,t} \tag{1.28}$$

If we denote R^L_t as the maximum average return achievable by a lender in equilibrium, any submarket that attracts lenders must offer the average return of R^L_t. In simpler terms, in any submarket that is active in equilibrium, the pair $(R^{IB}_{s,t}, \theta_{s,t})$ must satisfy $R^L_{s,t} = R^L_t$, or

$$\Gamma^L(\theta_{s,t})R^{IB}_{s,t} + (1 - \Gamma^L(\theta_{s,t}))R^{DF}_t \equiv R^L_t \tag{1.29}$$

Hence, for lenders to be willing to participate in a submarket that offers a lower rate $(R^{IB}_{s,t})$, they must be compensated through a higher market tightness $(\theta_{s,t})$, leading to an increased matching probability, $\Gamma^L(\theta_{s,t})$. Meanwhile, borrowers select the submarket that minimizes their borrowing cost (1.28) considering both $R^{IB}_{s,t}$ and $\theta_{s,t}$, subject to (1.29). The solution to this problem yields the following interbank rate:

$$R^{IB}_t = \varphi(\theta_t)R^{DF}_t + (1 - \varphi(\theta_t))R^{LF}_t \tag{1.30}$$

where $\varphi(\theta_t) \equiv \frac{d\Gamma^L(\theta_t)}{d\theta_t}\frac{\theta_t}{\Gamma^L(\theta_t)} = \frac{\partial\Upsilon(\Phi^L_t,\phi^B_t)}{\partial\Phi^B_t}\frac{\Phi^B_t}{\Upsilon(\Phi^L_t,\phi^B_t)} \in (0,1)$, is the elasticity of the matching function with respect to the number of borrowing orders.

The equilibrium interest rate for matched orders is determined by a weighted average of the respective outside return or cost. For lenders, the weight is given by the elasticity of the matching function with respect to the number of borrowing orders, denoted as $\varphi(\theta_t)$, and is combined with the deposit facility rate, R^{DF}_t. For borrowers, the weight is determined by $1 - \varphi(\theta_t)$ and is combined with the lending facility rate, R^{LF}_t. Consequently, when the elasticity $\varphi(\theta_t)$ is high, the interbank rate paid by borrowers and earned by lenders tends to be close to the lower bound of the interest rate corridor, reflecting the deposit facility

[8]Value maximization with respect to the choice of interbank submarket, for lending banks, is synonymous with maximizing the average return on lending orders. Conversely, for borrowing orders, it involves minimizing the cost of borrowing. For more details, see Appendix B.2 in Arce et al. (2020).

rate. In this context, $\varphi(\theta_t)$ represents the borrowers' portion of the joint surplus, which denotes the difference between the two policy rates.

Intuitively, as the ratio of borrowing to lending orders increases, it becomes more challenging for borrowers to find lenders (the market becomes wider). Therefore, borrowers must offer higher rates, closer to the lending facility rate, to attract lenders. Conversely, in a relaxed interbank market with ample lending orders (hence, a tight market), lenders are compelled to accept lower rates, closer to the deposit facility rate. Therefore, it is reasonable to consider (matching) technologies where φ decrease as the interbank market tightens. Indeed, according to Equation (1.30), the forgone return from funds deposited at the central bank can be expressed as:

$$R_t^{IB} - R_t^{DF} = (1 - \varphi(\theta_t))(R_t^{LF} - R_t^{DF}) \tag{1.31}$$

Assuming $\varphi' < 0$, an increase in excess reserves leads to a reduction in the difference between R_t^{IB} and R_t^{DF} (given a fixed width of the policy rate corridor, $R_t^{LF} - R_t^{DF}$).

1.4.5 Central Bank

Interest Rate Policy

The central bank sets two nominal policy rates: the gross deposit facility rate R_t^{DF} and the gross lending facility rate R_t^{LF}. It is assumed that these policy rates are determined in a manner that ensures the maintenance of a constant corridor with a width denoted as $\chi > 0$. Specifically, this means that:

$$R_t^{LF} = R_t^{DF} + \chi \tag{1.32}$$

The central bank aims to achieve a specific target level for its operational target, which in this case is assumed to be the interbank rate. This target level is determined based on a conventional Taylor rule,

$$R_t^{IB,*} = \rho R_{t-1}^{IB} + (1 - \rho)[\bar{R} + \nu(\pi_t - \bar{\pi}) + \tau(Y_t - \bar{Y})] \tag{1.33}$$

Here, $\bar{R}$, $\bar{\pi}$, and $\bar{Y}$ denote the steady-state values of the nominal interbank rate, inflation, and output, respectively. The parameter $\rho \in (0, 1)$ captures the persistence, while $\nu > 1$ (Taylor Principle) and $\tau > 0$ determine the sensitivity to deviations of net inflation and output, respectively, from their steady-state levels. I assume a zero steady-state value for inflation ($\bar{\pi} = 0$).

By combining Equations (1.30) and (1.32), we can derive the following relationship between the operational target and the deposit facility rate: $R_t^{IB} = R_t^{DF} + (1 - \varphi_t)\chi$, where $\varphi_t \equiv \varphi_t(\theta_t)$. Utilizing this relationship along with the Taylor rule (1.33), we can determine the deposit facility rate that enables the achievement of the desired level for the operational target,

$$R_t^{DF,*} = \rho \left[R_{t-1}^{DF} + (1 - \varphi_{t-1})\chi\right] + (1 - \rho)\left[\bar{R} + \nu(\pi_t - \bar{\pi}) + \tau(Y_t - \bar{Y})\right] - (1 - \varphi_t)\chi \tag{1.34}$$

It is assumed that all private agents in the economy have the option to save using an unmodeled technology such as a "mattress" or a "vault," which offers a net nominal rate of $-\kappa$ (or gross nominal interest rate of $1 - \kappa$), where $\kappa \geq 0$. This option represents a fallback savings mechanism with no financial intermediation, and while simple, it ensures that private agents would not accept nominal rates lower than $-\kappa$. As a result, there exists an effective lower bound (ELB) on all gross nominal interest rates, given by $1 - \kappa$. No rational agent would accept rates lower than this bound since they could resort to the mattress/vault option.

This ELB also imposes a constraint on the central bank's policy. If the central bank aims to set the deposit facility target rate, $R_t^{DF,*}$, above this ELB, the rate can be implemented without issue, resulting in $R_t^{DF} = R_t^{DF,*}$ and $R_t^{IB} = R_t^{IB,*}$. However, if the central bank attempts to set $R_t^{DF,*}$ below the ELB, the rate cannot fall below $1-\kappa$ due to this constraint. In such cases, the deposit facility rate becomes $R_t^{DF} = 1 - \kappa$, and the central bank must accept a positive deviation of the interbank rate from its target. In practical terms, the deposit facility rate is thus determined as the greater of the target rate, $R_t^{DF,*}$, or the ELB, $1 - \kappa$.

Mathematically, this relationship is summarized as:

$$R_t^{DF} = \max\{R_t^{DF,*}, 1 - \kappa\} \tag{1.35}$$

Market Rates and the Interest Rate Corridor

Based on equation (1.30), the interbank rate R_t^{IB} is a weighted average of the two policy rates (R_t^{DF} and R_t^{LF}), with its proximity to the floor being determined by the borrowers' surplus share $\varphi(\theta_t)$.

The effective returns on interbank lending and borrowing are as follows:

$$R_t^L = \Gamma^L(\theta_t)R_t^{IB} + (1 - \Gamma^L(\theta_t))R_t^{DF} \tag{1.36}$$

$$R_t^B = \Gamma^B(\theta_t)R_t^{IB} + (1 - \Gamma^B(\theta_t))R_t^{LF} \tag{1.37}$$

These expressions indicate that the effective returns (R_t^L and R_t^B) are weighted averages of the interbank rate and the respective outside-option return (R_t^{DF} and R_t^{LF}), with weights that depend on the matching probabilities Γ_t^L and Γ_t^B associated with the respective submarket tightness θ_t.

The deposit rate (R_t^D) falls between the effective interbank lending and borrowing rates, meaning $R_t^D \in [R_t^L, R_t^B]$. Its position relative to R_t^{IB} is in principle ambiguous.

Taking all of this into account, the equilibrium ordering of the nominal rates is as follows:

$$R_t^{DF} \leq R_t^L \leq R_t^{IB}, \quad R_t^D \leq R_t^B \leq R_t^{LF} \tag{1.38}$$

Balance Sheet Policy

The central bank has control over the real market value of its government bond holdings, denoted as $b_t^{G,CB}$. It is assumed that $b_t^{G,CB}$ is determined by the following rule:

$$b_t^{G,CB} = (1 - \zeta)b_{t-1}^{G,CB} + \zeta\bar{b}^{G,CB} + np_t + \zeta(b_{t-1}^{G,CB} - \bar{b}^{G,CB})ri_t \tag{1.39}$$

The central bank's bond holding equation describes how its portfolio evolves over time, balancing gradual adjustments and extraordinary measures. The first term, $(1 - \zeta)b_{t-1}^{G,CB}$, represents the portion of the previous period's bond holdings that persists. The adjustment parameter, ζ, controls how quickly the holdings shift toward the target value, $\bar{b}^{G,CB}$, which is reflected in the second term, $\zeta\bar{b}^{G,CB}$. A higher ζ leads to faster convergence to the target.

Extraordinary measures are introduced through two terms. The first, np_t, represents net purchases of bonds, which occur during special operations like QE. The second, $\zeta(b_{t-1}^{G,CB} - \bar{b}^{G,CB})ri_t$, captures reinvestments, enabled when the binary variable $ri_t = 1$, allowing proceeds from bond returns to be reinvested if holdings deviate from the target. Together, these terms ensure the bond portfolio adjusts dynamically, combining routine management with flexibility for extraordinary interventions.

The central bank's assets consist of government bonds, $b_t^{G,CB}$, and loans extended to banks through its lending facility, which is represented by the mass of borrowing orders that did not find matches in the interbank market: $\Phi_t^B(1 - \Gamma_t^B)$. On the other side, the central bank's liabilities are banks' reserves held at its deposit facility, represented by the mass of interbank lending orders that did not find a match: $\Phi_t^L(1 - \Gamma_t^L)$.

Assuming the central bank does not accumulate equity and allocates all profits to the government, the central bank's balance sheet expressed in real terms can be expressed as:

$$b_t^{G,CB} + \Phi_t^B(1 - \Gamma_t^B) = \Phi_t^L(1 - \Gamma_t^L) \tag{1.40}$$

Finally, the central bank's real profits (Π_t^{CB}) are calculated as follows:

$$\Pi_t^{CB} = \frac{R_t^G}{1+\pi_t} b_{t-1}^{G,CB} + \frac{R_{t-1}^{LF}}{1+\pi_t}\Phi_{t-1}^B(1 - \Gamma_{t-1}^B) - \frac{R_{t-1}^{DF}}{1+\pi_t}\Phi_{t-1}^L(1 - \Gamma_{t-1}^L) \tag{1.41}$$

1.4.6 Treasury

In real terms, the treasury's budget constraint is defined as:

$$\bar{b}_{t-1}\frac{R_t^G}{1+\pi_t} = \bar{b}_t + T_t + \Pi_t^{CB} \tag{1.42}$$

Here, $\bar{b}_t$ represents the real market value of government debt. Without loss of generality, it is assumed that the real market value of government debt remains constant at a certain level: $\bar{b}_t = \bar{b}$.

1.5 The Transmission Channel of the Central Bank's Bond Transactions

With the model in place, we can now explain how the central bank's balance sheet policies (QE and QT) influence interest rates and, consequently, its broader implications on the economy.

Combining the central bank's balance sheet (Equation 1.40) with the interbank market clearing condition ($\Gamma_t^B \Phi_t^B = \Gamma_t^L \Phi_t^L$) yields $b_t^{G,CB} = \Phi_t^L - \Phi_t^B$. Dividing by Φ_t^B and defining $\theta_t = \frac{\Phi_t^B}{\Phi_t^L}$ and $\tilde{b}_t^{G,CB} = \frac{b_t^{G,CB}}{\Phi_t^B}$, this produces the following expression $\theta_t = \frac{1}{\tilde{b}_t^{G,CB}+1}$ that links the government bond purchases with the interbank market tightness. This in turn affects the elasticity of the matching function with respect to the borrowing orders (φ_t), the matching probabilities ($\Gamma^x(\theta_t), x = L, B$), and the position of market rates inside the corridor (R_t^{IB}, R_t^L, and R_t^B). The effect of balance sheet policies on R_t^L and R_t^B is passed through to the households' deposit rate (R_t^D). The change in R_t^D in turn triggers a general equilibrium response similar to that triggered by a policy rate change in the standard New Keynesian model.

Conducting QE leads to an expansion in the mass of lending (Φ_t^L), while keeping the mass of borrowing constant (Φ_t^B). This, in turn, results in a reduction of market tightness (θ_t). Consequently, both φ_t and Γ_t^B increase, whereas Γ_t^L decreases. As a consequence, market rates and households' deposit rate (R_t^{IB}, R_t^L, R_t^B, and R_t^D) tend to converge toward R_t^{DF}, the deposit facility rate. The decline in R_t^D discourages saving (deposits) and encourages (current) consumption, thereby stimulating economic activity. On the contrary, the opposite effect applies when conducting QT.

1.6 Quantitative Analysis

1.6.1 Calibration

Table 1.1 presents the calibrated parameter values along with their respective sources and targets. The calibration of the parameters for the standard New Keynesian elements (α, δ, β, γ, ψ, κ, θ, ϵ, and ρ) follows the approach of Gertler and Karadi (2018). For the preference parameter ι, we follow Airaudo (2023), which is a similar study that uses deposit-in-utility function within a DSGE model to assess different exit strategies. For ν and τ, I follow the "Taylor Rules in the Quarterly Projection Model" report from the Bank of Canada, they have determined that a simple rule with a coefficient of 2 for the inflation gap (ν) and a coefficient of 0.5 for the output gap (τ) is the most suitable approach (Fung et al., 2002). Consequently, I set these parameters to align with the recommendations provided by the Bank of Canada.

The financial sector parameters (χ, $\bar{b}^{G,CB}$, ς, and ζ) are calibrated to align with pre-crisis data for Canada (Jun. 2010- Feb. 2020). Specifically, the corridor width χ is set at 0.5, consistent with the pre-crisis period. The central bank's holdings of government bonds, $\bar{b}^{G,CB}$, are set to zero to reflect the corridor system's reserve scarcity. The dividend ratio ς is chosen to capture the pre-crisis return on equity for banks, while the bond maturity parameter ζ is set to an average of five years, reflecting the typical bond duration before the crisis. λ_{SS} (steady-state matching function parameter) is borrowed from Arce et al. (2020). Borrowing λ_{SS} is reasonable for Canada's pre-crisis interbank market, given its structural efficiency and reliance on private liquidity management.

I calibrate the parameters μ_{dist} (mean of the idiosyncratic shock distribution), σ_{dist} (standard deviation of the shock distribution), $\bar{b}$ (steady-state government debt-to-GDP ratio), and ϕ_{SS} (steady-state leverage ratio) to ensure that the model accurately reflects empirical targets corresponding to the average structure of the aggregate balance sheet of depository institutions in Canada from 2011 to 2019. These targets, detailed in Table 1.2, include the Non-Productive Asset Ratio, Bond Ratio, and Equity Ratio—each represented as ratios within the model: the ratio of non-productive assets to total assets, government bonds to total assets, and equity to total assets, respectively.

To establish the calibration targets, I utilize publicly available data from the Office of the Superintendent of Financial Institutions in Canada on the "Consolidated Monthly Balance Sheet." This dataset provides detailed monthly information on the aggregate composition of the balance sheets of all banks in Canada. For the calibration, I focus on data from the pre-crisis period (2011-2019) and compute averages across this monthly data to derive a stylized balance sheet structure.

In deriving the stylized balance sheet, different asset and liability classes are categorized as follows: On the asset side, claims on the private sector are represented by the sum of loans and securities with private, non-banking counterparties, as well as investment fund shares, equity, non-financial assets, and remaining liabilities. Claims on the government consist of loans and securities with government counterparties. Interbank claims are calculated using loans and securities with non-central bank banking counterparties. On the liabilities side, deposits are defined as the sum of deposits with counterparties other than banks, in addition to securities other than liabilities to other banks. Equity corresponds to capital and reserves, while the remaining types of liabilities are categorized as interbank liabilities.

1.6.2 Simulation Results

In this analysis, I examine the dynamic consequences of different balance sheet policies when the economy experiences simultaneous negative demand and supply shocks, similar to the conditions observed during the COVID-19 pandemic, which is characterized by a decrease in inflation, output, and short-term interest rates.

The demand shock reflects a shift in consumer preferences, decreasing the importance of current consumption in favor of future savings. This preference shift, often seen as a proxy for the pandemic-driven uncertainty, reduces households' spending inclination. On the supply side, I model a supply shock as a total factor productivity (TFP) shock, representing a significant disruption in economic productivity. Pandemic-related factors—lockdowns, lower labor force participation, disrupted supply chains, and decreased business activity—drive this shock, impacting economic output, efficiency, industry composition, and prompting long-term structural changes (Garcia et al., 2023).

At time $t = 1$, the discount factor (β) unexpectedly increases, while total factor productivity (Z_t) decreases. Both variables gradually revert to their steady-state values following an AR(1) process. I set the persistence parameters at $\rho_\beta = 0.9$ and $\rho_Z = 0.9$, consistent with empirical estimates in the DSGE literature. These values imply that shocks to preferences and productivity decay gradually over time. The shock magnitudes, kept consistent across scenarios, are calibrated so that the effective lower bound (ELB) constraint binds for five quarters in scenario 1, mirroring the conditions during the COVID-19 pandemic. To simulate the recovery phase—marked by rising inflation and policy rates—a further negative supply shock, equivalent to 5 percent of annual steady-state GDP, is introduced in period 6, following McKibbin and Fernando (2021). This supply shock, dominant during the crisis, drove significant price increases (Cesa-Bianchi and Ferrero, 2021).[9][10]

I examine five distinct scenarios that vary based on the balance sheet policy implemented by the central bank. In all these scenarios, the interest rate policy follows the same

[9] In the DSGE literature, demand shocks typically outweigh supply shocks when combined. Therefore, an additional supply shock is introduced to replicate the inflationary rise observed post-pandemic.

[10] Garcia et al. (2023) argue that post-demand shock inflation remains elevated primarily due to reduced capital, which constrains supply. Though the inflation increase is moderate, it persists until the capital stock recovers.

Taylor rule, and it is assumed that the economy is in its steady state before the shocks occur. The five scenarios are as follows:

1. *Pure corridor system*: this scenario assumes that there is no unconventional policy response to the crisis.[11]

2. *Pure floor system*: in this scenario, I assume the presence of a large initial balance sheet size but no unconventional policy response to the crisis. Specifically, I consider an initial balance sheet size equal to 8% of GDP. This level is high enough that the steady state levels of the interbank rate and deposit facility rate become nearly identical, resulting in the economy effectively operating within a floor regime.[12]

3. *QT*: starting from a floor system with a large initial balance sheet (8% of GDP), I examine the implications of reducing the central bank's balance sheet by selling bonds over the course of the first six quarters after the shock at a speed of 0.7% of steady state GDP per quarter. This specific time frame of six quarters is chosen to mimic the duration it took the BoC to transition back to the pure corridor system after the financial crisis.[13]

4. *QE with tapering*: starting from a pure corridor system as in scenario (i), the central bank implements a temporary bond purchase program for 4 periods immediately after the shock at a speed of 1% of steady state GDP per quarter and maintains the enlarged central bank balance sheet for the whole period by engaging in new bond purchases to replace maturing bonds (re-investment).[14]

5. *QE followed by QT*: starting from the pure corridor system outlined in scenario 1, the central bank initiates a temporary bond purchase program that spans four periods, with a pace of 1% of steady-state GDP per quarter. Subsequently, the central bank

[11] The central bank balance sheet (Equation 1.39) is modeled as follows:

$$b_t^{G,CB} = (1-\zeta)b_{t-1}^{G,CB} + \zeta Y_{ss} \cdot \bar{b} \cdot \bar{b}^{G,CB} + Y_{ss} \cdot \bar{b} \cdot errBgcbNP + \zeta(b_{t-1}^{G,CB} - \bar{b}^{G,CB}) \cdot errBgcbRI \quad (1.43)$$

where $errBgcbNP$ denotes the shock associated with QE or the extraordinary real net purchases, while $errBgcbRI$ represents the extraordinary real re-investment shock. For the simulation of the pure corridor system, I make the assumption that both of these shocks have a value of zero.

[12] In reference to equation 1.43, I simulate the floor system by assuming an initial bond holdings of 5 percent of the GDP, or $\bar{b}^{G,CB} = 0.05$.

[13] In reference to equation 1.43 and starting from a floor system as explained in footnote 12, I assume that the value of the errBgcbNP is -0.7 percent for six quarters.

[14] In reference to equation 1.43 and starting from a corridor system as explained in footnote 11, I assume that the value of the errBgcbNP is 1 percent for four quarters, and errBgcbRI is equal to 1 for the whole period.

proceeds to sell these bonds over the next four periods, also at a rate of 1% of steady-state GDP per quarter.[15]

Figure 1.2 illustrates the five distinct strategies that central banks can employ in response to demand and supply shocks. Figure 1.3 shows the economy's response to each strategy.

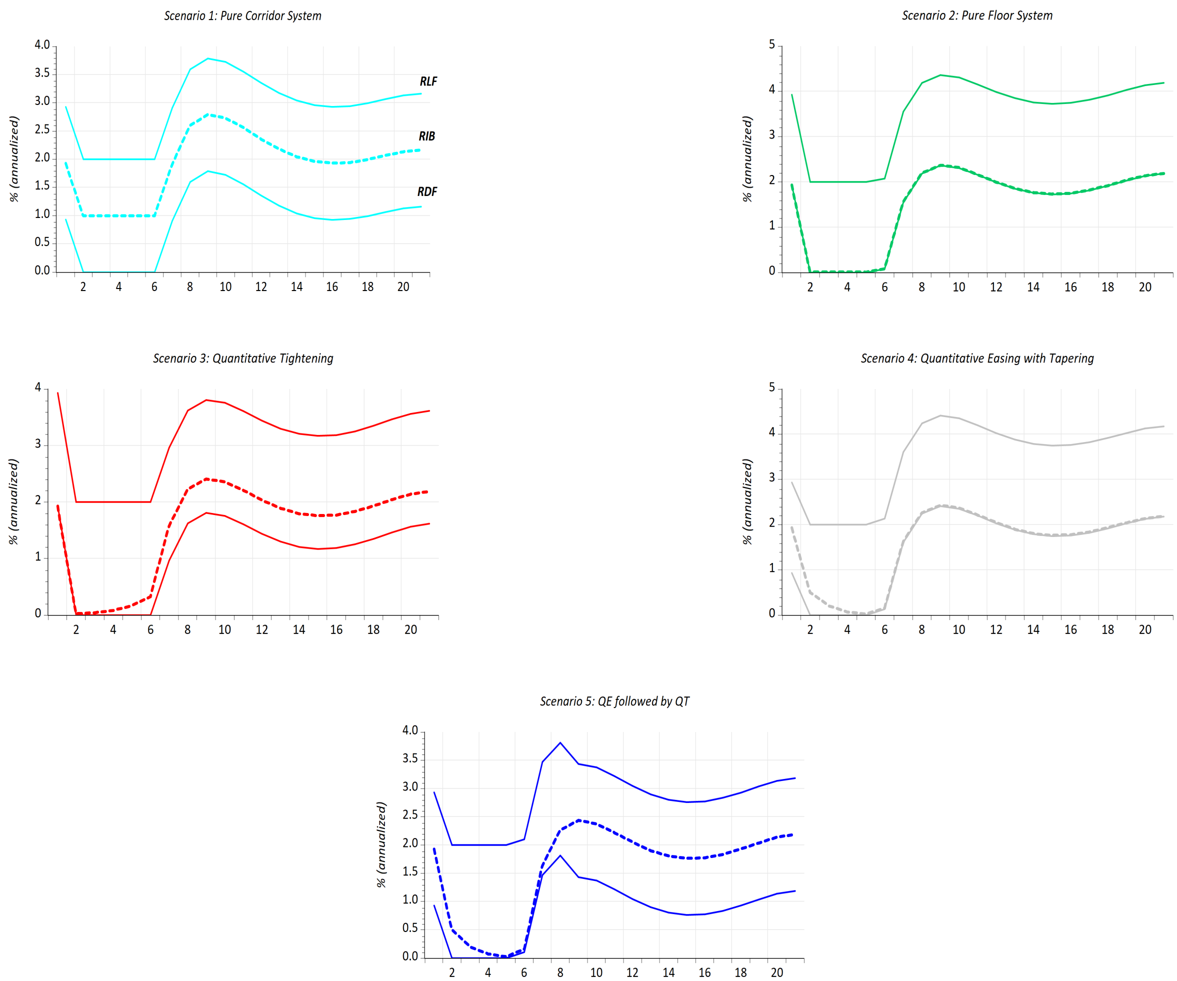

Figure 1.2: This figure shows the five different strategies that a central bank might adopt as a response to demand and supply shocks.

The Cyan blue lines in Figure 1.3 display the economy's response in scenario 1, i.e. under a pure corridor system. At the onset, the economy faces both negative demand and

[15]In reference to equation 1.43 and starting from scenario 4 and its related footnote 14, I assume that errBgcbNP is equal to -1 percent for the next four quarters and errBgcbRI remains at zero from the fifth period onward.

supply shocks, with the demand shock exerting a stronger influence than the supply shock, prompting households to delay their consumption, which in turn reduces overall demand and inflation. To counter the declining inflation, the central bank lowers its two policy rates while keeping the corridor width constant. However, the deposit facility rate reaches the ELB, limiting the central bank's ability to employ conventional monetary measures for a certain period. As time progresses, the supply shock becomes more significant, resulting in a less efficient production process. In this scenario, intermediate-good firms operate under monopolistic competition, leading them to raise their prices. The increase in prices prompts the central bank to raise its policy rates as a preemptive measure against future inflationary pressures.

The green lines depict the responses in scenario 2, where the central bank maintains a permanently large balance sheet, operating under a floor system. In this scenario, the output and inflation responses are more favorable, and welfare is higher compared to scenario 1.[16] This results from the fact that, as explained by Arce et al. (2020), in a floor system, the central bank has more policy space for conventional interest-rate policy, since the associated steady-state level of the R^{DF} is higher than under a pure corridor system.

The red lines display responses in scenario 3, where the economy starts from the same large balance sheet as in scenario 2, but the central bank engages in temporary asset sells (QT). As the central bank sells bonds, the supply of funds to the interbank market decreases, increasing its tightness and hence the interbank interest rate (for a given R^{DF}). The higher interbank rate is passed through to households' deposit rate, thus discouraging their consumption. A temporary QT program thus allows the central bank to add further austerity measures by pushing the interbank rate, and all other market rates across the economy, towards the middle of the interest rate corridor.

The grey lines display responses in scenario 4, where the economy starts from the same lean balance sheet as in scenario 1, but the central bank engages in temporary asset purchases (QE). As the central bank purchases bonds, the supply of funds to the

[16] I use the Consumption Equivalent Variation (CEV) welfare calculation that quantifies the welfare change from a policy by determining the percentage change in consumption needed to make the representative agent indifferent between the baseline and policy scenarios. CEV is calculated by comparing the welfare (utility) under each policy scenario with the baseline, using the formula:

$$\mathrm{CEV} = \left(\frac{W_{\text{policy}}}{W_{\text{baseline}}}\right)^{\frac{1}{1-\gamma}} - 1$$

where W_{policy} is the welfare under the policy scenario, W_{baseline} is the welfare under the baseline scenario, and γ is the coefficient of relative risk aversion. A positive CEV indicates a welfare improvement under the policy, while a negative CEV suggests a decline, providing a clear measure of the policy's impact on economic well-being. .

interbank market increases, lowering its tightness and hence the interbank interest rate (for a given R_t^{DF}). The lower interbank rate is passed through to households' deposit rate, thus stimulating their consumption. A temporary QE program thus allows the central bank to add further stimulus during a binding-ELB episode by pushing interbank interest rates, and all other market rates across the economy, towards the bottom of the interest rate corridor. In this case, the central bank adopts a re-investment approach to maintain the level of its balance sheet unchanged.

Finally, the blue lines display responses in scenario 5, where the economy starts from the same lean balance sheet as in scenario 1 but the central bank engages in temporary asset purchases (QE) and hence switching to a floor system. However, this followed by a temporary asset sells (QT) and hence switching back to a pure corridor system.

Scenarios 2 and 4 highlight that large reserves within the money market dampen monetary transmission, necessitating a greater number of policy rate hikes to achieve the desired interbank rate target. In contrast, scenarios 1, 3, and 5, where the central bank operates within a pure corridor system or implements QT, allow for more efficient alignment of interbank rates with targets, requiring fewer policy adjustments. This underscores that abundant reserves demand more substantial interventions to attain target rates compared to scenarios with leaner reserves or QT.

Figure 1.3 shows that the optimal monetary policy response during and after a crisis differs depending on whether the central bank operates within a corridor or floor system before the crisis. Under a pre-crisis corridor system, the preferred approach involves using QE during the crisis and QT during recovery. However, in a floor system, the best strategy is to maintain the floor throughout the crisis and pursue bond sales post-crisis. The findings suggest that switching to a corridor system during a crisis is unfavorable.

The CEV analysis further underscores that QE with QT provides the highest welfare improvement when the pure corridor system is the baseline, while QT alone proves most effective under the pure floor system. QE with QT consistently offers welfare gains across both systems, but its impact is more substantial under a corridor system than a floor system. These results highlight that the optimal policy choice depends on the initial monetary framework, with QT being particularly effective under a floor system and QE with QT proving more beneficial within a corridor setup.

Under a floor system, maintaining large reserves can simplify the control of policy rates but may limit the effectiveness of tightening measures, as abundant reserves can dampen monetary policy transmission. Contractionary steps, like bond sales, are critical to raising rates effectively in this context, as they drain reserves and lift interbank rates, influencing

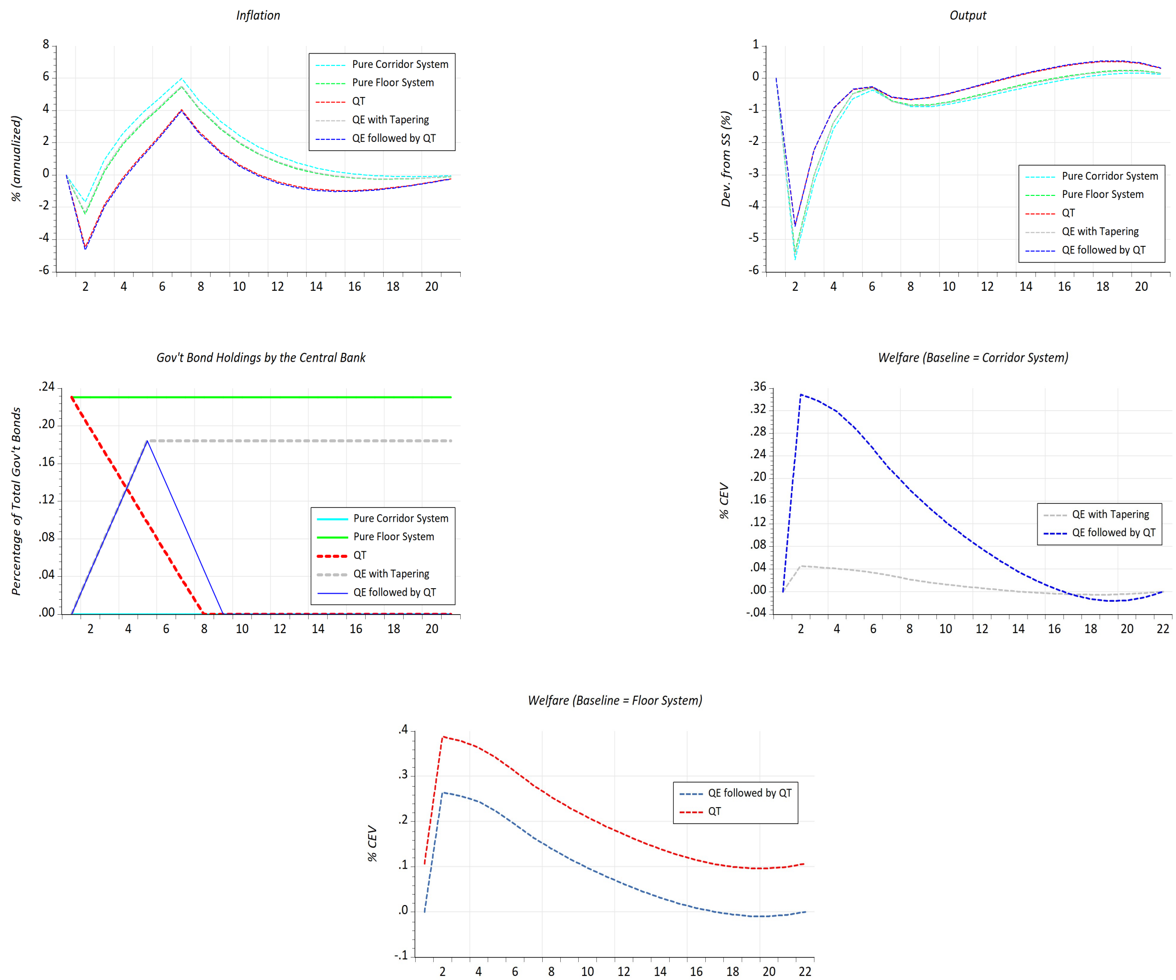

Figure 1.3: This figure shows the responses of key macroeconomic variables to demand and supply shocks under the different assumptions about unconventional monetary policy.

overall financial conditions. In contrast, a corridor system's temporary reserve expansion through QE during crises supports economic stability, while transitioning to QT during recovery allows for reserve reduction, aligning interbank rates with targets and restoring more traditional rate control. This approach is particularly effective in moderating inflation, as QT involves active asset sales that reduce banking system liquidity, placing upward pressure on short-term rates. The resulting higher rates can curtail borrowing and spending, enhancing savings incentives, and fostering disinflationary pressures. Consequently, the findings underscore that QT's impact on short-term rates is more pronounced than balance sheet tapering, making it a stronger tool for managing inflationary pressures during the recovery phase.

1.7 Conclusion

This paper analyzes the dynamic effects of central bank balance sheet policies in an economy subjected to simultaneous demand and supply shocks, as seen during the COVID-19 pandemic. By introducing dual shocks, I capture the initial crisis effects—such as declines in inflation, output, and short-term interest rates—and then introduce an additional negative supply shock to represent the post-crisis period, characterized by heightened inflationary pressures. This study considers five policy scenarios, each implementing a different balance sheet strategy, including combinations of QE and QT under corridor and floor system frameworks.

The findings indicate that abundant reserves demand more substantial interventions to attain target rates compared to scenarios with leaner reserves or QT. In addition, the pre-crisis monetary policy framework significantly influences the effectiveness of QE and QT during crisis and recovery phases. For a central bank operating under a corridor system, implementing QE during the crisis followed by QT in the recovery phase appears to control inflation effectively while also promoting welfare and output recovery. Under a floor system, by contrast, maintaining the floor during the crisis and initiating bond sales during recovery stabilizes inflation and output with less disruption. This framework-dependent analysis suggests that QE-QT combinations offer more targeted tools within the corridor system, while a stable balance sheet approach is more advantageous in a floor system, highlighting conditions under which each strategy best supports macroeconomic stability.

These findings also suggest that switching to a corridor system during a crisis may reduce stability, given the supportive reserve structure of the floor system during shocks. The welfare analysis, based on CEV, further indicates that a combined QE-QT strategy consistently improves welfare, with a notable effect when deployed in a corridor system. This analysis aligns with the theoretical framework outlined in Arce et al. (2020), showing that a floor system is better suited for crises requiring reserve stability, while QT within a corridor system provides targeted inflation control during recovery.

These results highlight the strengths and limits of active balance sheet adjustments for central banks during crises and recovery. Active strategies may better support economic stability than passive approaches, though with some limitations. This study isolates balance sheet policy, excluding interactions with other crisis measures that can influence outcomes. Future research could examine effects on financial stability, market dynamics, and lending conditions.

Appendix A: Monetary Policy Implementation

Monetary policy implementation frameworks are the strategies used by central banks to achieve their policy objectives, particularly controlling interest rates and money supply in the economy. Two commonly used frameworks are the corridor system and the floor system. Before delving into these frameworks, it is essential to first understand the different types of interest rates that exist within the economy. By analyzing these types of interest rates, we can gain insights into the functioning of the financial system and the impact of monetary policy on borrowing, lending, and overall economic activity.

A.1 Interest Rate Transmission Channel

Let's start by making a clear distinction among the different interest rates prevailing in the economy. The analysis will focus on three specific types of interest rates: (i) monetary policy interest rates, (ii) interbank rate, and (iii) market interest rates.

A.1.1 Monetary Policy Interest Rates

Monetary policy interest rates, also known as policy rates, are set by the central bank and apply to the lending and borrowing transactions between the central bank and financial institutions (mainly commercial banks). These rates are crucial tools in implementing monetary policy and achieving the central bank's objectives, such as controlling inflation, stabilizing the economy, and fostering sustainable growth. The policy rates serve as a benchmark for other interest rates in the economy. When the central bank wants to stimulate economic activity, it may lower policy rates to encourage borrowing and spending. Conversely, if the central bank aims to curb inflation, it may raise policy rates to make borrowing more expensive and reduce consumer spending.

Main policy rates are the deposit and lending facility rates. The deposit facility rate, also known as the interest rate on excess reserves or the overnight deposit rate, is the rate at which commercial banks can park their excess reserves with the central bank overnight. It serves as the lower bound of the central bank's interest rate corridor. When banks have excess reserves and do not want to lend them to other banks, they can deposit those funds with the central bank and earn the deposit facility rate as interest. On the other hand, the lending facility rate, also called the overnight lending rate, is the interest rate at which commercial banks can borrow funds from the central bank overnight. It serves as the upper bound of the central bank's interest rate corridor. When banks face temporary shortages of reserves, they can borrow from the central bank's lending facility to meet their reserve requirements or other liquidity needs. The lending facility rate is typically higher than the deposit facility rate.

Another important policy rate is the overnight rate target, which is also referred to as the central bank's key policy interest rate. This rate represents the interest rate that the central bank aims to see prevailing in the financial markets for overnight loans exchanged between financial institutions (interbank rate). Acting as a benchmark, this key rate is utilized by banks and other financial entities to determine the interest rates applied to consumer loans, mortgages, and various other types of lending.

A.1.2 Interbank Rate

Interbank rate is the interest rate at which commercial banks lend or borrow funds from one another in the money (or interbank) market. Banks need to maintain a certain level of reserves to meet regulatory requirements and handle day-to-day transactions. Sometimes, a bank may face a temporary shortage of reserves, and it can borrow from other banks with excess reserves at the interbank lending rate. This rate is typically close to the central bank's key policy rate, as it reflects the cost of borrowing reserves from other banks. The interbank lending rate is essential for maintaining stability in the banking system and ensuring that all banks can meet their reserve requirements and other liquidity needs.

A.1.3 Market Interest Rates

Market interest rates encompass a wide range of rates that apply to lending and borrowing activities between commercial banks and their customers, such as individuals, businesses, or government. They are not directly set by the central bank, but they are affected by the central bank's policy rates and other market forces. When the central bank adjusts its policy rates, it can influence the general level of market interest rates throughout the economy.

A.1.4 The Interest Rate Transmission Channel

Now that I have clarified the definitions of the three types of interest rates, let's delve into the interest rate transmission channel of monetary policy. This channel represents the process by which adjustments in the central bank's key interest rate (monetary policy rate) influence a range of interest rates in the economy, leading to impacts on economic activity, inflation, and overall financial conditions. Understanding this channel is crucial as it sheds light on how monetary policy decisions affect households, businesses, and the functioning of financial markets.

The central bank adjusts its key interest rate (policy rate) based on its assessment of economic conditions and its policy objectives. If the central bank aims to stimulate economic activity and boost inflation, it may lower the policy rate. Conversely, if it wants to curb inflation or control economic overheating, it may raise the policy rate. The change in the policy rate influences short-term market interest rates, such as the interbank lending rate and other money market rates. As the central bank's policy rate serves as a reference rate, other interest rates in the economy tend to move in the same direction. Commercial banks' lending and borrowing rates are impacted by changes in short-term market interest rates. When the policy rate is lowered, banks' borrowing costs decrease, and they pass on these lower costs to borrowers by reducing the interest rates on loans, such as mortgages, personal loans, and business loans. Lower borrowing costs for consumers and businesses encourage increased borrowing and spending. This, in turn, boosts consumption and investment, contributing to economic growth.

Lower interest rates tend to boost asset prices which may lead to wealth effects, where individuals feel wealthier and tend to spend more, further supporting economic activity. In addition, changes in interest rates can influence inflation expectations. Lower interest rates may signal the central bank's intention to stimulate the economy and increase inflation. As a result, households and businesses may anticipate higher inflation and adjust their spending and pricing behaviors accordingly.

By influencing these various interest rates and economic indicators, the interest rate transmission channel allows monetary policy to impact the overall economic environment. However, the effectiveness of the interest rate transmission channel may vary based on factors such as the level of interest rates, the strength of financial institutions, and the responsiveness of households and businesses to changes in interest rates. Central banks continually monitor and adapt their monetary policy measures to achieve their economic objectives while ensuring stability and sustainable growth.

A.2 Corridor System

The corridor system is designed to steer short-term interest rates towards a target rate set by the central bank. In this framework, the central bank establishes a floor and a ceiling around its policy rate, using a deposit facility and a lending rate, respectively.

By adjusting liquidity through open market operations (OMOs), the central bank aims to maintain actual interest rates close to the target policy rate, which is the rate the central bank seeks to prevail in the financial markets for overnight loans between financial institutions.

The corridor system prevents abrupt changes in liquidity from causing significant fluctuations in market rates. Banks with insufficient required reserves have no reason to borrow at a rate higher than the central bank's lending facility rate (ceiling) for overnight funds. Conversely, banks with excess reserves have no reason to accept a rate lower than the central bank's deposit facility rate (floor). Consequently, at rates between the floor and ceiling, banks with surplus funds have an incentive to lend to those with a shortage, creating an active interbank market for overnight liquidity. The range between the deposit facility rate and the lending facility rate is called the corridor width and it can vary in size.

The challenge for the central bank in the corridor system lies in accurately determining the necessary amount of reserves in the banking system to encourage trading near the target overnight interest rate. Effective reserve management is crucial, as an inadequate supply of reserves can push the overnight rate above the target rate, leading to higher borrowing costs for banks and potentially affecting other market interest rates. Conversely, an excess of reserves can push the overnight rate below the target, impacting the central bank's ability to control monetary conditions.

To address this challenge, the central bank needs to estimate the demand for reserves accurately and adjust its open market operations accordingly. By doing so, the central bank can maintain stability in the interbank market and achieve its monetary policy objectives within the corridor system.

Panel (a) of Figure 1.6 illustrates the overnight interbank funding market within a pure corridor system. In this setup, the supply of reserves curve intersects the downward-sloping segment of the demand for reserves curve. In this intentional scarcity of reserves, central banks employ open market operations to precisely adjust the reserves supply. The goal is to steer the overnight interbank rate to align closely with the policy rate, often positioned in the middle of the rate corridor.

A.3 Quantitative Easing

QE is an unconventional monetary policy tool employed by central banks to stimulate economic activity and support financial markets when conventional policy measures, such as lowering interest rates, are less effective or insufficient due to being near zero (known as the zero lower bound). In QE, the central bank purchases long-term financial assets, like government bonds, from the open market to increase the money supply and lower long-term interest rates, encouraging borrowing and investment. While QE can be effective in specific circumstances, there are concerns about potential risks, including asset price bubbles, financial imbalances, and long-term inflationary pressures.

It is crucial to distinguish between QE and open market operations (OMOs), both monetary policy tools used by central banks. OMOs manage short-term interest rates by buying or selling short-term government securities to maintain the policy rate close to the target. In contrast, QE focuses on long-term rates through the purchase of longer-maturity assets, with the central bank holding them on its balance sheet for an extended period. OMOs are conducted more frequently to manage short-term liquidity needs, while QE is less frequent and employed strategically during economic distress or when conventional tools are limited in efficacy. The size of purchases or sales in OMOs is typically smaller and focused on managing short-term liquidity conditions and fine-tuning the level of reserves in the banking system. QE, on the other hand, involves large-scale and significant purchases of longer-term financial assets.

As illustrated in Panel (b) of Figure 1.6, QE can lead to a switch from a corridor system to a floor system in the implementation of monetary policy. This transition occurs due to the significant increase in the level of reserves in the banking system resulting from large-scale asset purchases conducted during QE. During QE, the central bank purchases a substantial amount of long-term financial assets, injecting a large volume of money into the financial system. These purchases increase the reserves held by commercial banks with the central bank. As a consequence of QE, many banks find themselves with excess reserves beyond their required levels. These excess reserves are not utilized for lending to other banks or investing in the interbank market.

A.4 Floor System

In a corridor system, the central bank manages short-term interest rates by varying the level of reserves in the banking system within a specified corridor, with a deposit facility rate as the floor and a lending facility rate as the ceiling. However, during QE, the substantial accumulation of surplus reserves in the banking system may result in the overnight interest rate consistently falling to the deposit facility rate (the rate paid by the central bank on excess reserves). This situation can reduce the interbank market activity, as banks have no incentive to lend to each other at a rate lower than what they can earn on their surplus reserves by depositing them with the central bank. To address the challenges posed by the surplus reserves and the reduced effectiveness of the corridor system, the central bank may opt to switch to a floor system.

In a floor system, the central bank sets the policy rate as the interest rate paid on excess reserves (similar to the deposit facility rate in the corridor system), as illustrated in Panel (c) of Figure 1.6. The floor system eliminates the need for a lending facility rate, as banks have no reason to borrow from other banks when they can earn interest on their excess reserves from the central bank. With the floor system, the overnight interest rate is effectively anchored at the policy rate (the rate on excess reserves), providing a more stable and predictable interest rate environment. The central bank can control short-term interest rates by adjusting the rate paid on excess reserves, which influences the entire yield curve.

A.5 Quantitative Tightening

Transitioning from a floor system to a corridor system during the recovery period can be achieved through the implementation of aggressive QT. QT is the reverse of QE, wherein the central bank reduces the size of its balance sheet by selling financial assets and draining excess reserves from the banking system. This process effectively reduces the money supply and increases short-term interest rates.

As the central bank conducts aggressive QT, the reduction in reserves leads to a scarcity of funds available for interbank lending. With reduced excess reserves, banks may compete for the remaining available funds by offering higher interest rates on short-term loans. Consequently, short-term interest rates, such as the overnight rate, would start to move towards the upper bound of the corridor, which is the lending facility rate set by the central bank.

As the central bank continues with aggressive QT and the demand for credit remains strong, the overnight interest rate may reach or exceed the lending facility rate, becoming constrained within the corridor. The central bank can then set its policy rate as the midpoint of the corridor, with the deposit facility rate serving as the lower bound and the lending facility rate as the upper bound, as illustrated in Panel (d) of Figure 1.6.

With the transition to a corridor system, the central bank can fine-tune its control over short-term interest rates through open market operations. The central bank can now manage the level of reserves in the banking system to keep the overnight rate close to its target policy rate within the corridor.

During both the 2009 global financial crisis and the COVID-19 pandemic, central banks resorted to QE, leading to a transition from the corridor system to the ample reserve or floor system for monetary policy implementation. Notably, some countries, such as the United States and the United Kingdom, made the strategic decision to continue operating under the floor system even after implementing QE during the global financial crisis. The primary rationale behind this choice was their belief that the floor system proved more effective in exerting control over market interest rates, successfully steering them close to the desired policy or target rate, irrespective of the prevailing interest rate conditions.

Appendix B: Remaining Parts of the Model

B.1 Firms

B.1.1 Retail Good Firms

It is assumed that monopolistic competition prevails at the retail level. Retailers purchase units of intermediate goods and convert them on a one-to-one basis into various retail goods, which are then sold to final good producers. Each retailer, denoted by i, operates under the sticky price model introduced by Calvo (1983). In this framework, retailers set their prices $P_{i,t}$ based on the demand curve $Y_t^d(P_{i,t})$ and the price of intermediate goods, P_t^y.

In each period, a fraction $1-\theta$ of firms has the opportunity to adjust their prices, while the remaining fraction θ keeps their prices unchanged. Retailers that can change prices in period t select a new optimal price P_t^* to maximize their expected discounted stream of profits:

$$\max_{P_{i,t}} \sum_{k=0}^{\infty} \theta^k \mathbb{E}_t \left[\Lambda_{t,t+k} \left(\frac{P_{i,t}}{P_{t+k}} - MC_{t+k} \right) \left(\frac{P_{i,t}}{P_{t+k}} \right)^{-\epsilon} Y_{t+k} \right], \tag{1.44}$$

where $\Lambda_{t,t+k}$ is the stochastic discount factor, MC_{t+k} represents the marginal cost, and ϵ is the elasticity of demand.

The first-order condition resulting from this optimization problem implies that all retailers who are able to adjust prices in period t will set a common price P_t^*. The overall price level P_t then evolves according to the following equation:

$$P_t^{1-\epsilon} = \theta P_{t-1}^{1-\epsilon} + (1-\theta)(P_t^*)^{1-\epsilon}. \tag{1.45}$$

B.1.2 Final Good Firms

A competitive representative final good producer aggregates a continuum of differentiated retail goods, indexed by $i \in [0,1]$, using a Dixit-Stiglitz aggregation technology:

$$Y_t = \left(\int_0^1 Y_{i,t}^{\frac{\epsilon-1}{\epsilon}} \, di \right)^{\frac{\epsilon}{\epsilon-1}}, \tag{1.46}$$

where $\epsilon > 1$ represents the elasticity of substitution across retail goods. It's important to note that the index i refers to retail goods produced by retail goods producers, whereas the index j mentioned earlier referred to islands, banks, and intermediate goods producers on those islands.

The final good producers minimize their costs by solving the following problem:

$$\min_{Y_{i,t}} \; P_{i,t}Y_{i,t} \quad \text{subject to} \quad Y_t = \left(\int_0^1 Y_{i,t}^{\frac{\epsilon-1}{\epsilon}} \, di \right)^{\frac{\epsilon}{\epsilon-1}}, \tag{1.47}$$

which implies the demand function for each retail good i:

$$Y_{i,t} = \left(\frac{P_{i,t}}{P_t} \right)^{-\epsilon} Y_t, \tag{1.48}$$

where P_t is the aggregate price level of the final good. Total expenditure on intermediate inputs across all retail goods is given by $\int_0^1 P_{i,t}Y_{i,t} \, di = P_t Y_t$.

In equilibrium, the free entry condition ensures that profits are driven to zero, resulting in the final good's equilibrium price equaling the aggregate price level, P_t.

B.2 Banks

Banks derive their earnings through three channels: (i) the profit gained from investing in local firms, (ii) the income generated by lending funds in the interbank market, and (iii) the return obtained from investing in government bonds. Concurrently, banks incur costs in two ways: (i) paying interest on the funds borrowed from the interbank market and (ii) paying interest on deposits made by households.

B.2.1 Investing in the Local Firms

As indicated before, banks finance firms' investment in the form of perfectly state-contingent debt, A_t^j. After production in period $t+1$, island j's firm pays the bank the entire cash flow from the investment project (equation 1.10). Iterating one period ahead, then dividing and multiplying by Q_t^K and rearranging yields the gross return on the bank's investment:

$$R_{t+1}^A Q_t^K \omega_t^j A_t^j \tag{1.49}$$

where $R_{t+1}^A \equiv \frac{R_{t+1}^K + (1-\delta)Q_{t+1}^K}{Q_t^K}$ is gross return on assets.

B.2.2 Borrowing or Lending Funds in the Interbank Market

In addition to investing in local firms, the bank has the option to engage in borrowing or lending activities in the interbank market through one-period nominal loans. Let $B_t^{+,j}$ represent the real amount borrowed at time t, and $B_t^{-,j}$ denote the real amount lent at time t, where $B_t^{+,j}, B_t^{-,j} \geq 0$.

At time t, when the bank lends a unit in the interbank market, it receives a non-contingent gross nominal return of R_t^L at period $t+1$. Conversely, when the bank borrows a unit, it incurs a cost of the non-contingent gross nominal rate R_t^B at $t+1$. Therefore, the real returns on lending and borrowing in the interbank are:

$$\frac{R_t^L}{1+\pi_{t+1}} B_t^{-,j} \tag{1.50}$$

$$\frac{R_t^B}{1+\pi_{t+1}} B_t^{+,j} \tag{1.51}$$

These rates are considered predetermined by the bank. I will explore their determination later, but for now, it is important to note that in equilibrium, $R_t^B \geq R_t^L$.

B.2.3 Purchasing Bonds

The bank has the option to purchase nominal long-term Treasury bonds. Specifically, I assume that a newly issued bond at time t will pay $\zeta(1-\zeta)^s$ units of currency $s+1$ periods later, where $s \geq 0$. A convenient aspect of this specification is that a bond issued s periods ago is equivalent to $(1-\zeta)^s$ new bonds. Thus, we only need to track the price of one bond cohort in each period.

Let Q_t^G represent the nominal price of a bond issued at time t. Therefore, the nominal return at the start of period $t+1$ on government bonds is denoted as $R_{t+1}^G \equiv \frac{\zeta+(1-\zeta)Q_{t+1}^G}{Q_t^G}$. Additionally, I use $b_t^{j,G}$ to denote the real market value of the bank's government bond portfolio at the end of period t.

The return from investing in government bonds is:

$$\frac{R_{t+1}^G}{1+\pi_{t+1}} b_t^{j,G} \tag{1.52}$$

B.2.4 Households' Deposits

Lastly, the bank accepts a real amount D_t^j in deposits from households, which yield a gross nominal return of R_t^D.

The gross interest rate paid on households' deposits is:

$$\frac{R_t^D}{1+\pi_{t+1}} D_t^{j.B} \tag{1.53}$$

B.2.5 Bank's Net Earnings

Combining equations from 1.49 to 1.53 yields the bank's real net earnings at the start of the following period, denoted by E_{t+1}^j:

$$E_{t+1}^j = R_{t+1}^A Q_t^K \omega_t^j A_t^j + \tfrac{R_t^L}{1+\pi_{t+1}} B_t^{-,j} - \tfrac{R_t^B}{1+\pi_{t+1}} B_t^{+,j} + \tfrac{R_{t+1}^G}{1+\pi_{t+1}} b_t^{j,G} - \tfrac{R_t^D}{1+\pi_{t+1}} D_t^{j,B} \tag{1.54}$$

B.2.6 lemma 1 (Bank's problem)

The solution to the bank's problem is given by demand policies for the local firm's assets and for interbank borrowing,

$$A_t^j = \begin{cases} \frac{\phi N_t^j}{Q_t^K} & \text{if } \omega_t^j > \omega_t^B \\ \frac{N_t^j + D_t^j}{Q_t^K} & \text{if } \omega_t^L \leq \omega_t^j \leq \omega_t^B \\ 0 & \text{if } \omega_t^j < \omega_t^L \end{cases} \tag{1.55}$$

$$B_t^{+,j} = \begin{cases} (\phi - 1) N_t^j - D_t^j & \text{if } \omega_t^j > \omega_t^B \\ 0 & \text{if } \omega_t^L \leq \omega_t^j \leq \omega_t^B \\ 0 & \text{if } \omega_t^j < \omega_t^L \end{cases} \tag{1.56}$$

where

$$\omega_t^B \equiv \frac{E_t\left[\tilde{\Lambda}_{t,t+1} R_t^B/(1+\pi_{t+1})\right]}{E_t\left[\tilde{\Lambda}_{t,t+1} R_{t+1}^A\right]}, \quad \omega_t^L \equiv \frac{E_t\left[\tilde{\Lambda}_{t,t+1} R_t^L/(1+\pi_{t+1})\right]}{E_t\left[\tilde{\Lambda}_{t,t+1} R_{t+1}^A\right]} \tag{1.57}$$

$$\tilde{\Lambda}_{t,t+1} \equiv \Lambda_{t,t+1}\left(1-\varsigma+\varsigma\lambda^N_{t+1}\right) \tag{1.58}$$

and λ^N_t is the marginal value of equity. Demand for government bonds and interbank lending satisfies:

$$b^{G,j}_t = B^{-,j}_t = 0, \text{ if } \omega^j_t \geq \omega^L_t \tag{1.59}$$

$$b^{G,j}_t + B^{-,j}_t = N^j_t + D^j_t, \quad (b^{G,j}_t, B^{-,j}_t) \geq 0, \text{ if } \omega^j_t < \omega^L_t \tag{1.60}$$

Banks' individual deposit demand satisfies:

$$D^j_t \in [0, (\phi-1)N^j_t] \tag{1.61}$$

The ex-ante return on government bonds and the return on interbank lending satisfy a no-arbitrage condition:

$$E_t\left(\tilde{\Lambda}_{t,t+1}\frac{R^G_{t+1}}{1+\pi_{t+1}}\right) = E_t\left(\tilde{\Lambda}_{t,t+1}\frac{R^L_t}{1+\pi_{t+1}}\right) \tag{1.62}$$

Finally, the nominal deposit rate equals:

$$\begin{aligned} R^D_t &= \left[1-F(\omega^B_t)\right]R^B_t + F(\omega^L_t)R^L_t \\ &\quad + \left[F(\omega^B_t)-F(\omega^L_t)\right]E\left(\omega \mid \omega^L_t \leq \omega \leq \omega^B_t\right)\frac{E_t\left[\tilde{\Lambda}_{t,t+1}R^A_{t+1}\right]}{E_t\left[\tilde{\Lambda}_{t,t+1}/(1+\pi_{t+1})\right]} \end{aligned} \tag{1.63}$$

with $R^D_t \in [R^L_t, R^B_t]$.

To summarize, this lemma outlines how banks adjust their investment and borrowing strategies based on the specific shocks (ω^j_t) affecting local firms. When the shock is highly positive, banks maximize their investment in the firm's assets and borrow from the interbank market, constrained by a leverage ratio. For moderate shocks, banks invest all available equity and deposits in the firm without borrowing further. In the case of negative shocks, banks avoid investing in the firm and instead focus on safer investments like government bonds and interbank lending. The deposit rate is set as a weighted average of expected returns, reflecting the distribution of shocks, while ensuring a no-arbitrage condition between government bonds and interbank lending.

B.3 Aggregation, Market Clearing and Equilibrium

B.3.1 Capital

Capital is supplied by households (K_t) and demanded by intermediate-good firms ($\int_0^1 K_t^j \, dj$). As mentioned previously, the assumption is made that $K_t^j = A_t^j$ on each island j, which implies ($K_t = \int_0^1 A_t^j \, dj$). Here, A_t^j represents the local firm's assets, and these assets are sought after by three types of banks based on the capital quality shock:

$$A_t^j = \begin{cases} \frac{\phi N_t^j}{Q_t^k} & \text{if} \quad \omega_t^j > \omega_t^B \\ \frac{N_t^j + D_t^j}{Q_t^k} & \text{if} \quad \omega_t^L \leq \omega_t^j \leq \omega_t^B \\ 0 & \text{if} \quad \omega_t^j < \omega_t^L \end{cases} \tag{1.64}$$

When aggregating across banks j, I arrive at the following expression for K_t:

$$K_t = \int_{j:\omega_t^j > \omega_t^B} \frac{\phi N_t^j}{Q_t^k} \, dj + \int_{j:\omega_t^j \in [\omega_t^L, \omega_t^B]} \frac{\phi N_t^j + D_t^j}{Q_t^k} \, dj \tag{1.65}$$

Simplifying further, we get:

$$K_t = \frac{\phi[1 - F(\omega_t^B)]N_t + [F(\omega_t^B) - F(\omega_t^L)](N_t + D_t)}{Q_t^k} \tag{1.66}$$

B.3.2 Capital Quality Shock

Using equation (1.66), we can find an expression for the index of capital efficiency (Ω_t):

$$\int_0^1 \omega_t^j K_t^j \, dj = \Omega_t K_t \tag{1.67}$$

where:

$$\Omega_t \equiv \frac{\phi[1 - F(\omega_t^B)]E(\omega \mid \omega \geq \omega_t^B) + \frac{N_t + D_t}{N_t}[F(\omega_t^B) - F(\omega_t^L)]E(\omega \mid \omega_t^L \leq \omega < \omega_t^B)}{\phi[1 - F(\omega_t^B)] + \frac{N_t + D_t}{N_t}[F(\omega_t^B) - F(\omega_t^L)]} \tag{1.68}$$

is an index of capital efficiency.

B.3.3 Labor

Households supply labour (L_t) and intermediate-good firms demand labour ($\int_0^1 L_t^j \, dj$). The optimal (aggregate) labour demand by intermediate-good firms:

$$\int_0^1 L_t^j \, dj = \left(\frac{MC_t(1-\alpha)Z_t}{W_t} \right)^{\frac{1}{\alpha}} \int_0^1 \omega_{t-1}^j K_{t-1}^j \, dj \tag{1.69}$$

or:

$$L_t = \left(\frac{MC_t(1-\alpha)Z_t}{W_t} \right)^{\frac{1}{\alpha}} \Omega_{t-1} K_{t-1} \tag{1.70}$$

B.3.4 Intermediate Goods

Given the production function of the intermediate-good firms:

$$Y_t^j = Z_t(\omega_{t-1}^j K_{t-1}^j)^{\alpha} (L_t^j)^{1-\alpha} \tag{1.71}$$

Aggregating (1.71) across intermediate-good firms and using :

$$\int_0^1 Y_t^j \, dj = Z_t(\omega_{t-1}^j K_{t-1}^j)^{\alpha} (L_t^j)^{1-\alpha} \tag{1.72}$$

Using 1.70, 1.68, $Y_{i,t} = \left(\frac{P_{i,t}}{P_t} \right)^{-\epsilon} Y_t$ and $\Delta_t \equiv \int_0^1 \left(\frac{P_{i,t}}{P_t} \right)^{-\epsilon} di$ we obtain the market clearing for the intermediate good:

$$Y_t = \frac{Z_t}{\Delta_t} L_t^{1-\alpha} (\Omega_{t-1} K_{t-1})^{\alpha} \tag{1.73}$$

B.3.5 Final Goods

Aggregate supply of final goods must be equal to consumption and investment demand by households:

$$Y_t = C_t + I_t \tag{1.74}$$

B.3.6 Government Bonds

The total (fixed) supply of government bonds is equal to the demand by banks and central bank:

$$\bar{b}_t = b_t^G + b_t^{G,CB} \tag{1.75}$$

B.3.7 Deposits

Deposits supplied by households (D_t^H) is equal to those demanded by banks ($D_t^B = \int_0^1 D_t^{j,B}\, dj$):

$$D_t^H = D_t^B (\equiv D_t) \tag{1.76}$$

B.3.8 Banks' Equity

Aggregating equation (1.11) across banks and using ($N_t^i = \varsigma E_t^j$) to find an expression for aggregate bank equity:

$$\begin{aligned} N_t = \varsigma \Bigg[& R_t^A Q_{t-1}^K \omega_{t-1} K_{t-1} + \frac{R_{t-1}^L}{1+\pi_t} \Phi_{t-1}^L \\ & - \frac{R_{t-1}^B}{1+\pi_t} \Phi_{t-1}^B + \frac{R_t^G}{1+\pi_t} b_{t-1}^G - \frac{R_{t-1}^D}{1+\pi_t} D_{t-1} \Bigg] \end{aligned} \tag{1.77}$$

B.4 Transitional Dynamics

B.4.1 Households

The representative household maximizes her utility (Equation 1.1) subject to her capital production rule (Equation 1.3) and her budget constraint (Equation 1.5) by choosing her consumption (C_t), labor (L_t), investment (I_t), and deposit (D_t^H). The first order condition are as follows:

$$1 = \frac{u'(D_t^H)}{u'(C_t)} + \Lambda_{t,t+1} \frac{R_t^D}{1+\pi_{t+1}} \tag{1.78}$$

$$\Lambda_{t,t+1} = \beta \frac{u'(C_{t+1})}{u'(C_t)} \tag{1.79}$$

$$W_t = \frac{\nu'(L_t)}{u'(C_t)} \tag{1.80}$$

$$1 = Q_t^K \left[1 - S\left(\frac{I_t}{I_{t-1}}\right) - S'\left(\frac{I_t}{I_{t-1}}\right)\frac{I_t}{I_{t-1}}\right] + \Lambda_{t,t+1} Q_{t+1}^K S'\left(\frac{I_{t+1}}{I_t}\right)\left(\frac{I_{t+1}}{I_t}\right)^2 \tag{1.81}$$

$$K_t = \left[1 - S\left(\frac{I_t}{I_{t-1}}\right)\right] I_t + (1-\delta)\Omega_{t-1}K_{t-1} \tag{1.82}$$

where $u'(C_t) = \left[C_t^{1-\iota}(D_t^H)^\iota\right]^{-\gamma}(1-\iota)C_t^{-\iota}(D_t^H)^\iota$, $\nu'(L_t) = L_t^\psi$, $u'(D_t^H) = \left[C_t^{1-\iota}(D_t^H)^\iota\right]^{-\gamma}$ $\iota C_t^{1-\iota}(D_t^H)^{\iota-1}$, $S\left(\frac{I_t}{I_{t-1}}\right) = \frac{\varepsilon}{2}\left[\frac{I_t}{I_{t-1}} - 1\right]^2$, $S'\left(\frac{I_t}{I_{t-1}}\right) = \varepsilon\left[\frac{I_t}{I_{t-1}} - 1\right]\left(\frac{1}{I_{t-1}}\right)$, and $\Lambda_{t,t+1}$ is the stochastic discount factor.

B.4.2 Firms

The optimality conditions for the firms sector are as follows:

$$Y_t = Z_t(\Omega_{t-1}K_{t-1})^\alpha(L_t)^{1-\alpha} \tag{1.83}$$

$$1 - \epsilon + \epsilon MC_t = \theta(\pi_t - 1)\pi_t - \theta\mathbb{E}_t\left[\Lambda_{t,t+1}(\pi_{t+1}-1)\pi_{t+1}\frac{Y_{t+1}}{Y_t}\right] \tag{1.84}$$

$$R_t^A = \frac{R_t^k + (1-\delta)Q_t^K}{Q_{t-1}^K} \tag{1.85}$$

$$R_t^k = \alpha MC_t Z_t \left[\frac{(1-\alpha)MC_t Z_t}{W_t}\right]^{\frac{(1-\alpha)}{\alpha}} \tag{1.86}$$

$$L_t = \left(\frac{MC_t(1-\alpha)Z_t}{W_t}\right)^{\frac{1}{\alpha}} \Omega_{t-1}K_{t-1} \tag{1.87}$$

B.4.2 Banks

$$Q_t^K K_t = \{N_t \phi[1 - F(\omega_t^B)] + (N_t + D_t^B)[F(\omega_t^B) - F(\omega_t^L)]\} \tag{1.88}$$

$$N_t = \varsigma \left[R_t^A Q_{t-1}^K \Omega_{t-1} K_{t-1} - \tfrac{R_{t-1}^B}{1+\pi_t} \Phi_{t-1}^B + \tfrac{R_{t-1}^L}{1+\pi_t} \Phi_{t-1}^L + \tfrac{R_t^G}{1+\pi_t} b_{t-1}^G - \tfrac{R_{t-1}^D}{1+\pi_t} D_{t-1}^B \right] \tag{1.89}$$

$$\omega_t^B = \frac{R_t^B}{R_{t+1}^A (1 + \pi_{t+1})} \tag{1.90}$$

$$\omega_t^L = \frac{R_t^L}{R_{t+1}^A (1 + \pi_{t+1})} \tag{1.91}$$

$$R_{t+1}^G = R_t^L \tag{1.92}$$

$$R_t^D = [1 - F(\omega_t^B)] R_t^B + F(\omega_t^L) R_t^L + [F(\omega_t^B) - F(\omega_t^L)](R_{t+1}^A (1 + \pi_{t+1}) E[\omega_t \mid \omega_t^B > \omega_t > \omega_t^L]) \tag{1.93}$$

B.4.3 Interbank Market

$$\Phi_t^B = [1 - F(\omega_t^B)][(\phi - 1) N_t - D_t^B] \tag{1.94}$$

$$\Phi_t^L = F(\omega_t^L)[N_t + D_t^B] - b_t^G \tag{1.95}$$

$$\Gamma^B = \Upsilon \left(\frac{\Phi_t^L}{\Phi_t^B}, 1 \right) \tag{1.96}$$

$$\Gamma^L = \Upsilon \left(1, \frac{\Phi_t^B}{\Phi_t^L} \right) \tag{1.97}$$

$$R_t^B = \varphi_t \Gamma_t^B R_t^{DF} + [1 - \varphi_t \Gamma_t^B] R_t^{LF} \tag{1.98}$$

$$R_t^L = (1-\varphi_t)\Gamma_t^L R_t^{LF} + (1-(1-\varphi_t)\Gamma_t^B)R_t^{LF} \tag{1.99}$$

$$\varphi_t = \frac{1}{(\frac{\Phi_t^B}{\Phi_t^L})^\lambda + 1} \tag{1.100}$$

B.4.4 Central Bank

$$R_t^{LF} = R_t^{DF} + \chi \tag{1.101}$$

$$R_t^{DF} = \max\{\rho(R_{t-1}^{DF}) + (1-\rho)[\bar{R} + \nu(\pi_t - \bar{\pi}) + \tau(Y_t - \bar{Y})], 1-\kappa\} \tag{1.102}$$

$$b_t^{G,CB} + \Phi_t^B(1-\Gamma_t^B) = \Phi_t^L(1-\Gamma_t^L) \tag{1.103}$$

$$b_t^{G,CB} = (1-\zeta)b_{t-1}^{G,CB} + \zeta\bar{b}^{G,CB} + np_t + \zeta(b_{t-1}^{G,CB} - \bar{b}^{G,CB})ri_t \tag{1.104}$$

B.4.5 Government

$$\bar{b} = b_t^{G,CB} + b_t^G \tag{1.105}$$

$$R_t^G = \frac{\zeta + (1-\zeta)Q_t^G}{Q_{t-1}^G} \tag{1.106}$$

B.4.6 Aggregation Constraints

$$\begin{aligned}\Omega_t = &\frac{\phi[1-F(\omega_t^B)]E(\omega \mid \omega \geq \omega_t^B)}{\phi[1-F(\omega_t^B)] + \frac{N_t+D_t}{N_t}[F(\omega_t^B) - F(\omega_t^L)]} \\ &+ \frac{\frac{N_t+D_t}{N_t}[F(\omega_t^B) - F(\omega_t^L)]E(\omega \mid \omega_t^L \leq \omega < \omega_t^B)}{\phi[1-F(\omega_t^B)] + \frac{N_t+D_t}{N_t}[F(\omega_t^B) - F(\omega_t^L)]}\end{aligned} \tag{1.107}$$

$$Y_t = C_t + I_t \tag{1.108}$$

$$D_t^H = D_t^B \tag{1.109}$$

B.5 Steady State

B.5.1 Households

$$1 = \frac{\iota}{1-\iota}\frac{C}{D^H} + \beta R^D \tag{1.110}$$

$$\Lambda = \beta \tag{1.111}$$

$$W = \frac{L^{\psi}}{C^{-(1-\iota)\gamma-\iota}(D^H)^{\iota(1-\gamma)}} \tag{1.112}$$

$$Q^K = 1 \tag{1.113}$$

$$I = K[1-(1-\delta)\Omega] \tag{1.114}$$

B.5.2 Firms

$$Y = (\Omega K)^{\alpha} L^{1-\alpha} \tag{1.115}$$

$$MC = \frac{\epsilon - 1}{\epsilon} \tag{1.116}$$

$$R^A = R^K + 1 - \delta \tag{1.117}$$

$$R^K = \alpha MC \left(\frac{(1-\alpha)(\epsilon-1)Z}{W\epsilon}\right)^{\frac{1-\alpha}{\alpha}} \tag{1.118}$$

$$L = \left(\frac{(\epsilon-1)(1-\alpha)Z}{W\epsilon}\right)^{\frac{1}{\alpha}} \Omega K \tag{1.119}$$

B.5.3 Banks

$$K = \{N\phi[1-F(\omega^B)] + (N+D^B)[F(\omega^B)-F(\omega^L)]\} \tag{1.120}$$

$$N = \varsigma \left[R^A \Omega K - R^B \Phi^B + R^L \Phi^L + R^G b^G - R^D D^B\right] \tag{1.121}$$

$$\omega^B = \frac{R^B}{R^A} \tag{1.122}$$

$$\omega_t^L = \frac{R^L}{R^A} \tag{1.123}$$

$$R^G = R^L \tag{1.124}$$

$$\begin{aligned} R^D = &[1 - F(\omega^B)]R^B + F(\omega^L)R^L \\ &+ [F(\omega^B) - F(\omega^L)] \left(R^A E[\omega \mid \omega^B > \omega > \omega^L]\right) \end{aligned} \tag{1.125}$$

B.5.4 Interbank Market

$$\Phi^B = [1 - F(\omega^B)][(\phi - 1)N - D^B] \tag{1.126}$$

$$\Phi^L = F(\omega^L)[N + D^B] - b^G \tag{1.127}$$

$$\Gamma^B = \Upsilon \left(\frac{\Phi^L}{\Phi^B}, 1\right) \tag{1.128}$$

$$\Gamma^L = \Upsilon \left(1, \frac{\Phi^B}{\Phi^L}\right) \tag{1.129}$$

$$R^B = \bar{R} - \Gamma^B \varphi \chi \tag{1.130}$$

$$R^L = \bar{R} - (1 - (1 - \varphi)\Gamma^L)\chi \tag{1.131}$$

$$\varphi = \frac{1}{(\frac{\Phi^B}{\Phi^L})^\lambda + 1} \tag{1.132}$$

B.5.5 Central Bank

$$R_t^{LF} = \bar{R} \tag{1.133}$$

$$R^{DF} = \bar{R} - \chi \tag{1.134}$$

$$b^{G,CB} + \Phi^B(1 - \Gamma^B) = \Phi^L(1 - \Gamma^L) \tag{1.135}$$

$$b^{G,CB} = \bar{b}^{G,CB} \tag{1.136}$$

B.5.6 Government

$$\bar{b} = b^{G,CB} + b^G \tag{1.137}$$

$$Q^G = \frac{\zeta}{R^L + \zeta - 1} \tag{1.138}$$

B.5.7 Aggregation Constraints

$$\begin{aligned} \Omega = & \frac{\phi[1 - F(\omega^B)]E(\omega \mid \omega \geq \omega^B)}{\phi[1 - F(\omega^B)] + \frac{N+D}{N}[F(\omega^B) - F(\omega^L)]} \\ & + \frac{\frac{N+D}{N}[F(\omega^B) - F(\omega^L)]E(\omega \mid \omega^L \leq \omega < \omega^B)}{\phi[1 - F(\omega^B)] + \frac{N+D}{N}[F(\omega^B) - F(\omega^L)]} \end{aligned} \tag{1.139}$$

$$Y = C + I \tag{1.140}$$

$$D^H = D^B \tag{1.141}$$

Appendix C: Figures

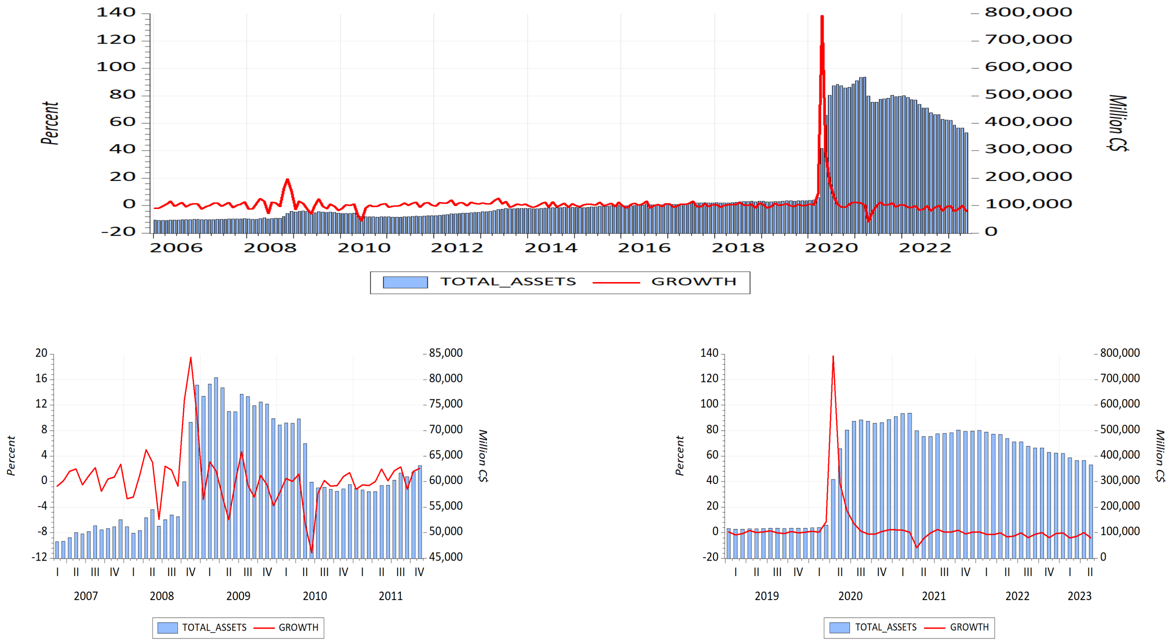

Figure 1.4: Developments of the Bank of Canada balance sheet.

Source: Office of the Superintendent of Financial Institutions, Haver analytics.

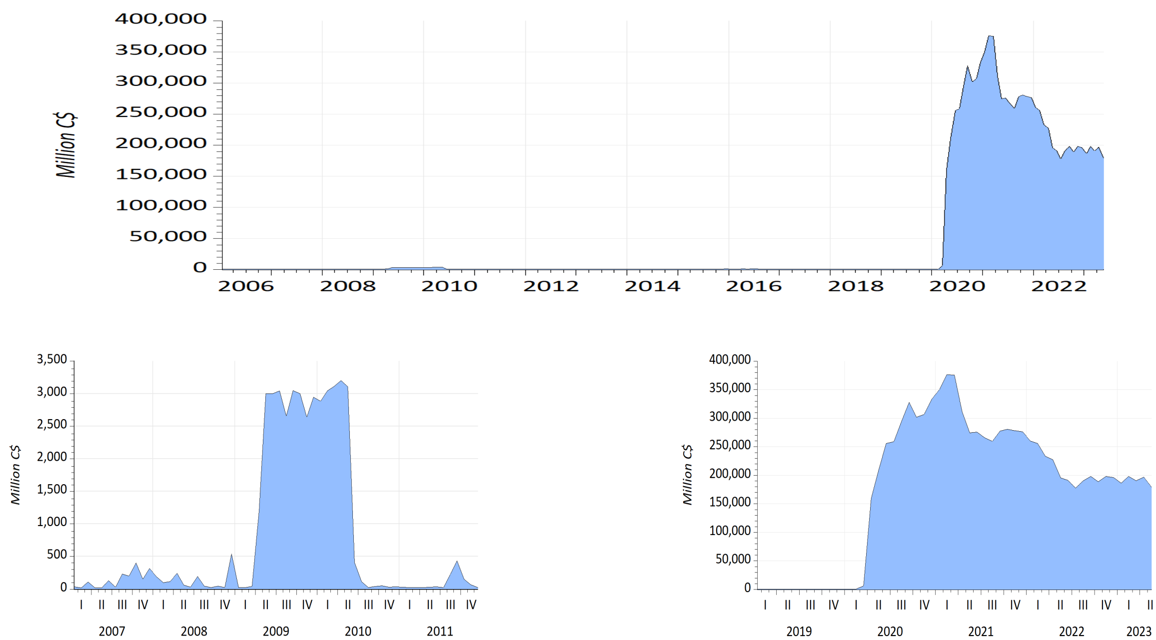

Figure 1.5: BoC Liabilities: Canadian Dollar deposits of the Canadian Payment Association members.

Source: Office of the Superintendent of Financial Institutions, Haver analytics.

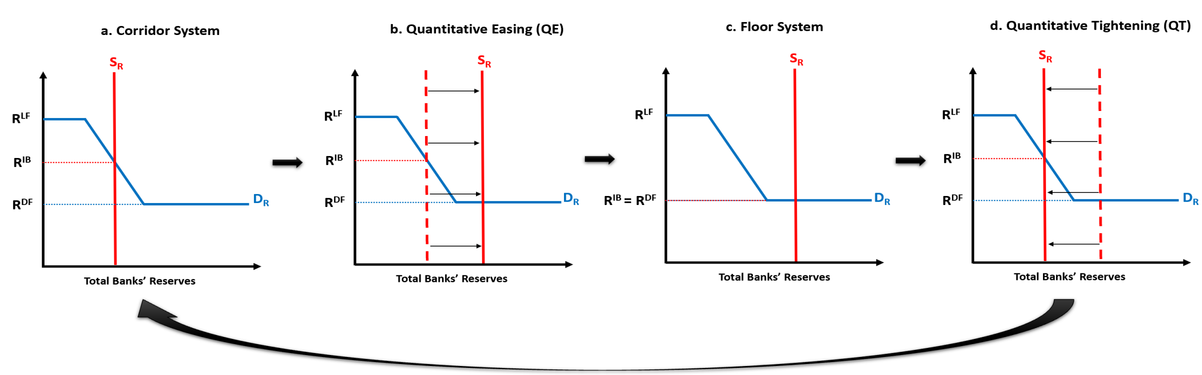

Figure 1.6: The figure shows the overnight interbank funding market, where R^{LF} denotes the central bank's lending facility rate, R^{IB} the interbank rate, and R^{DF} the central bank's deposit facility rate.

Appendix D: Tables

Table 1.1: Calibration: calibrated parameter values

Parameter	Value	Explanation	Source/Target
ρ	0.8	Taylor rule persistence	GK2018
λ^{SS}	225	Matching function parameter	Arce et al. (2020), Ratio of interbank to CB lending.
ν	2	Taylor rule inflation	BOC
τ	0.5	Taylor rule output	BOC
ε	1.728	Investment adjustment	GK2018
ι	0.0023	Preference parameter	Airaudo (2023)
γ	1	Inverse intertemporal elasticity	GK2018
ψ	0.276	Inverse Frisch elasticity	GK2018
β	0.995	Discount factor	GK2018
δ	0.025	Depreciation	GK2018
α	0.33	Capital share	GK2018
θ	0.779	Calvo parameter	GK2018
ϵ	4.167	Markup	GK2018
χ	0.005	Corridor width	Pre-crisis data for Canada, Pre-crisis corridor width
$\overline{B}$	1.34	Government debt	Numerically calibrated, Banks' steady state bond holdings
μ^{dist}	-0.003	Mean of idiosyncratic shocks	Numerically calibrated, Normalize $\Omega = 1$
σ^{dist}	0.0031	Std of idiosyncratic shocks	Numerically calibrated, Ratio of redistribution to productive assets
$\widetilde{B}^{G,CB}$	0	Government debt held by CB	Pre-crisis data for Canada, No QE pre-crisis
ς	0.975	Dividend ratio	Pre-crisis data for Canada, RoE of Banks
ζ	0.05	Bond maturity	Pre-crisis data for Canada, 5 years average maturity
ϕ^{SS}	25.5	Steady-state leverage ratio	Numerically calibrated

Table 1.2: Calibration: aggregate bank balance sheet

Assets		Liabilities	
Item	**Share**	**Item**	**Share**
Claims on private nonfinancial	0.556	Equity	0.058
Claims on government	0.156	Deposits	0.654
Interbank claims	0.288	Interbank liabilities	0.288

Note: The table reports the share of each balance sheet item as a fraction of total assets or liabilities. Figures are expressed as proportions, with values summing to unity within the assets and liabilities categories.

Chapter 2

News Sentiments and the Identification of Monetary Policy Shocks

2.1 Introduction

Monetary policy tools have evolved significantly, now extending beyond traditional adjustments in policy rates and balance sheets to include qualitative strategies. Central banks, such as the Federal Reserve (Fed), use forward guidance (FG) on future interest rates and balance sheet policies alongside detailed economic assessments to enhance transparency and guide market expectations. This shift represents a more sophisticated approach to policy but introduces analytical challenges due to the subjective and anticipatory nature of these qualitative measures, necessitating careful interpretation of central bank communications.

Studies employing principal component analysis (PCA) investigate the effects of monetary policy tools, such as interest rate adjustments, asset purchases, and forward guidance, on financial conditions. While these studies provide valuable insights into immediate market reactions, they face criticism for their limited ability to isolate true policy impacts due to issues like information leakage and market expectations. This limitation is further complicated by the "information effect," wherein policy announcements unintentionally reveal economic insights, potentially skewing interpretations. Textual analyses of Federal Open Market Committee (FOMC) statements and nonverbal cues also explore market responses, yet tend to capture only overall sentiment rather than the distinct impacts of specific policy tools. Refining these approaches to disentangle the unique components of FG could significantly improve our understanding of monetary policy influences on economic and financial indicators.

Market reactions to FOMC announcements are shaped not only by the content of official statements and nonverbal cues from Fed officials but also by how these communications are interpreted by the media, which serves as an intermediary in conveying economic policy to the public. Media narratives play a critical role, reflecting and potentially reshaping public expectations around policy changes based on editorial choices and framing (Munday and Brookes, 2021; Ter Ellen et al., 2022). By analyzing sentiment in news articles around FOMC meetings, researchers can detect shifts in sentiment as shaped by media interpretations, offering insights into the broader impact of monetary policy as perceived by the public and investors (Ter Ellen et al., 2022).

This study seeks to address a critical gap in capturing the distinct impacts of monetary policy communication by asking: *How can we effectively identify monetary policy sentiment shocks across distinct dimensions of forward guidance—interest rate guidance (IRG), balance sheet policies (BSP), and economic outlook assessment (EOA)?* Conventional approaches to assessing policy impacts often fail to consider the media's framing effects and the distinct ways these components influence public sentiment. By analyzing sentiment shifts in news coverage around FOMC meetings, this study reveals how the media interprets and conveys unexpected policy elements, subsequently shaping market and public reactions. Tailored lexicons for IRG, BSP, and EOA enable precise classification of sentiment as hawkish or dovish, providing a focused view of how each component influences financial markets as perceived through media narratives.

This study introduces a novel approach for identifying sentiment shocks in monetary policy through sentiment analysis of news articles related to FOMC meetings. Following methods established by prior research, I use the Dictionary Method of Content Analysis to evaluate shifts in media sentiment, drawing on the work of Apel and Grimaldi (2014), Tadle (2022), and Gardner et al. (2022). Newspaper articles are categorized by timing: "before-meeting articles" include those published from one day prior up to the meeting's start, while "after-meeting articles" encompass those released immediately following the meeting until the end of the same day. The resulting sentiment scores reflect media interpretations of each policy element, signaling whether expectations lean toward a hawkish or dovish stance.

The sentiment measures developed in this study show a strong alignment with actual Fed policy actions, accurately capturing FOMC decisions on interest rates and balance sheet policies. Robustness checks, conducted across multiple sentiment indexes, shock specifications, and subsample periods, including both pre-ZLB and ZLB eras, confirm the consistency and generalizability of these measures. This rigorous validation reinforces the stability and reliability of the sentiment indicators, demonstrating that they hold up under various market conditions and reflect real-time shifts in policy accurately.

The findings demonstrate that analyzing news articles to distinguish between FG components reveals unique insights into each component's specific impact on financial indicators. IRG sentiment, which strongly correlates with rate changes and bond yields, shapes immediate market expectations about borrowing costs, giving a clear view of short-term policy impact. BSP sentiment, however, reflects shifts in liquidity perceptions and long-term asset values, with hawkish signals suggesting reduced liquidity and dovish signals pointing to potential expansion. EOA sentiment primarily influences stock market behavior, with positive EOA sentiment aligned with stock gains and negative sentiment indicating economic concerns. By breaking down FG into its distinct components, the study provides a clearer understanding of how each element uniquely drives market responses, enriching the overall interpretation of forward guidance's impact on financial conditions.

This paper is organized as follows: Section 2 reviews the related literature. Section 3 describes data collection, covering newspaper articles and financial variables. Section 4 details the dictionary-based sentiment analysis and specialized lexicons for IRG, BSP, and EOA. Sections 5 and 6 present the results, with Section 5 focusing on the sentiment indexes developed for each FG component and examining their alignment with FOMC actions, while Section 6 analyzes the sentiment shocks, capturing unexpected policy elements, and assesses their impact on key financial indicators. Finally, Section 7 concludes by summarizing the main findings, discussing policy implications, and offering suggestions for future research.

2.2 Literature Review

Many studies use PCA to isolate and measure the effects of monetary policy tools on macroeconomic variables and financial indicators (e.g., Gürkaynak et al., 2005; Rosa, 2014; Swanson, 2021). By examining data around policy announcements, these studies aim to capture the immediate impacts of adjustments to the federal funds rate, large-scale asset purchases, and forward guidance on financial conditions, providing a clearer understanding of how these tools influence market responses.

Recent research, however, raises concerns about the effectiveness of these approaches in isolating monetary policy impacts due to potential information leakage, market anticipations, and the challenge of disentangling reactions to broader economic signals. Studies reliant on immediate data surrounding policy announcements inadvertently capture correlations with publicly accessible information available before FOMC releases. Cieslak (2018) questions the reliability of these "surprises" as exogenous tools, noting errors in short-term rate forecasts. Similarly, Miranda-Agrippino and Ricco (2021) points out potential inaccuracies, while Bauer and Swanson (2023a) suggests a "Fed response to news" framework. Additionally, the information effect, where announcements convey unexpected economic insights, skews interpretations, as argued by Jarociński and Karadi (2020) and Janson and Jia (2020). Furthermore, these studies often treat FG as a single tool, though it comprises three different elements: interest rate path, balance sheet, and economic outlook guidance.

Research on central bank communication increasingly incorporates textual analysis to identify unexpected elements in FOMC statements (e.g., Rosa, 2011; Kiley, 2014) and minutes (e.g., Rosa, 2013; Apergis, 2015; Tadle, 2022), along with the impact of nonverbal cues from Fed officials on financial markets (e.g., Curti and Kazinnik, 2023; Gorodnichenko et al., 2023; Alexopoulos et al., 2024). Studies by Apel and Grimaldi (2014), Stekler and Symington (2016), Tadle (2022), and Aruoba and Drechsel (2024) underscore the importance of both verbal and nonverbal cues in shaping market reactions to policy messages, demonstrating how factors like vocal tone, facial expressions, and textual sentiment influence financial conditions. For example, Gorodnichenko et al. (2023) show that positive vocal tones from Fed Chairs boost stock prices and reduce volatility, while Curti and Kazinnik (2023) and Alexopoulos et al. (2024) use facial recognition and machine learning to reveal how emotional cues affect financial indicators. Despite these advancements, most studies capture the overall tone of monetary policy without breaking down the distinct components of FOMC communications. Additionally, they often focus solely on official FOMC communications, overlooking the broader media interpretation of policy shocks.

Financial markets are driven by perceptions that can differ significantly from the intended message. For example, during the June 18-19, 2013, FOMC meeting, markets misinterpreted the suggestion of potential tapering in the asset purchase program as an imminent end to stimulus measures, causing market volatility and rising bond yields. Similarly, in the December 2023 FOMC meeting, markets misread Chairman Powell's dovish comments on potential future rate cuts as an immediate policy shift, leading to increased expectations for rate cuts in 2024 and significant market fluctuations. These instances highlight that official statements alone do not fully capture market responses. Therefore, it is crucial to develop a method to accurately capture the market interpretation of FOMC announcements.

This study addresses gaps in the literature by breaking down FG into IRG, BSP, and EOA components and examining their impacts on financial markets. Through sentiment analysis of FOMC-related newspaper articles, I capture public and market interpretations of monetary policy. Unlike prior research, this method uses specialized dictionaries and refined scoring to assess each policy element's influence on financial indicators, improving predictions of Fed decisions. Analyzing media accounts for asymmetric information between the public and the central bank, revealing subtle market reactions and enhancing insights into monetary policy shocks beyond traditional high-frequency methods and studies centered on official FOMC communications.

Economic models often overlook the media's filtering process, simplifying its role by treating monetary policymakers' messages as direct signals to individuals. In reality, households depend on mass media as their primary source of economic information (Carroll, 2003; Lamla and Maag, 2012). As noted by Neuenkirch (2014, p. 52), economic and financial news "only emerges after it goes through a filtering process by the media," emphasizing the critical intermediary role the media play in shaping and disseminating economic information. Typically, the media analyze central bank announcements to derive insights into anticipated changes in monetary policy interest rates (Hayo and Neuenkirch, 2015a). Unlike market indicators, extracting relevant monetary policy information from media reports is complex and necessitates translating textual content into numerical representations. Ideally, this quantitative indicator should reflect the media's interpretation of the central bank's message, indicating whether expectations lean toward tightening (hawkish perception) or easing (dovish perception) (Tobback et al., 2017).

2.3 Data

This analysis examines newspaper articles published around each FOMC meeting, sourced from prominent U.S. financial news outlets: The Wall Street Journal, The New York Times, The Washington Post, Financial Times, USA Today, and Reuters. These publications offer valuable insights into investor expectations before and after the 194 scheduled FOMC meetings held between January 2000 and May 2024. A comprehensive list of these meetings is provided in Table 2.11 in Appendix F.

I categorize the articles into two groups: those published before the meetings and those published afterward. Articles labeled "before meeting" include those from one day prior until just minutes before the meeting begins, while "after meeting" articles cover the period from immediately following the meeting until the end of that day. This approach excludes unscheduled meetings, which typically involve significant surprises and lack corresponding pre-meeting articles, ensuring the analysis aligns with existing literature and enhances the reliability of sentiment comparisons. In total, I collect 5,679 articles, evenly distributed between the two categories.

To confirm the relevance of collected articles, I employ specific search criteria in Factiva, requiring each article to contain at least one of the keywords "Fed" or "Meeting" and limiting the search to U.S. publications. Each of the 5,679 articles undergoes a manual review to verify its classification and ensure I have the most recent version, addressing potential inaccuracies in Factiva's date records. For example, articles dated after a scheduled FOMC meeting may actually have been published before the meeting upon closer examination of their timestamps.

After confirming their relevance, I compile the articles for each meeting, resulting in 194 PDF files for pre-meeting articles and another 194 for post-meeting articles. Given that the text in these PDFs is not directly extractable, I utilize Amazon Web Services (AWS) to convert all 388 PDF files into text format. On average, each PDF contains around 25 pages, yielding a total of approximately 10,000 pages of text for analysis.

This study, building on related works (e.g., Baker et al., 2016, Strohsal et al., 2016, Swanson, 2021, Tadle, 2022, Gorodnichenko et al., 2023), assembles a range of financial indicators to capture the broader economic context surrounding each Fed policy communication. These indicators, listed in Table 2.12 in Appendix F, measure the log daily change from the prior day's closing price to the FOMC statement release day, providing an effective means of assessing the impact of policy announcements due to their sensitivity to macroeconomic shifts and investor sentiment. The analysis includes stock market performance (S&P 500 and DJIA) as a measure of economic health and investor confidence, market volatility (VIX and DJVIX) as an indicator of perceived risk and stability, bond yields (2-year and 30-year Treasuries) as reflections of borrowing costs and economic expectations, the Euro/USD exchange rate for a global perspective on economic conditions, and corporate bond yields (Moody's Aaa and Baa) to evaluate credit risk and sentiment toward corporate debt.

2.4 Dictionary Method of Sentiment Analysis

Quantifying qualitative information can be achieved through manual or automated content analysis. Manual analysis involves reading and coding text based on context, while automated content analysis employs computer programs to count word frequencies using a predefined dictionary that categorizes words by tone, such as positive or negative. This lexicon-based method assigns sentiment scores to words, allowing for an overall sentiment score based on cumulative matches. Automated analysis reduces labor, minimizes subjective judgment, and enhances replicability, making it particularly useful for large volumes of text like newspaper articles, speeches, or financial reports (Apel and Grimaldi, 2014).

However, a limitation of this approach is that word meanings can vary by context. For instance, while "recovery" typically conveys positivity, the phrase "sluggish recovery" implies negativity. To address this, Apel and Grimaldi (2014) proposed analyzing noun-adjective pairs to capture nuanced policy stances, such as "higher inflation" or "slower growth." Ochs (2021) further refined this method by creating keyword lists that differentiate sentiment related to inflation, employment, and output. Additionally, Tadle (2022) utilized a semi-automated approach for FOMC document analysis, focusing on texts that reflect economic indicators tied to the Fed's dual mandate, like unemployment and inflation.

Building on this literature, I adopt the Dictionary Method of Content Analysis, which classifies and scores sentiment in texts using a predefined word list, ensuring consistency across large document sets that manual analysis cannot achieve at scale. Following previous studies on FOMC text sentiment analysis (e.g., Apel and Grimaldi, 2014, Ochs, 2021, Tadle, 2022), I categorize sentiment into hawkish and dovish classifications. Hawkish sentiment indicates a positive economic outlook and rising inflation, suggesting a higher likelihood of monetary tightening, while dovish sentiment reflects weaker economic conditions and modest price pressures, signaling a greater chance of monetary easing.

2.4.1 Constructing Dictionaries

To prepare the text data for sentiment analysis, I perform comprehensive cleaning and preprocessing using Python, as detailed in Appendix A. Then, I created three specialized dictionaries corresponding to the monetary policy communication tools: IRG, BSP, and EOA. While all dictionaries are newly developed from newspaper articles related to FOMC meetings, the economic outlook assessment dictionary includes some keywords from existing literature, such as those identified by Apel and Grimaldi (2014), Ochs (2021), and Tadle (2022).

For the keyword extraction, I provided explicit instructions to ChatGPT tailored to each category. Specifically, for future interest rate paths, the model was prompted to identify sentences discussing expected changes in the policy rate, such as anticipated increases or decreases by a certain number of basis points. For balance sheet policies, the prompt instructed the model to extract sentences mentioning quantitative easing, quantitative tightening, bond purchases or sales, tightening or easing policies, or discussions related to the central bank's balance sheet expansion or contraction. Finally, for economic outlook assessments, ChatGPT was directed to extract sentences explicitly evaluating the current or projected state of the economy.

I ensure the accuracy of these sentences through double-checking for each meeting.[1]

This method is preferred due to the lack of viable automated techniques for identifying specific keywords across over 10,000 pages, as the variety of keywords complicates precise extraction without narrowing the search scope. AI techniques are more effective in understanding sentence context for accurate classification.

Once sentences are extracted, keywords within each sentence are categorized as hawkish, dovish, positive, or negative according to clear guidelines. Positive and negative terms are straightforward to classify based on standard definitions. For hawkish and dovish classifications, I follow the classification rules established in the literature (Apel and Grimaldi, 2014; Ochs, 2021; Tadle, 2022): a keyword is classified as hawkish if pairing it with a positive term signals a hawkish stance. Conversely, if pairing the keyword with a positive term signals a dovish stance, it is classified as dovish. Similarly, if combining a keyword with a negative term results in a dovish stance, it is considered hawkish. If the pairing with a negative term creates a hawkish stance, it is classified as dovish. For example, "employment" with the positive term "increased" implies a hawkish stance (indicating a tendency toward rising interest rates), whereas "unemployment" with "increased" suggests a dovish stance (potentially lowering interest rates).

Accounting for negations in sentiment analysis is crucial because negations can significantly alter the meaning and sentiment of a sentence. Negations such as "not," "never," or "no" can reverse the sentiment conveyed by positive or negative words. For example, the word "happy" expresses a positive sentiment, but when preceded by the word "not," as in "not happy," the sentiment becomes negative. Failing to account for these issues can lead to incorrect sentiment classification, resulting in inaccurate analysis.

For the analysis, I construct distinct dictionaries for each policy tool to allow for separate identification. For IRG, words are manually classified as positive (e.g., *hike*, *increases*)

[1] To avoid repetition and confusion, I upload each text file separately into ChatGPT and subsequently verify the extracted sentences against the originals. This method achieves approximately 90% accuracy in extraction, although the classification of sentences into IRG, BSP, or EOA categories is about 60%, necessitating manual verification.

or negative (e.g., *cuts*, *decrease*) in relation to interest rate expectations. The complete IRG dictionary is detailed in Table 2.1.

Table 2.1: IRG dictionary

Positive Terms
climb, climbing, hike, hikes, higher, high, hiking, increases, lift, move, moves, raise, raising, rise, rises, upward
Negative Terms
back, cuts, cut, cutting, decrease, decreases, downward, fall, lower, reductions, trimmed
Negation Terms
arent, cannot, cant, couldnt, didnt, doesnt, dont, done, isnt, less, no, not, slow, slower, slowing, stop, stopping, unlikely, wont, wouldnt, zero
Related Words
anticipate, anticipates, april, august, bets, betting, by the end, december, end of the year, expected, expectations, fall, february, forecast, forecasts, january, july, june, march, may, midyear, next year, november, october, odds, penciled, possibility, possible, predict, projected, projections, september, signal, spring, summer, this year, winter, year, one, two, three, four, five, six, seven

For BSP, words are categorized concerning balance sheet actions, with hawkish keywords like QT, *tapering*, and dovish terms such as *assets*, *liquidity*. This dictionary is listed in Table 2.2.

Table 2.2: BSP dictionary

Hawkish QT
exit, normalization, qt, runoff, run off, slowdown, taper, tapering, tighten, tightening, unwinding, quantitative tightening
Dovish QE
assets, backstop, bills, bond, bond buying, bondholdings, cash, ease, easing, easy money, funds, help, lending, liquidity, money, qe, quantitative easing, reinvesting, securities, sheet, stimulation, stimulus, support
Positive Terms
accelerate, accelerating, bought, boosting, buy, buying, continue, doubled, expand, expanding, extended, faster, further, grew, increase, increases, inject, large, launch, launched, more, pumping, purchase, purchases, resume, start, stimulate, surge, swelled, up
Negative Terms
back, cut, cutting, done, down, eliminating, end, fall, fallen, fell, finish, reduce, reducing, reduction, reductions, removing, retreat, scale, scale back, scaling, sell, selling, shed, shrink, shrinking, taper, tapering, trim, trimming, withdraw, withdrawing, phasing
Negation Terms
arent, cannot, cant, couldnt, didnt, doesnt, dont, extinguishing, fail, faded, far from, hadnt, hardly, hasnt, havent, hold off, isnt, less, little, neither, never, no, none, nor, not, opposed, prevent, rarely, scarcely, shouldnt, unlikely, wait longer, without, wont, wouldnt

Lastly, the EOA dictionary classifies words related to economic conditions, with hawkish keywords such as *activities*, *consumption*, and dovish terms including *crisis*, *depression*, and *unemployment*. The full EOA dictionary is provided in Table 2.3.

Table 2.3: EOA dictionary

Hawkish Keywords
activities, activity, business, businesses, capacity, confidence, construction, consumption, cost, costs, cpi, credit, data, demand, economic, economy, earnings, employment, energy, equities, equity, expenditures, expansion, financial, gdp, goal, growth, hiring, home, housing, income, indicators, inflation, inflationary, investment, investments, job, jobs, labor, labour, lending, loan, loans, manufacturing, monetary, nonmanufacturing, outlook, output, payroll, pce, performance, policy, price, prices, product, production, productivity, recovery, resource, salaries, sales, slack, spending, stagflation, stock, supply, target, toll, trade, wage, wages, workers
Dovish Keywords
accommodation, accommodative, crisis, depression, deflation, devastation, doldrums, downturn, joblessness, lay offs, layoffs, recession, savings, securities, uncertainties, uncertainty, unemployment
Positive Terms
abating, above, accelerated, acceleration, add, added, advance, advanced, advances, aiding, appealing, augmented, balanced, best, better, blockbuster, bolsters, boom, booming, boost, boosted, brightened, brighter, brisk, chugging, climb, climbed, climbing, comfort, considerable, control, doubled, ease, eased, elevated, elevating, excited, expand, expanded, expanding, expansion, expansionary, extend, extended, fast, faster, fastest, firmer, firming, flexed his muscles, full, fuel, gains, good, grew, growing, healed, healing, healthy, heightened, high, higher, highest, highs, hike, hikes, hot, hotter, hottest, improved, improvement, improvements, improving, increase, increased, increases, increasing, intense, jump, jumped, lift, lot, massive, mend, moderating, momentum, more, new, optimism, optimistic, overheating, peak, pick up, plentiful, positive, power, progress, raise, rapid, rebound, rebounded, recovering, regained, resilience, resilient, rise, risen, rises, rising, robust, rose, run, running, significant, soared, solid, sooner, spike, spikes, spiking, stabilised, stabilized, stable, stoking, strength, strengthen, strengthened, strengthening, strengthens, strong, stronger, sturdy, supportive, surge, surged, sustain, thrived, top, topped, underpin, up, upbeat, upside, upswing, uptick, upward, well behaved
Negative Terms
abrupt, adverse, anaemic, anemic, back, battered, bearishness, below, bleak, bottomed, brake, bumpy, challenge, chills, chipped, collapse, complicate, concern, concerns, constrained, contract, contracting, contraction, cool, cooled, cooler, cooling, cools, correction, curbing, cut, cutting, damp, dampen, dampened, damping, darkened, decelerated, decelerating, deceleration, decline, declined, declines, declining, decrease, decreases, decreasing, deepening, depressed, denting, deteriorated, deteriorating, deterioration, difficult, diminish, diminished, dimmed, dip, disappointing, discomfort, discouraging, dislocation, dismal, disputes, disrepair, disrupted, disruption, disruptions, distress, dormant, down, downbeat, downgraded, downside, downward, drop, dropped, dropping, drops, ebbed, ebbing, erosion, erodes, erratic, exacerbate, exacerbating, expensive, fade, faded, fading, fall, fallen, falling, faltered, faltering, fears, feeble, fell, fewer, halt, hampered, hardship, hasn't, hazy, hit, hurt, insufficient, instability, jitters, lacklustre, less, limit, loose, loss, losses, lost, low, lower, lowest, lull, menace, moderated, moderating, moderation, muted, negative, overburdening, painful, pared, pessimistic, petered, plunge, plunged, poor, pressures, rattled, receded, reduce, reduced, reduction, reflationary, relapse, reluctant, removed, reservations, restraint, restrain, restrained, restraining, resumption, reversed, retreat, retreated, retreating, risk, risks, setback, shaky, shock, short, shortages, shrank, shrinking, sink, slack, slipped, slow, slowdown, slowed, slower, slowest, slowing, slowly, sluggish, sluggishness, slump, slumped, slumps, soft, softened, softening, stalled, stalling, stimulate, strained, strains, stress, struggles, stubborn, subdued, suppressed, swooned, tamer, tempered, tensions, tenuous, threaten, tight, tighten, tighter, tragic, troubling, tumbled, tumbling, turbulence, turmoil, underutilization, undershot, volatile, volatility, vulnerable, war, wary, weak, weaken, weakened, weakening, weaker, weakness, withdrawal, wobbling, worries, worsen, wrong
Negation Terms
arent, cannot, cant, couldnt, didnt, doesnt, dont, extinguishing, fail, faded, far from, hadnt, hardly, hasnt, havent, hold off, isnt, less, little, neither, never, no, none, nor, not, opposed, prevent, rarely, scarcely, shouldnt, unlikely, wait longer, without, wont, wouldnt

2.4.2 Identification Strategy

My approach to identifying monetary policy sentiment shocks is grounded in a structured and robust identification strategy designed to isolate the impact of three distinct monetary policy tools. I achieve this by developing a specialized dictionary for each tool, tailored to capture specific sentiment accurately.

To ensure clear differentiation between BSP and EOA, I use unique lists of hawkish and dovish keywords assigned exclusively to each tool. This minimizes overlap in sentiment calculations and strengthens precision in categorization. Unlike BSP and EOA, IRG does not rely on defined hawkish or dovish keywords. Instead, I introduce a new approach that leverages "related words," commonly present in discussions about the future path of interest rates (e.g., anticipate, expected, forecast, odds). Through detailed analysis, I confirm that these terms consistently appear in sentences addressing interest rate expectations, which helps us identify IRG sentiment without explicit hawkish or dovish language.

The BSP and EOA algorithm follows a two-step process: first, it detects hawkish or dovish keywords, then analyzes the context of each sentence containing these keywords. Sentences without relevant keywords are excluded, keeping only pertinent data. For each detected keyword, the algorithm assesses nearby positive or negative terms, adding a refined sentiment layer. For IRG, the algorithm tags sentences with related terms and evaluates sentiment using positive or negative cues.

By narrowing the news sample to a focused window around each FOMC meeting, I include only the information available to the public leading up to the meeting. This approach reduces endogeneity issues, as any surprises captured are likely to stem from unexpected meeting-related news, while economic and financial data from prior periods are already accounted for.

2.4.3 Measuring Sentiment Score

I use Python to perform sentiment analysis for IRG, BSP, and EOA, applying scoring at both the sentence and document levels. For IRG, the software first identifies sentences containing any related terms and tags them as relevant. It then searches each tagged sentence for positive and/or negative terms, assigning $+1$ for positive terms and -1 for negative terms. If a term is near a negation term (within three words), its sign is reversed. The score is determined by calculating the difference between positive and negative term counts: sentences with more positive terms lean hawkish, while those with more negative terms lean dovish.

For BSP and EOA, sentences containing hawkish or dovish keywords are identified, and the context within three words of each keyword is examined for positive or negative terms. Scoring is proximity-based: hawkish keywords near positive terms score +1 (hawkish) and near negative terms score -1 (dovish). Conversely, dovish keywords near positive terms score dovish, and near negative terms score hawkish. Negation terms adjust the sentiment as needed. Sentences without positive or negative terms receive a default score based on the keyword's nature.

To ensure that the scores are proportionate to sentence length, I normalize by dividing the difference by the sentence's total word count.

$$\text{Sentiment}_s = \frac{\#\text{Positive\_terms}_s - \#\text{Negative\_terms}_s}{\text{Total\_words}_s} \tag{2.1}$$

where $Sentiment_s$ represents the sentiment score for a sentence s. $\#Positive\_terms_s$ is the count of positive terms in sentence s, with adjustments for negations as necessary. Positive terms are predefined in the dictionary and contribute a score of +1. Similarly, $\#Negative\_terms_s$ counts the negative terms, adjusted for negations, with each term contributing a score of -1. $Total\_words_s$ is the total number of words in sentence s, allowing normalization of the sentiment score to adjust for sentence length.

To compute the overall sentiment score for an entire document, I aggregate the sentiment scores of all relevant sentences, dividing by the total number of sentences:

$$Sentiment_t = \frac{1}{N_t} \sum_{s=1}^{A_t} Sentiment_s \tag{2.2}$$

where t represents the day of the FOMC meeting, $Sentiment_t$ is the aggregated sentiment score for all articles, A_t is the number of analyzed sentences, and N_t is the total number of sentences. This calculation is performed on articles published before and after the FOMC meeting.

The detailed sentiment analysis algorithm for calculating IRG-related sentiment is provided in Appendix B.1, while the algorithm for BSP and EOA sentiment can be found in Appendix B.2. Examples of sentence scoring are presented in Table 2.13 in Appendix F.

2.5 Monetary Policy Sentiment Indexes

I now visualize the six monetary policy sentiment indexes—before- and after-meeting IRG, BSP, and EOA indexes—and examine their correlation with actual changes in the federal funds rate (ΔFFR) and the proxy funds rate (ΔPFR), as well as with monetary policy shocks from other studies.[2] Specifically, I draw comparisons to the factors identified in Swanson (2021) using PCA: the federal funds rate factor (FFRF), large-scale asset purchases factor (LSAPF), and forward guidance factor (FGF). Additionally, I examine the indexes alongside the shocks identified by RR (Romer and Romer, 2004), which are derived by regressing FFR changes on the Fed's internal economic forecasts, using the residuals as the shocks. Table 2.14 in Appendix F presents these correlations along with their confidence intervals.

2.5.1 Interest Rate Guidance (IRG)

A positive IRG sentiment score indicates expectations of rate hikes, reflecting a hawkish outlook anticipating a tighter stance to manage inflation. In contrast, a negative score suggests anticipated rate cuts, signaling a dovish, accommodative policy outlook.

The strong correlation (0.72) between the before- and after-meeting IRG sentiment indexes (Figure 2.1) suggests that market expectations often align with FOMC outcomes. However, deviations in the early 2000s, 2002, 2005-2006, and the financial crisis of 2007-2009 reveal periods when FOMC decisions differed from expectations, likely due to unexpected policy shifts or new economic data. During the COVID-19 pandemic (mid-2020 to early 2023), smaller deviations reflect the impact of economic uncertainties on sentiment. This pattern highlights the importance of clear Fed communication, especially in turbulent times.

Additionally, the sentiment indexes align closely with actual FFR changes, showing correlations of 0.70 with before-meeting sentiment and 0.61 with after-meeting sentiment. This alignment, particularly during major policy actions, underscores how responsive market sentiment is to FOMC decisions, indicating these indexes' effectiveness in capturing market reactions to monetary policy and providing insights into the influence of FOMC communications on expectations.

The correlation analysis indicates that the IRG indexes have a stronger relationship with actual FFR changes compared to Swanson's FFRF, as illustrated in Figures 2.7 and 2.8 in Appendix E.1. This suggests that media-captured sentiment provides a more immediate reflection of real-time policy shifts, offering a clearer view of how FOMC announcements influence market expectations.

[2]The proxy rate indicates what the federal funds rate would typically be under current financial market conditions if these conditions were driven solely by the funds rate (Foerster and Martinez, 2024). Since daily data for this variable is not available, I use its weekly change.

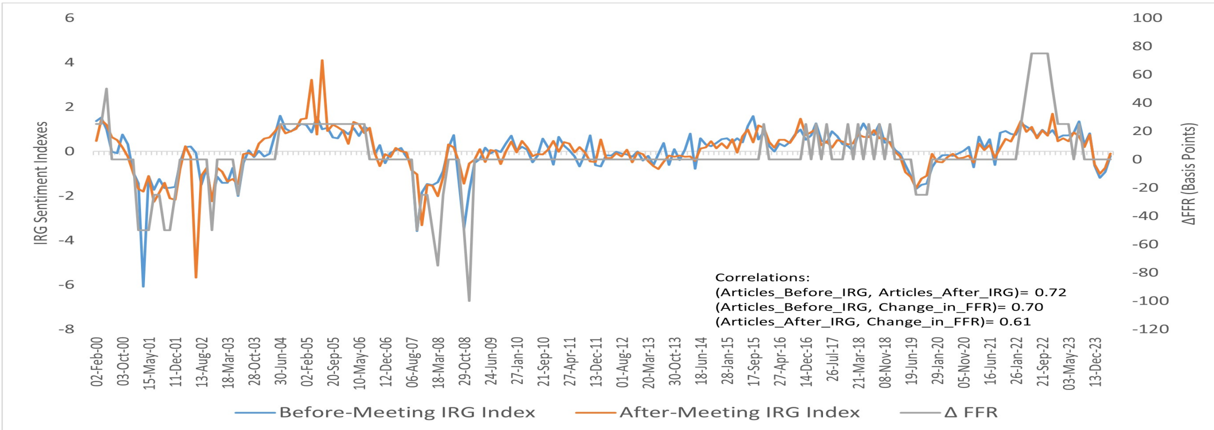

Figure 2.1: Before- and after-meeting IRG indexes and ΔFFR (Feb. 2000–May 2024).

Moreover, the IRG indexes (both before and after FOMC meetings) show substantial alignment with RR's monetary policy shock measure, with correlations of 0.67 and 0.5, respectively, as depicted in Figure 2.9 in Appendix E.1. This alignment indicates that the sentiment-based IRG indexes effectively capture unexpected elements of policy changes, mirroring key components of RR's shocks.

2.5.2 Balance Sheet Policies (BSP)

A positive BSP score suggests expected tightening, indicating that the Fed may reduce asset holdings to limit liquidity, while a negative score implies anticipated expansion to support growth.

Figure 2.2 shows the before- and after-meeting BSP indexes, with a moderate correlation (0.53), suggesting partial alignment between market expectations and FOMC outcomes. The BSP indexes also broadly align with FFR trends, showing a 30% correlation, and tend to decline during QE periods (red lines) and rise before and during QT periods (yellow lines), as depicted in Figure 2.3.

Figure 2.4 illustrates a negative correlation between BSP sentiment and the daily percentage change in the Fed's balance sheet ($\%\Delta BS$) on meeting days, indicating that lower sentiment corresponds to a dovish (QE) stance, while higher sentiment aligns with QT.

In Figure 2.12 in Appendix E, the after-meeting BSP index is compared with Swanson's LSAPF, showing the expected negative correlation, as an increase in Swanson's LSAPF (expansion) corresponds to a decrease in the BSP index (expansion). Figure 2.13 in Appendix E further compares both measures to actual changes in the Fed's balance sheet, confirming a negative correlation for my index and a positive one for Swanson's LSAPF.

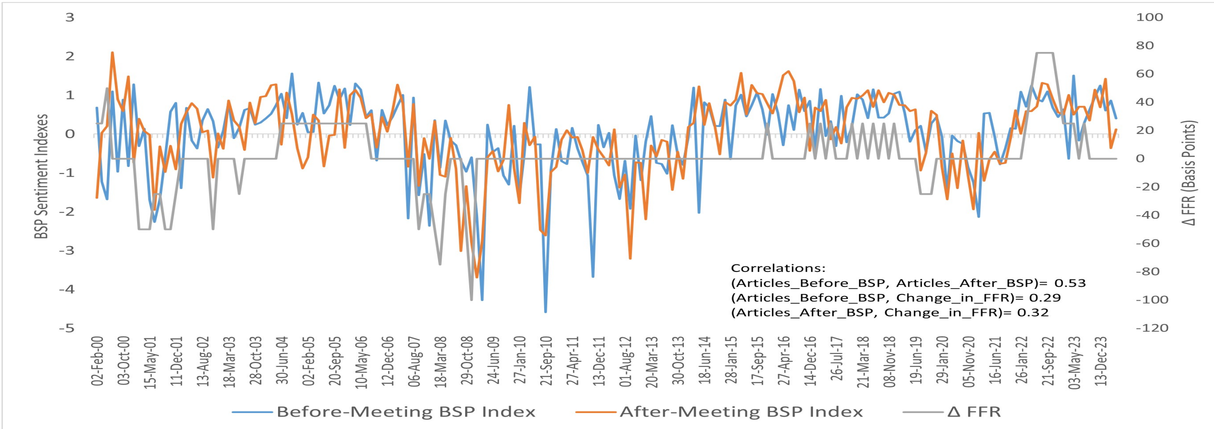

Figure 2.2: Before- and after-meeting BSP sentiment and the ΔFFR (Feb. 2000–May 2024).

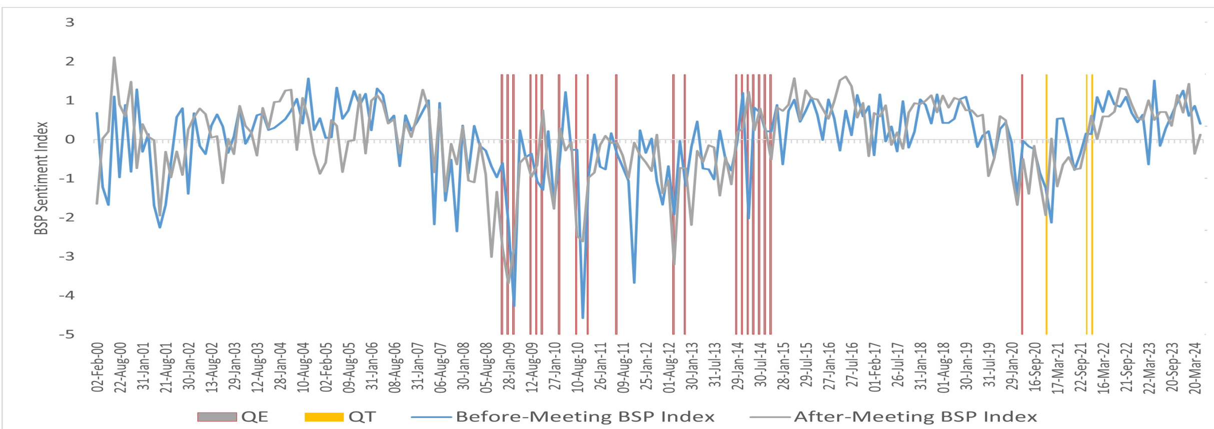

Figure 2.3: Before- and after-meeting BSP sentiment and QE and QT periods (Feb. 2000–May 2024).

Finally, Figure 2.14 in Appendix E reveals moderate correlations between the BSP indexes and RR's shock measure (0.33 and 0.21 for before- and after-meeting indexes), higher than Swanson's LSAPF correlation of 0.17 with the same measure.

2.5.3 Economic Outlook Assessment (EOA)

A positive EOA score reflects optimism about the economy, indicating improved expectations for growth, employment, and inflation stability, with reduced need for accommodative policies. Conversely, a negative score signals pessimism, suggesting concerns over economic slowdown or unemployment that may prompt supportive Fed actions.

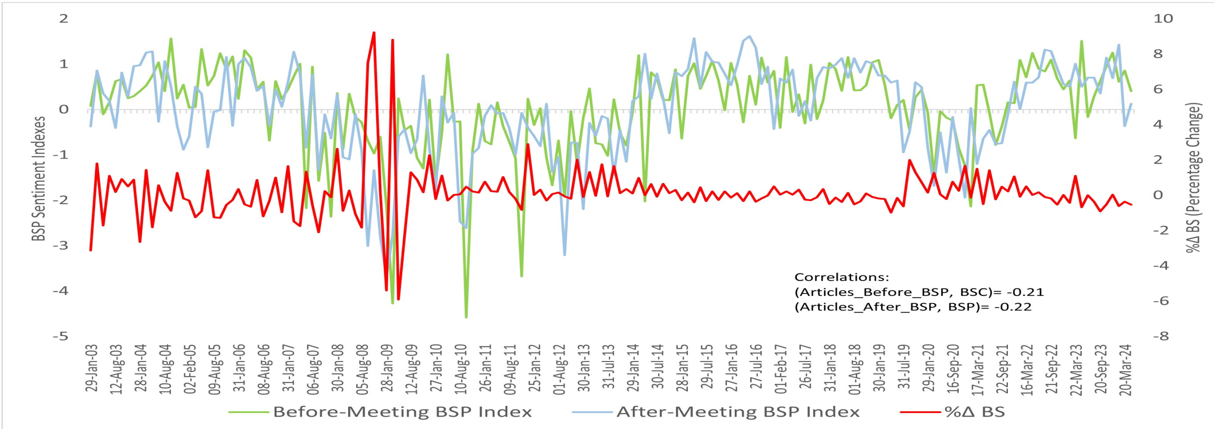

Figure 2.4: Before- and after-meeting BSP sentiment and %ΔBS (Jan. 2003–May 2024).

Figure 2.5 shows a moderate positive correlation (0.37) between the before- and after-meeting EOA indexes, suggesting that surprises often stem from the Fed's economic outlook assessments, unlike the stronger correlations seen in IRG and BSP.

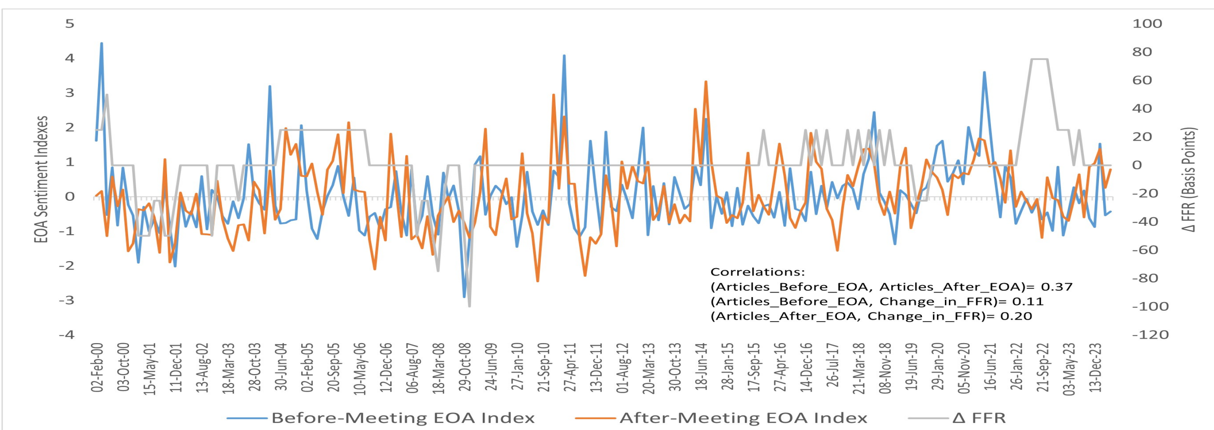

Figure 2.5: Before- and after-meeting EOA sentiment and ΔFFR (Feb. 2000–May 2024).

In Figure 2.6, recession periods (shaded areas) reveal significant declines in EOA sentiment indexes, with sentiment dropping sharply during the dot-com bubble, Great Recession, and COVID-19 pandemic. This pattern reflects the media's role in capturing public concerns and economic distress, particularly evident in times of major downturns.

Figure 2.17 in Appendix E compares the after-meeting EOA index with Swanson's FFRF, showing a similar correlation with FFR changes (0.30 for EOA vs. 0.35 for FFRF). Figure 2.18 in Appendix E illustrates the weak positive correlation (0.09) between the EOA index and Swanson's FGF, likely because Swanson's measure combines all types of forward guidance, while my index isolates economic outlook assessments.

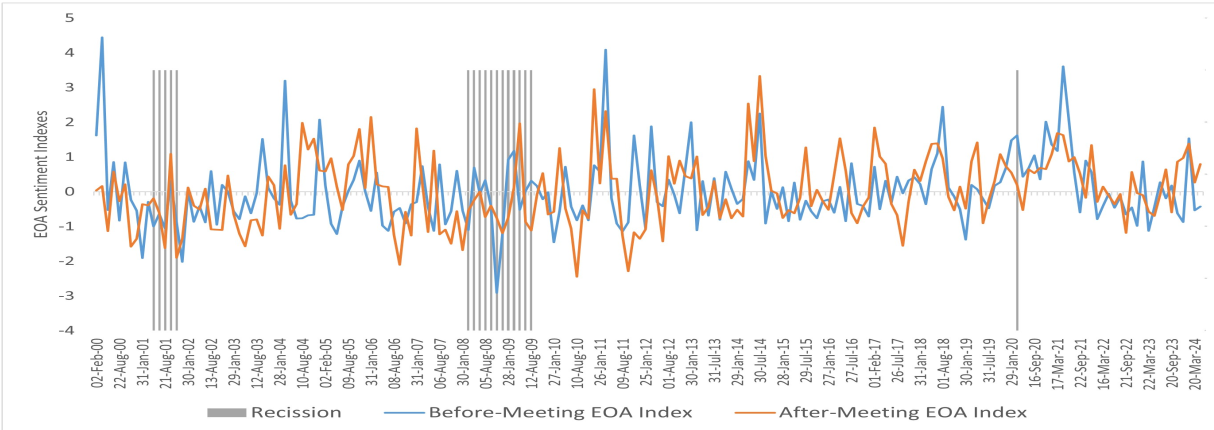

Figure 2.6: Before- and after-meeting EOA sentiment compared to recession periods (Feb. 2000–May 2024).

Finally, Figure 2.19 in Appendix E shows a moderate correlation (0.35) between the after-meeting EOA index and RR's shock measure, which is higher than the 0.09 correlation observed between Swanson's FGF and Romer and Romer's shocks.

2.5.4 Predictive Power Testing

I assess the predictive strength of my sentiment measures by examining their ability to forecast upcoming policy decisions on interest rates and the Fed's balance sheet. Following the approaches of Apel and Grimaldi (2014), Ochs (2021), and others, I evaluate whether before-meeting sentiment index can predict the policy decision made during the same FOMC meeting and whether after-meeting sentiment index can signal the decision at the subsequent meeting.

To forecast changes in the FFR using the IRG and EOA sentiment indexes, I specify:

$$\Delta FFR_t = \alpha_0 + \alpha_1 XX_t^{Before} + \alpha_2 \Delta FFR_{t-1} + \epsilon_t \tag{2.3}$$

$$\Delta FFR_{t+1} = \beta_0 + \beta_1 XX_t^{After} + \beta_2 \Delta FFR_t + \epsilon_{t+1} \tag{2.4}$$

where ΔFFR_t represents the daily change in the FFR from the day before the FOMC meeting to the meeting day itself. XX refers to either the IRG or EOA sentiment indexes, with XX_t^{Before} and XX_t^{After} denoting the before- and after-meeting sentiment values, respectively.

For predicting changes in the Fed's balance sheet, I use the BSP sentiment indexes:

$$\%\Delta BS_t = \alpha_0 + \alpha_1 BSP_t^{Before} + \%\Delta BS_{t-1} + \varepsilon_t \tag{2.5}$$

$$\%\Delta BS_{t+1} = \alpha_0 + \alpha_1 BSP_t^{After} + \%\Delta BS_t + \varepsilon_{t+1} \tag{2.6}$$

where $\%\Delta BS_t$ is the log change in the Fed's balance sheet from the day prior to the FOMC meeting, with BSP_t^{Before} and BSP_t^{After} representing the before- and after-meeting BSP sentiment indexes.

Following studies on discretionary dependent variables (e.g., Apel and Grimaldi (2014)), I use ordered probit techniques to evaluate the predictive power of IRG and EOA sentiment indexes.[3] This method is ideal for ordinal dependent variables with a natural order but inconsistent spacing between outcomes, as it estimates probabilities for each category. For BSP analysis, I apply OLS regression with Newey-West standard errors to address heteroskedasticity and autocorrelation.

Table 2.4 shows that prior FFR changes (ΔFFR_{t-1}) positively predict current FFR adjustments. The before-meeting IRG sentiment index also positively correlates with same-day FFR changes, suggesting that hawkish pre-meeting sentiment aligns with rate hikes. Additionally, after-meeting IRG sentiment is predictive of the next meeting's policy direction, where an increase in hawkish sentiment links to a higher likelihood of a future rate increase, while dovish sentiment points to potential cuts.

Table 2.4: Ordered probit estimation results for IRG.

Dependent variable:	ΔFFR_t				
	(i)	(ii)	(iii)	(iv)	(v)
ΔFFR_{t-1}	0.0466***		0.0411***		0.0346***
	(0.005)		(0.006)		(0.0051)
IRG_t^{Before}		1.810***	0.8814***		
		(0.138)	(0.155)		
IRG_{t-1}^{After}				0.9679***	0.6729***
				(0.1048)	(0.1206)
Pseudo R-squared	0.28	0.31	0.48	0.25	0.36
Prob(LR)	0.000	0.000	0.000	0.000	0.000

*Note: Standard errors in parentheses. *, **, *** denote significance at the 10% level, 5% level, and 1% level, respectively. Number of observations: 193. Equations are estimated with ordered probit.*

[3] ΔFFR_t takes values such as +100, +75, +25, 0, -25, -50, -75, and -100. Coefficients from the ordered probit model show how changes in sentiment indexes influence the likelihood of the FOMC selecting different policy rate categories, with positive coefficients indicating a higher probability of an increase in rates and negative coefficients indicating a shift toward rate reductions.

Table 2.5: Ordered probit estimation results for EOA.

Dependent variable:	ΔFFR_t				
	(i)	(ii)	(iii)	(iv)	(v)
ΔFFR_{t-1}	0.0466***		0.045***		0.045***
	(0.005)		(0.005)		(0.005)
EOA_t^{Before}		0.107	0.102		
		(0.082)	(0.092)		
EOA_{t-1}^{After}				0.321***	0.242**
				(0.087)	(0.1)
Pseudo R-squared	0.28	0.004	0.29	0.03	0.30
Prob(LR)	0.000	0.1907	0.000	0.0002	0.000

*Note: Standard errors in parentheses. *, **, *** denote significance at the 10% level, 5% level, and 1% level, respectively. Number of observations: 193. Equations are estimated with ordered probit.*

In Table 2.5, the before-meeting EOA index has an insignificant association with FFR changes, but the after-meeting EOA index is a significant predictor of the subsequent meeting's policy, with economic optimism correlating with rate hikes and pessimism with rate cuts.

Table 2.6 indicates that before-meeting BSP sentiment negatively correlates with Fed balance sheet changes, implying that hawkish sentiment aligns with balance sheet reductions. After-meeting BSP sentiment also predicts balance sheet adjustments at the next meeting, where higher hawkish sentiment is linked to reductions and dovish sentiment to expansions.

Table 2.6: OLS estimation results for BSP.

Dependent variable:	$\%\Delta\text{BS}_t$				
	(i)	(ii)	(iii)	(iv)	(v)
$\%\Delta\text{BS}_{t-1}$	−0.144		−0.148		−0.2049
	(0.19)		(0.1778)		(0.165)
BSP_t^{Before}		−0.3323*	−0.335*		
		(0.1872)	(0.0569)		
BSP_{t-1}^{After}				−0.3651**	−0.4341**
				(0.1778)	(0.167)
R-squared	0.01	0.04	0.06	0.05	0.09
Adjusted R-squared	0.01	0.04	0.05	0.05	0.09

*Note: HAC standard errors in parentheses. *, **, *** denote significance at the 10% level, 5% level, and 1% level, respectively. Number of observations: 169. Equations are estimated with OLS.*

In the cross-correlation analysis, I evaluate how sentiment indices align with policy changes over time. Figures 2.10 and 2.11 in Appendix E.1 show that both before- and after-meeting IRG sentiment indexes have strong positive correlations with FFR changes around the meeting date, suggesting that sentiment effectively captures both immediate and lasting expectations about interest rate decisions. As illustrated in Figures 2.15 and 2.16 in Appendix E.1, the BSP sentiment indices exhibit predominantly negative correlations with balance sheet changes, reinforcing the link between hawkish sentiment and expected balance sheet reductions. Figures 2.20 and 2.21 in Appendix E.1 indicate that the EOA sentiment index is positively correlated with FFR changes, especially in the months following the meetings, suggesting that an optimistic economic outlook aligns with anticipated future rate hikes.

2.6 Monetary Policy Sentiment Shocks

2.6.1 Capturing Monetary Policy Sentiment Shocks

To capture the surprise component of the monetary policy sentiment indexes, I use three distinct specifications. The first specification (Equation 2.7) regresses the after-meeting sentiment index on its before-meeting value, while also controlling for the previous after-meeting index. This approach isolates the unexpected, or "shock," component, represented by the residual XX_t^{Shock1}.

Basic specification:

$$XX_t^{After} = \gamma_0 + \gamma_1 XX_t^{Before} + \gamma_2 XX_{t-1}^{After} + XX_t^{Shock1} \tag{2.7}$$

where XX represents the sentiment indexes for IRG, BSP, and EOA.

In the second specification (Equation 2.8), I include the actual change in the FFR as an additional control variable. By accounting for this adjustment, I interpret the resulting residuals as a refined measure of my shocks, labeled as XX_t^{Shock2}.

FFR specification:

$$XX_t^{After} = \gamma_0 + \gamma_1 XX_t^{Before} + \gamma_2 XX_{t-1}^{After} + \delta \Delta FFR_t + XX_t^{Shock2} \tag{2.8}$$

In the third specification (Equation 2.9), I include the actual change in the PFR as an additional control variable on the basic specification. By accounting for this adjustment, I interpret the resulting residuals as a refined measure of my shocks, labeled as XX_t^{Shock3}.

Proxy specification:

$$XX_t^{After} = \gamma_0 + \gamma_1 XX_t^{Before} + \gamma_2 XX_{t-1}^{After} + \lambda \Delta PFR_t + XX_t^{Shock3} \tag{2.9}$$

My approach uses before-meeting sentiment as a baseline to isolate sentiment shifts specifically triggered by FOMC announcements. By comparing after-meeting sentiment with prior expectations, I capture unexpected changes or "surprises" that reveal new information introduced during the meeting. This method addresses endogeneity by filtering out pre-existing market expectations, allowing us to identify exogenous shocks in the Fed's communication regarding interest rates, balance sheet policies, and economic outlook. The estimation results for equations 2.7 to 2.9 for IRG, BSP, and EOA are presented in Tables 2.15, 2.16, and 2.17 in Appendix F, respectively.

I present the IRG, BSP, and EOA shocks under three specifications in Appendix E.4, each capturing sentiment shifts with consistent patterns. In Figure 2.22, IRG shocks display spikes at certain points, potentially indicating market reactions to changes in interest rate guidance. Figure 2.23 reveals that BSP shocks are more frequent and volatile, reflecting market sensitivity to balance sheet policy signals, with consistent fluctuations across specifications. Lastly, Figure 2.24 shows EOA shocks with recurring peaks and troughs, indicating that economic outlook sentiment adjusts to varying economic conditions. The close alignment across specifications for all shock types implies that my methodology is robust in capturing meaningful variations in sentiment related to Fed policy communications.

The correlation analysis in Tables 2.18 and 2.19 in Appendix F shows that each sentiment shock index is highly consistent across its specifications, with near-perfect correlations. This consistency suggests that each construction method yields a similar measure within each index, reinforcing the robustness of the IRG, BSP, and EOA indexes as distinct sentiment dimensions.

Correlations between different indexes (IRG, BSP, and EOA) are low, supporting their conceptual separation. For instance, IRG and BSP shocks show low and negative correlations (e.g., Correlation $= -0.07$ for IRG^{Shock1} and BSP^{Shock1}), while correlations between IRG and EOA are minimal (e.g., Correlation $= 0.03$ for IRG^{Shock1} and EOA^{Shock1}). This suggests that each index captures a distinct aspect of Fed communication, with IRG, BSP, and EOA shocks relating independently to interest rate guidance, balance sheet policy, and economic outlook.

The slightly positive correlation between BSP and EOA shocks (e.g., Correlation = 0.23 for BSP^{Shock1} and EOA^{Shock1}) suggests that balance sheet policy sentiment and economic outlook sentiment are somewhat aligned, potentially reflecting the Fed's response to underlying economic conditions that influence both areas. Despite this mild correlation, the values remain low enough to confirm that BSP and EOA shocks capture largely independent dimensions of sentiment, with each index providing unique insights into the Fed's policy communications.

2.6.2 Impact of Monetary Policy Sentiment Shocks on Financial Indicators

With the shocks identified, I proceed to assess their impact on the financial market using the following regression:

$$
\begin{aligned}
y_t = \alpha_0 + \alpha_1 IRG_t^{Shock} + \alpha_2 BSP_t^{Shock} + \alpha_3 EOA_t^{Shock} + \\
+ \alpha_5 \sum_{j=0}^{n} X_{t-j} + \alpha_6 \sum_{i=0}^{n} y_{t-i} + \epsilon_t
\end{aligned}
\tag{2.10}
$$

Here, y_t represents the percentage log change in the financial indicator from the day before the release of the statements to the release day itself. X_t represents a set of control variables included to account for other factors influencing the financial indicators. These controls help isolate the effects of sentiment shocks by adjusting for other relevant financial indicators and historical data, enhancing the robustness of the results.[4]

The descriptive statistics in Table 2.20 in Appendix F provide insights into the monetary policy shocks (IRG, BSP, and EOA) and daily changes in financial variables, highlighting the characteristics and variability of these shocks. By construction, IRG, BSP, and EOA shocks have a mean of zero, capturing unexpected deviations from anticipated sentiment around FOMC communications. The IRG shocks, with standard deviations around 0.65-0.67, indicate substantial fluctuations in market expectations related to interest rate guidance, characterized by negative skewness and high kurtosis, suggesting frequent dovish sur-

[4] I employ heteroskedasticity and autocorrelation consistent (HAC) standard errors using the Bartlett kernel with a Newey-West fixed bandwidth to ensure robust inference. This approach accounts for potential heteroskedasticity and autocorrelation in the residuals, preventing bias in standard error estimates and significance tests. Additionally, I perform Variance Inflation Factor (VIF) checks to address multicollinearity concerns and confirm that all variables used in the regression are stationary (integrated of order zero, $I(0)$).

prises and extreme values. In contrast, BSP shocks, while also zero-mean, display slightly higher variability (0.76-0.90) with less extreme distributional features, indicating more balanced hawkish and dovish surprises. EOA shocks show the highest variability among the shocks, with standard deviations exceeding 0.99, reflecting greater market sensitivity to unexpected changes in economic outlook assessments, often tied to broader economic uncertainty.

Financial variables exhibit slight mean changes, with indices such as $\Delta SP500$ and $\Delta DJIA$ showing positive mean trends, indicative of overall market growth. Meanwhile, high kurtosis in $\Delta VIXCLS$ and $\Delta VXDCLS$ points to occasional volatility spikes, underscoring the market's sensitivity to shocks. The exchange rate $\Delta DEXUSEU$ shows high skewness and kurtosis, reflecting sporadic yet sharp appreciations of the USD against the EUR.

The regression results in Table 2.7 present the impact of IRG, BSP, and EOA shocks using the three specifications (Equations 2.7, 2.8, and 2.9) on various financial indicators. For stock prices, specifically the Dow Jones Industrial Average (DJIA), I find that IRG shocks exert a statistically significant negative effect, with unexpected rate hikes increasing the discount rate, thereby lowering the present value of expected cash flows and signaling slower growth. This downward pressure is consistent with findings by Bernanke and Kuttner (2005), Gürkaynak et al. (2005), and Swanson (2021). Similarly, BSP shocks negatively affect stock prices, as quantitative easing boosts liquidity and supports stocks. Notably, Swanson (2021) also identifies this relationship, though it is statistically insignificant. Lastly, EOA shocks positively influence stock prices by elevating earnings expectations during favorable economic assessments while moderating values under cautious outlooks.

In terms of stock market volatility, particularly the CBOE DJIA Volatility Index (VXD), the results show a statistically significant negative effect of IRG shocks. Hawkish IRG shocks reduce volatility by affirming the Fed's inflation control commitment, thus enhancing predictability and curbing speculative activity, countering the leverage effect theory that typically associates declining stock prices with increased volatility due to higher financial leverage. This finding adds novel insights to the relatively underexplored relationship between monetary policy shocks and stock market volatility, specifically through forward guidance's role in market stability. The results are in line with Caraiani and Călin (2020), who demonstrates that monetary policy shocks reduce volatility in developed markets, aligning asset prices with fundamentals and discouraging speculation. Gorodnichenko et al. (2023) similarly find that a positive tone during FOMC press conferences decreases volatility by conveying confidence and stability, which lowers perceived risks among investors. Conversely, BSP and EOA shocks have statistically insignificant effects on volatility, suggesting that IRG shocks uniquely drive volatility responses in financial markets.

For the 2-year Treasury bond (DGS2) yield, IRG shocks exhibit a significant negative effect, as tighter interest rate guidance shifts investor expectations towards higher future rates, favoring long-term securities. In contrast, BSP shocks show a positive but statistically insignificant effect, consistent with Swanson (2021). Balance sheet tightening, which signals a restrictive Fed stance, increases short-term borrowing costs and pressures rates upward. EOA shocks, however, have a statistically significant positive effect on DGS2, as expectations of strong economic growth and potential inflation drive demand for higher yields on short-term securities, shifting interest away from safe-haven assets.

For Moody's Seasoned Aaa Corporate Bond Yield (DAAA), IRG shocks significantly raise its yield, signaling tighter anticipated monetary conditions that increase both short- and long-term interest rates. While Swanson (2021) finds a positive but statistically insignificant effect, he notes a significant negative relationship during the post-ZLB period. BSP shocks similarly have a positive impact, as balance sheet tightening reduces liquidity, raising corporate funding costs—a result consistent with Swanson (2021). Notably, IRG shocks have the largest impact on DAAA yields, followed by BSP, contrasting with Swanson's findings where LSAPF shows the largest impact. EOA shocks, however, reduce DAAA yields, as an improved economic outlook lowers the credit risk premium on corporate bonds, enhancing investor confidence.

A noteworthy contrast arises between the effects of IRG shocks on Treasury and corporate bond yields. While IRG shocks lower Treasury yields, reflecting a "flight to quality" as investors turn to safer government securities, they simultaneously raise corporate bond yields as concerns over economic slowdown and corporate profitability elevate the credit risk premium. This divergence highlights the distinct risk dynamics under hawkish forward guidance, with investors demanding higher yields on corporate bonds to offset increased risk amid policy tightening.

Finally, the findings reveal that monetary policy sentiment shocks distinctly influence the USD/Euro exchange rate (DEXUSEU). Consistent with Swanson (2021), IRG shocks have a significant negative effect, strengthening the dollar as higher rates attract foreign capital. In contrast, BSP shocks are statistically insignificant, suggesting limited influence on currency dynamics from balance sheet adjustments. EOA shocks, however, significantly depreciate the dollar, potentially due to expectations of rising inflation without parallel rate increases, which reduces the real interest rate differential.

Table 2.7: Estimated effects of IRG, BSP, and EOA shocks on financial indicators

Dep. Variable	Shocks	Specification 1		Specification 2		Specification 3	
		Coefficient	(HAC S.E.)	Coefficient	(HAC S.E.)	Coefficient	(HAC S.E.)
DJIA	IRG^{Shock}	-0.2109^{***}	(0.0655)	-0.1397^{**}	(0.0670)	-0.1754^{**}	(0.0607)
	BSP^{Shock}	-0.2218^{**}	(0.1061)	-0.1879^{*}	(0.0972)	-0.1950^{*}	(0.1085)
	EOA^{Shock}	0.1138^{**}	(0.0573)	0.1280^{**}	(0.0603)	0.0917	(0.0580)
	R-Squared	47.63%		46.41%		46.45%	
	Controls	VXDCLS, DGS5, DJIA(-1), DJIA(-2)					
VXD	IRG^{Shock}	-1.3086^{***}	(0.3938)	-0.9389^{**}	(0.3719)	-1.1336^{***}	(0.3582)
	BSP^{Shock}	-0.5592	(0.4409)	-0.3417	(0.4203)	-0.4302	(0.4435)
	EOA^{Shock}	0.4292	(0.4178)	0.5312	(0.4264)	0.3168	(0.4253)
	R-Squared	45.22%		44.64%		44.77%	
	Controls	DJIA, DJIA(-1), DJIA(-2), DEXUSEU, DEXUSEU(-1)					
DGS2	IRG^{Shock}	-1.1570^{*}	(0.6713)	-1.2089^{*}	(0.6614)	-1.0152	(0.6740)
	BSP^{Shock}	0.0400	(0.6615)	0.0516	(0.6683)	0.1530	(0.6260)
	EOA^{Shock}	0.7740^{**}	(0.3479)	0.7728^{**}	(0.3468)	0.6836^{**}	(0.3236)
	R-Squared	23.59%		23.63%		23.19%	
	Controls	CORPOAS, DAAA, DEXUSEU, DGS2(-1), DGS2(-2), DGS2(-3)					
DAAA	IRG^{Shock}	0.1607^{***}	(0.0561)	0.1915^{***}	(0.0562)	0.1704^{***}	(0.0615)
	BSP^{Shock}	0.0905^{*}	(0.0543)	0.1039^{*}	(0.0536)	0.0990^{*}	(0.0575)
	EOA^{Shock}	-0.1127^{*}	(0.0611)	-0.1093^{*}	(0.0618)	-0.1184^{*}	(0.0604)
	R-Squared	70.79%		71.08%		70.90%	
	Controls	DGS30, CORPOAS, DAAA(-1)					
DEXUSEU	IRG^{Shock}	-0.1206^{**}	(0.0570)	-0.1062^{*}	(0.0619)	-0.1059^{*}	(0.0602)
	BSP^{Shock}	0.0257	(0.0491)	0.0385	(0.0480)	0.0402	(0.0517)
	EOA^{Shock}	0.0979^{**}	(0.0453)	0.1049^{**}	(0.0484)	0.0871^{*}	(0.0450)
	R-Squared	13.99%		14.19%		13.03%	
	Controls	DEXUSEU, VXDCLS, DJIA(-1), DJIA(-2), DGS2					

Notes: - Standard errors in parentheses. *, **, *** denote significance at the 10% level, 5% level, and 1% level, respectively. OLS estimation.
- HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000).
- Full Sample period: Feb. 2000 - May 2024.

The analysis highlights the diverse impacts of monetary policy sentiment shocks on financial markets, illustrating the importance of distinguishing between IRG, BSP, and EOA components within forward guidance. IRG shocks notably reduce stock prices and volatility, lower Treasury yields, and strengthen the U.S. dollar, while simultaneously raising corporate bond yields as investors adjust to tighter monetary expectations. BSP shocks, though less significant in some areas, influence corporate funding costs and stock prices through liquidity changes. EOA shocks, reflecting economic outlook adjustments, positively impact stock prices and yield dynamics, while influencing exchange rates through shifts in growth expectations. These findings underscore the unique role each type of policy shock plays in shaping market behavior, enriching our understanding of forward guidance's multifaceted effects on asset prices and stability.

Extensive robustness checks for the results are presented in Appendix C, and the exogeneity testing of shocks is addressed in Appendix D.

2.6.3 Predictive Power Testing

I assess the predictive strength of my shock measures by examining their ability to forecast upcoming policy decisions on interest rates and the Fed's balance sheet.

To forecast changes in the FFR using the IRG and EOA shocks, I specify:

$$\Delta FFR_t = \beta_0 + \beta_1 XX_{t-1}^{Shock} + \beta_2 \Delta FFR_{t-1} + \epsilon_t \tag{2.11}$$

XX refers to either the IRG or EOA shocks.

For predicting changes in the Fed's balance sheet, I use the BSP shock:

$$\%\Delta BS_t = \alpha_0 + \alpha_1 BSP_{t-1}^{Shock} + \alpha_2 \%\Delta BS_{t-1} + \varepsilon_t \tag{2.12}$$

The estimation results for IRG, BSP, and EOA shocks are presented in Tables 2.15, 2.16, and 2.17 in Appendix F, respectively.

The results in Tables 2.8 and 2.9 show that both the IRG and EOA shocks demonstrate predictive power regarding changes in the FFR. Specifically, I observe that the coefficients for both IRG_{t-1}^{Shock} and EOA_{t-1}^{Shock} are statistically significant across multiple specifications, suggesting that these shocks contain information relevant to anticipating shifts in the Fed's policy stance. Notably, the significance of the lagged FFR term (ΔFFR_{t-1}) further underscores the role of historical interest rate trends in shaping future policy decisions.

In examining the results for the Fed's balance sheet adjustments, Table 2.10 indicates that the BSP shock variable consistently exhibits a negative and significant association with the log change in the balance sheet. This negative coefficient implies that, following a BSP shock, there tends to be a contractionary adjustment in the Fed's balance sheet, aligning with the expected tightening effect.

2.7 Conclusion and Future Work

This study introduces a novel method for identifying monetary policy sentiment shocks by analyzing the sentiment of news articles surrounding FOMC meetings. Unlike traditional

Table 2.8: Ordered probit model results for predicting ΔFFR based on IRG^{Shock}

	Specification 1	Specification 2	Specification 3
ΔFFR_{t-1}			
Coefficient	0.0466^{***}	0.0484^{***}	0.0465^{***}
S.E.	(0.0047)	(0.0048)	(0.0047)
IRG^{Shock}_{t-1}			
Coefficient	0.3265^{**}	0.4141^{***}	0.2538^{**}
S.E.	(0.1321)	(0.1322)	(0.1351)
Pseudo R-squared	%29.85	%30.72	%29.24

Note: Dependent variable is ΔFFR_t. Standard errors are in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 2.9: Ordered probit model results for predicting ΔFFR based on EOA^{Shock}

	Specification 1	Specification 2	Specification 3
ΔFFR_{t-1}			
Coefficient	0.0463^{***}	0.0472^{***}	0.0462^{***}
S.E.	(0.0046)	(0.0047)	(0.0047)
EOA^{Shock}_{t-1}			
Coefficient	0.1883^{*}	0.1935^{*}	0.2343^{**}
S.E.	(0.1059)	(0.1062)	(0.1071)
Pseudo R-squared	%29.18	%29.22	%29.59

Note: Dependent variable is ΔFFR_t. Standard errors are in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 2.10: OLS regression results for predicting $\%\Delta BS$ based on BSP^{Shock}

	Specification 1	Specification 2	Specification 3
$\%\Delta BS_{t-1}$			
Coefficient	-0.1736	-0.1722	-0.1708
HAC S.E.	(0.1660)	(0.1669)	(0.1719)
BSP^{Shock}_{t-1}			
Coefficient	-0.4842^{*}	-0.5089^{*}	-0.4316^{*}
HAC S.E.	(0.2717)	(0.3024)	(0.2378)
R-squared	%8.02	%8.46	%6.82

Note: Dependent variable is $\%\Delta BS_t$. Standard errors are in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively. HAC standard errors and covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000).

approaches, this method captures real-time market perceptions, offering insights into how interest rate guidance, balance sheet policies, and economic outlook assessments are interpreted. My sentiment measures closely align with actual market data and predictive factors, proving effective in forecasting policy changes. Extensive robustness checks, including different indexes, shock specifications, and subsample analyses, confirm the reliability of my findings, highlighting the value of sentiment-based analysis for policymakers and market participants.

The findings of this study underscore the importance of analyzing FG components—IRG, BSP, and EOA—independently, as each influences market sentiment and expectations in unique ways. Traditional approaches often treat FG as a single, uniform tool, which may overlook how each component conveys specific signals to the market. By distinguishing IRG, BSP, and EOA, this study highlights the value of a detailed view of FG that deepens our understanding of how the Fed's communication affects financial markets.

The IRG results show that sentiment related to interest rate guidance is a reliable predictor of both short- and long-term rate movements. Market participants interpret hawkish IRG sentiment as a sign of upcoming rate hikes, while dovish sentiment suggests potential rate cuts. This strong alignment with bond yields indicates that IRG sentiment directly impacts expectations of borrowing costs, supporting the research question's premise that a distinct analysis of IRG improves our grasp of its influence on interest rate expectations and financial conditions.

In contrast, BSP sentiment primarily affects market liquidity perceptions and long-term asset prices, as BSP communicates the Fed's stance on quantitative easing or tightening. A hawkish BSP sentiment signals a reduction in liquidity, while a dovish sentiment suggests expansion, impacting financial stability and investor expectations for the long term. This finding demonstrates that BSP operates at a structural level, with markets viewing balance sheet actions as more enduring commitments compared to IRG.

The EOA results further distinguish forward guidance's components by linking EOA sentiment with broader economic expectations rather than specific policy actions. Positive EOA sentiment boosts stock prices by reflecting optimism around economic growth, employment, and inflation stability. This response suggests that EOA sentiment serves as a psychological anchor, offering insight into the Fed's view of economic resilience, particularly during periods of uncertainty. This dimension of FG captures investor confidence regarding the Fed's economic outlook, reinforcing the value of a separate analysis for understanding market reactions.

These findings emphasize that FG is not a monolithic tool but a complex mechanism through which the Fed communicates multi-dimensional messages to the market. By isolating IRG, BSP, and EOA, the study provides a clearer perspective on how each component contributes to shaping financial expectations, allowing for a more targeted understanding of forward guidance's impacts on market dynamics. This approach has meaningful implications for policymakers, enabling them to communicate more effectively by aligning FG elements with specific economic objectives, thereby enhancing forward guidance's effectiveness as a policy tool.

Future research can build on this study by broadening the scope of sentiment analysis to include a wider range of media sources and applying machine learning techniques to enhance sentiment classification accuracy. Additionally, extending the analysis to cover other central banks and international contexts could offer a more global perspective on the impact of monetary policy. Further refinements might also include real-time sentiment tracking and the development of dynamic models to better capture interactions between policy announcements and financial markets. Analyzing FOMC statements and minutes individually with tailored dictionaries for each policy tool can yield precise insights into distinct policy effects, while comparing after-meeting sentiment indexes with existing literature on FOMC documents can highlight the unique role of media narratives. Improved control variables and advanced dictionary construction methods can refine shock identification and sentiment measurement, while a comparative study of FOMC documents versus media articles could uncover how different sources influence or reflect the Fed's messaging.

Appendix A: Data Pre-processing

I perform a rigorous text cleaning and preprocessing procedure using Python to prepare the data for sentiment analysis. This process follows established best practices in natural language processing (NLP), ensuring that the text is clean, consistent, and well-suited for analysis. Given the detailed nature of news articles compared to the concise FOMC statements, this careful approach is essential. By applying comprehensive preprocessing steps, I improve the quality and relevance of the data, thereby enhancing the precision and significance of the sentiment analysis.

Data cleaning and preprocessing steps:

1. Duplicate Removal: Duplicate articles or sentences were identified and removed to avoid redundancy in the analysis.

2. Removal of Punctuation and Numbers: Punctuation marks (except periods, which were kept to isolate sentences) and numbers were removed from the text to reduce noise.

3. Sentence Segmentation: Each text file was divided into individual sentences to facilitate sentiment examination at the sentence level.

4. Lowercasing: All text was converted to lowercase to ensure uniformity and reduce the risk of misinterpretation due to capitalization differences.

5. Removal of Irrelevant Information: Any irrelevant information, such as authors, journal names, headers, footers, and non-textual elements, was removed to focus on the main content.

6. Exclusion of Non-FOMC Related Content: Paragraphs containing references to other central banks (e.g., European Central Bank, ECB, Bank of Japan, BOJ, Bank of Canada, BOC, Bank of England, BOE) were removed to maintain focus on FOMC-related content.

7. Removal of Boilerplate Text: Recurring boilerplate text such as disclaimers, copyright statements, or repeated sections that did not contribute to sentiment analysis was eliminated.

8. Handling Special Characters and HTML Tags: Any remaining special characters or HTML tags that may have been overlooked in earlier steps were removed.

Appendix B: Sentiment Analysis Algorithm

B.1 Interest Rate Guidance (IRG)

- Identify and tag sentences containing one of the words listed in the 'Related Words' in the dictionary in Table 2.1.
- Within these sentences, look for any positive and/or negative terms listed in the dictionary.
  - Assign a score of +1 for positive terms if is not near (within a proximity of three words) any of the negation terms listed in the dictionary.
  - Assign a score of -1 for negative terms if is not near (within a proximity of three words) any of the negation terms listed in the dictionary.
  - Assign a score of -1 for positive terms if is near (within a proximity of three words) any of the negation terms listed in the dictionary. Then this positive term becomes a negative term.
  - Assign a score of +1 for negative terms if is near (within a proximity of three words) any of the negation terms listed in the dictionary. Then this negative term becomes a positive term.
- Calculate the difference between the number of positive and negative scores, and then divide this difference by the total number of words in the sentence.
- Calculate the average score for the document by summing the normalized sentence scores and dividing by the total number of sentences.
- Standardize the document scores by transforming them to have a mean of zero and a standard deviation of one for before and after meeting documents separately. This facilitates easier comparison with other studies and improves the interpretability of regression coefficients.

B.2 Balance Sheet Policies (BSP) and Economic Outlook Assessment (EOA)

- Identify and tag sentences containing hawkish and/or dovish keywords.
- For each relevant sentence:

    - Locate hawkish or dovish keywords.
    - Look for positive or negative terms within three words before or after each keyword.
    - Apply the following rules to assign sentiment scores:
        * If a hawkish keyword is near a positive term, assign a score of +1 (hawkish).
        * If a hawkish keyword is near a negative term, assign a score of -1 (dovish).
        * If a dovish keyword is near a positive term, assign a score of -1 (dovish).
        * If a dovish keyword is near a negative term, assign a score of +1 (hawkish).
        * If a keyword is not near any positive or negative terms, assign a score of +1 (hawkish) for hawkish keywords or -1 (dovish) for dovish keywords.
        * If a keyword is near equal numbers of positive and negative terms, assign a score of zero (neutral).
        * If a hawkish keyword is near more positive terms (positive > negative), assign a score of +1 (hawkish).
        * If a hawkish keyword is near more negative terms (negative > positive), assign a score of -1 (dovish).
        * If a hawkish keyword is near a positive term and the positive term is near a negation, assign a score of -1 (dovish).
        * If a hawkish keyword is near a negative term and the negative term is near a negation, assign a score of +1 (hawkish).
        * If a dovish keyword is near a positive term and the positive term is near a negation, assign a score of +1 (hawkish).
        * If a dovish keyword is near a negative term and the negative term is near a negation, assign a score of -1 (dovish).

- Normalize each sentence's score by dividing it by the total number of words in the sentence.

- Calculate the average score for the document by summing the normalized sentence scores and dividing by the total number of sentences.

- Standardize the document scores by transforming them to have a mean of zero and a standard deviation of one.

Appendix C: Robustness Checks

For robustness checks, I perform several analyses to confirm the stability of the results. First, I use alternative indexes for each financial variable, to verify that the findings are consistent across various financial measures. Second, I apply 11 shock specifications, detailed in Table 2.24, to ensure the robustness of the results across alternative approaches to modeling monetary policy shocks. Specifications 4 through 7 build on specification 2 by adding current and lagged values of the Economic Uncertainty Index (EUI).[5] Similarly, specifications 8 through 11 enhance specification 3 by incorporating current and lagged values of EUI. The estimation results for shock specifications from 4 to 11 for IRG, BSP, and EOA are presented in Tables 2.25, 2.26, and 2.27, respectively.

Following Swanson (2006, 2021), I further conduct a subsample analysis by dividing the sample into two distinct policy periods: the pre-ZLB period (February 2000–December 2008), characterized by conventional monetary policy, and the ZLB period (January 2009–October 2015), marked by the use of unconventional monetary tools. This division allows us to evaluate the robustness of the sentiment measures across different monetary policy regimes. Specifically, I identify IRG and EOA shocks for the pre-ZLB period, and BSP and EOA shocks for the ZLB period.

The robustness checks confirm the consistency of associations between monetary policy shocks and various financial indicators across different specifications, subsamples, and indices. First, the negative relationship between IRG shocks and stock prices (DJIA) holds across 11 different shock specifications and remains consistent when using the pre-ZLB subsample and an alternative stock price index (S&P500). Similarly, the negative association between BSP shocks and DJIA is stable under the ZLB period and also holds with the S&P500, while EOA shocks exhibit a positive association with DJIA across these variations. Estimation results for DJIA and S&P500 are provided in Tables 2.28 and 2.29, respectively.

In terms of stock market volatility, the negative relationship between IRG shocks and the VXD index is robust across all shock specifications and with the VIX index. For BSP shocks, a significant negative association with VXD is observed specifically during the ZLB period, although this relationship is more consistently significant across all specifications

[5]The EPU index tracks sentiment shifts around U.S. monetary policy through news mentions of uncertainty and key terms, spiking during major policy events and indicating market volatility and economic impact. Including the EUI as a control variable helps to isolate sentiment shifts specifically linked to the Fed's actions and communications, reducing the influence of general economic uncertainty on the identified shocks.

with the VIX index. Estimation results for VXD and VIX are provided in Tables 2.30 and 2.31, respectively.

Robustness checks for Treasury yields reveal stable associations as well. The negative relationship between IRG shocks and DGS2 and DGS30 is observed across various specifications, and the positive association between BSP and EOA shocks with DGS2 and DGS30 holds under both pre-ZLB and ZLB periods, as applicable. Estimation results for DGS2 and DGS30 are provided in Tables 2.32 and 2.33, respectively.

Additionally, positive associations between IRG and BSP shocks with DAAA yields are consistent across most specifications and the pre-ZLB subsample, whereas EOA shocks show a generally negative relationship with DAAA, although this effect weakens in the pre-ZLB period. For corporate bond yields (DBAA), positive associations for IRG and BSP shocks remain stable across specifications, with BSP effects turning insignificant during the ZLB period, while EOA shocks display a negative relationship that diminishes in the pre-ZLB period. Estimation results for DAAA and DBAA are provided in Tables 2.34 and 2.35, respectively.

Finally, exchange rate robustness reveals that the negative association between IRG shocks and the USD/Euro exchange rate (DEXUSEU) holds consistently across specifications and pre-ZLB samples. The impact of BSP shocks on DEXUSEU during the ZLB period indicates potential depreciation pressures on the USD, possibly reflecting heightened risk aversion amid balance sheet tightening. Conversely, the positive relationship between EOA shocks and DEXUSEU is robust across different specifications and pre-ZLB samples, underscoring consistent effects of FG on exchange rates. Estimation results for DEXUSEU is provided in Table 2.36.

Appendix D: Exogeneity Testing of Policy Shocks

In addition to employing 11 shock specifications and verifying that the sentiment shocks show no significant correlation, as validated in Table 2.18, I performed additional exogeneity tests on the constructed monetary policy shocks (IRG, BSP, and EOA). Specifically, I regressed each shock on lagged values of key financial indicators—S&P500, VIX, DGS2, and EUI—to examine whether prior movements in these variables systematically influenced the shocks, which would indicate endogeneity. To enhance robustness, these tests span the first three shock specifications and analyze the lagged indicators both individually and collectively.

The results, presented in Tables 2.37, 2.38, and 2.39, display the outcomes of regressing the lagged financial indicators individually on the IRG, BSP, and EOA shocks, respectively. Table 2.40 provides a combined estimation, regressing all four lagged financial indicators together on each shock, allowing for a comprehensive assessment of potential endogeneity influences.

The regression results show that most coefficients for the lagged financial indicators are statistically insignificant, indicating that past values of SP500, VIX, DGS2, and EUI do not systematically predict the IRG, BSP, and EOA shocks. Additionally, the R-squared values are consistently low, further suggesting minimal explanatory power from the lagged indicators on the shocks. These results support the interpretation that the shocks represent unexpected, exogenous disturbances rather than predictable responses to past financial conditions. Although certain lagged terms of the EUI showed marginal significance at the 10% level, these instances were limited and did not significantly impact the overall findings of exogeneity.

To further test exogeneity, I follow Miranda-Agrippino and Ricco (2021) by including the Fed's Greenbook/Tealbook projections for GDP growth, inflation, and unemployment from February 2000 to December 2018. These projections reflect the Fed's expectations over multiple horizons: one quarter prior ($RGDP_{q-1}$, INF_{q-1}, $UNEMP_{q-1}$), the current quarter ($RGDP_q$, INF_q, $UNEMP_q$), and up to three quarters ahead ($RGDP_{q+1}$ to $RGDP_{q+3}$, etc.). By incorporating these forecasts, I assess whether the shocks could be anticipated by the Fed's economic outlook, which would indicate endogeneity. However, as shown in Table 2.41, these projections generally do not predict the shocks significantly. Only a few coefficients display marginal significance, reinforcing the exogeneity assumption.

The exogeneity tests confirm that the constructed shocks are not predictably influenced by prior financial indicators, economic uncertainty, or Fed forecasts, highlighting their independence from available information at the time. The use of HAC standard errors with Newey-West adjustments and multiple specifications strengthens these results. This supports the validity of these shocks as exogenous, unexpected monetary policy disturbances, making them appropriate for further analysis of monetary policy impacts on financial indicators.

Appendix E: Figures

E.1 Interest Rate Guidance (IRG)

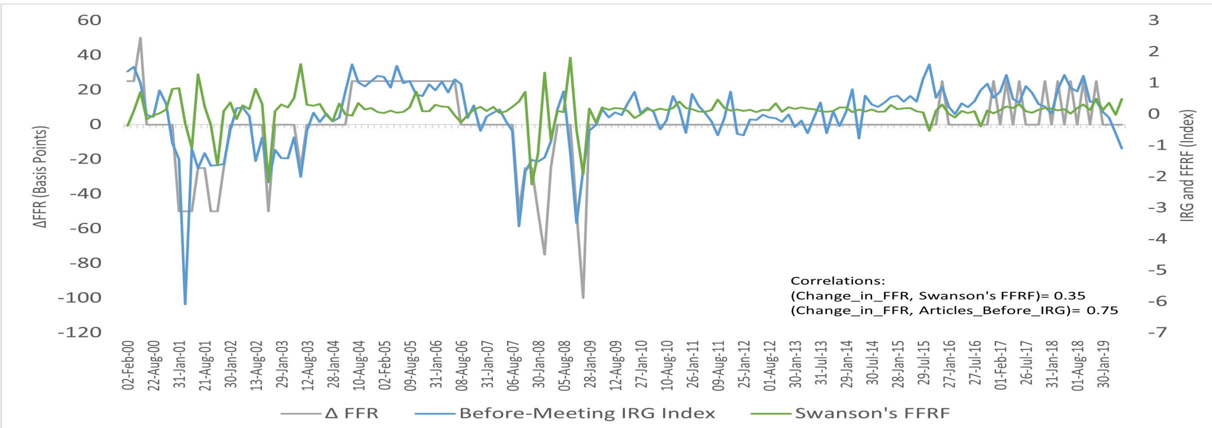

Figure 2.7: Before- and after-meeting IRG indexes, the actual change in the FFR, and Swanson's FFRF (Feb. 2000–Mar. 2019).

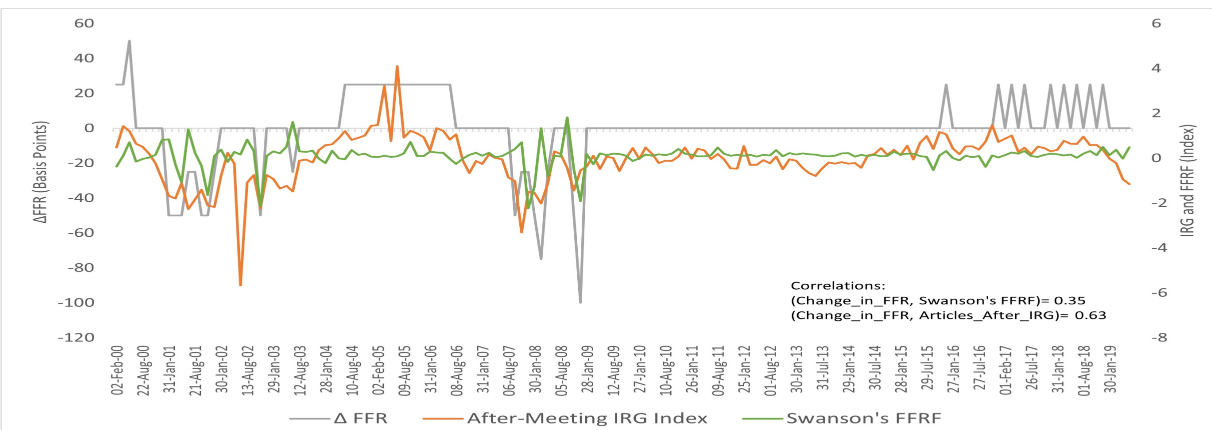

Figure 2.8: After-meeting IRG index, the actual change in the FFR, and Swanson's FFRF (Feb. 2000–Mar. 2019).

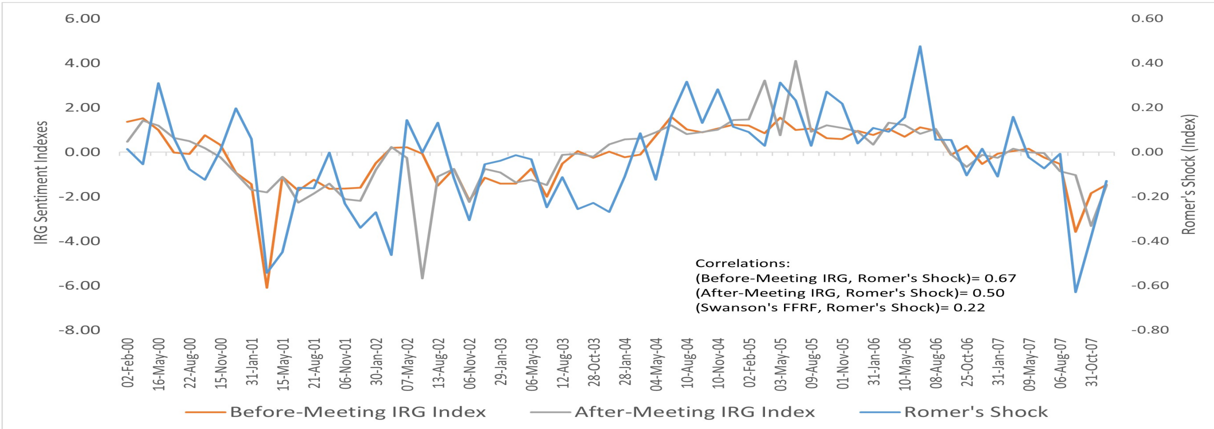

Figure 2.9: Romer's shock versus IRG sentiment indexes (Feb. 2000–Dec. 2007).

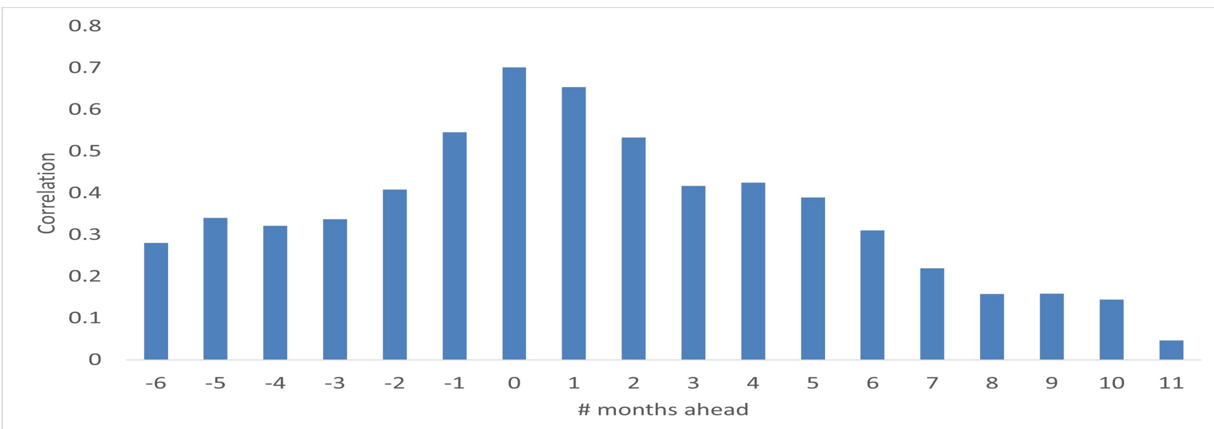

Figure 2.10: Cross-correlation between before-meeting IRG index and Δ FFR.

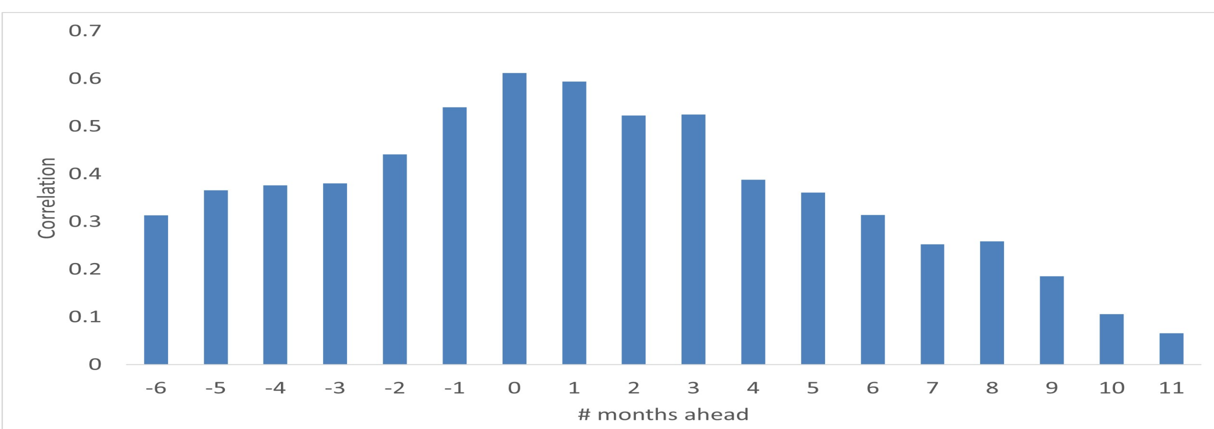

Figure 2.11: Cross-correlation between after-meeting IRG index and Δ FFR.

E.2 Balance Sheet Policies (BSP)

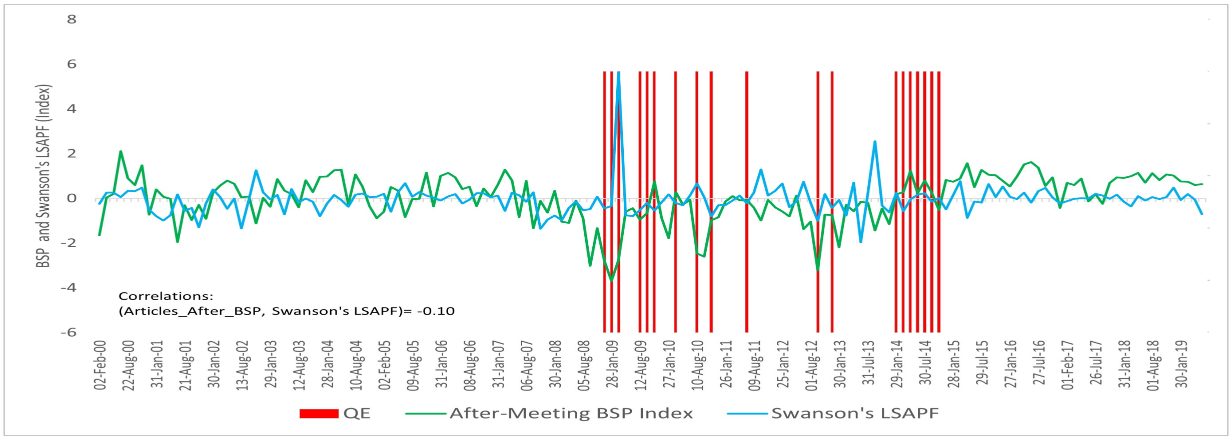

Figure 2.12: After-meeting BSP sentiment compared to Swanson's LSAPF and QE periods (Feb. 2000–Mar. 2019).

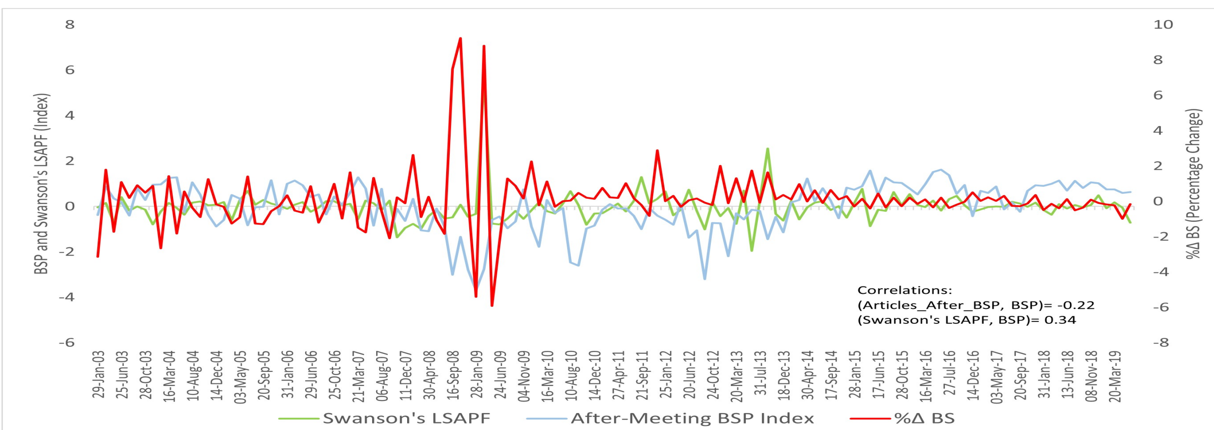

Figure 2.13: After-meeting BSP sentiment compared to Swanson's LSAPF and %ΔBS (Feb. 2000–Mar. 2019).

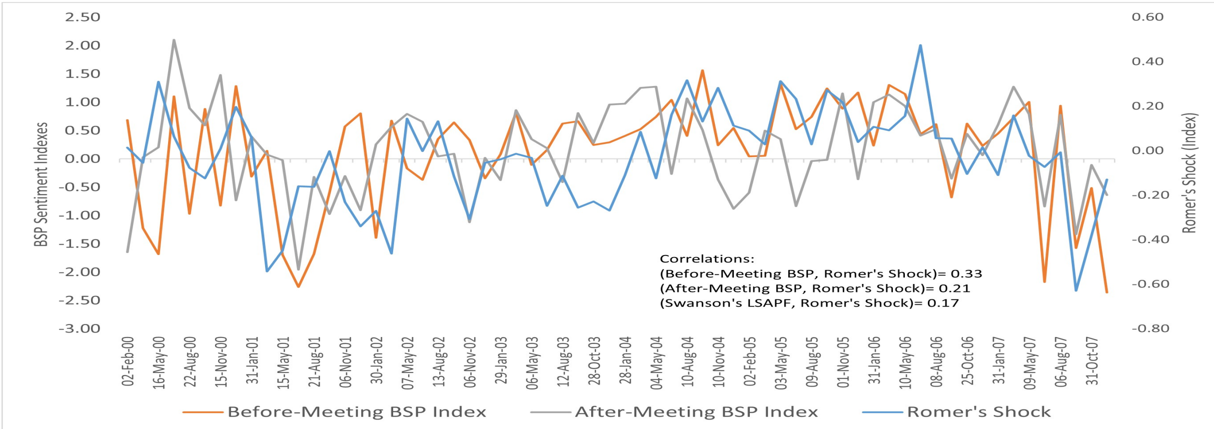

Figure 2.14: Romer's shock versus BSP sentiment indexes (Feb. 2000–Dec. 2007).

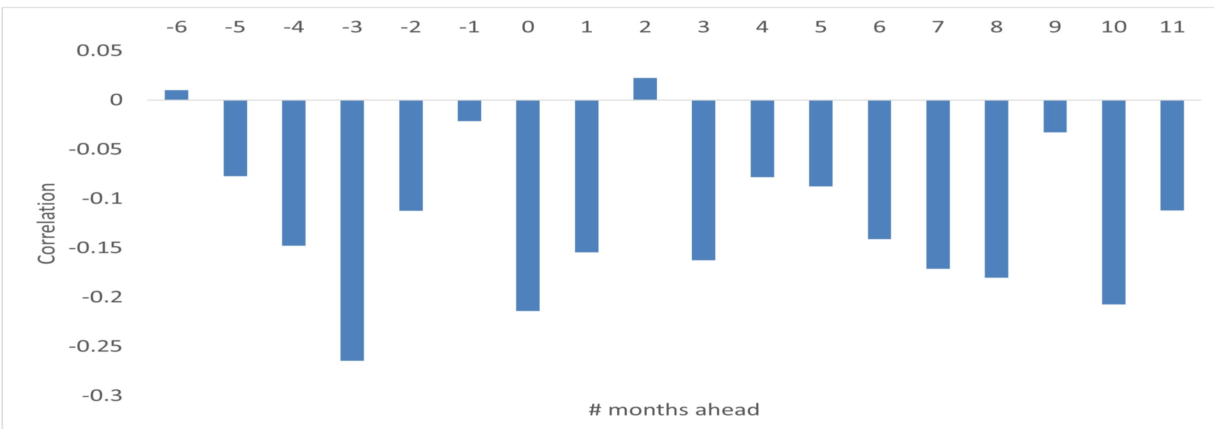

Figure 2.15: Cross-correlation between before-meeting BSP index and %ΔBS.

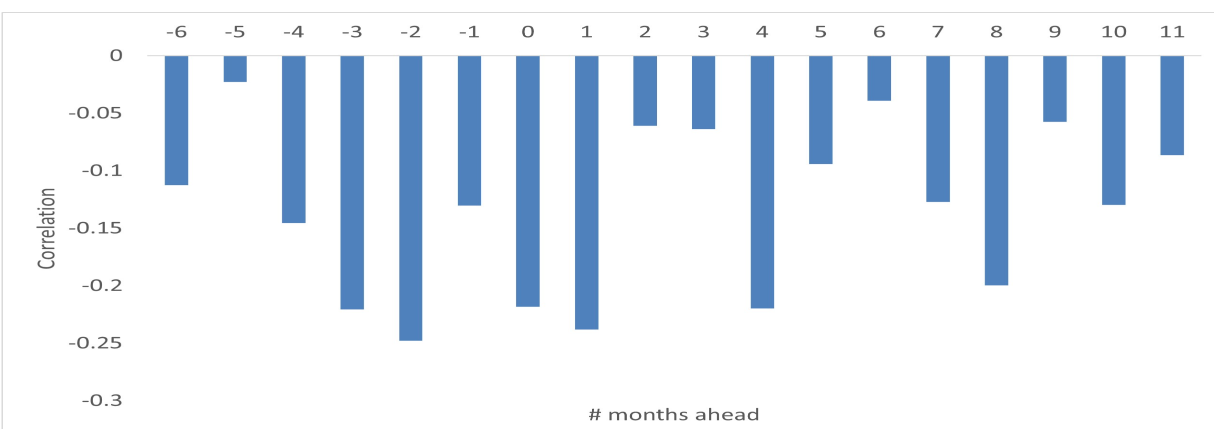

Figure 2.16: Cross-correlation between after-meeting BSP index and %ΔBS.

E.3 Economic Outlook Assessment (EOA)

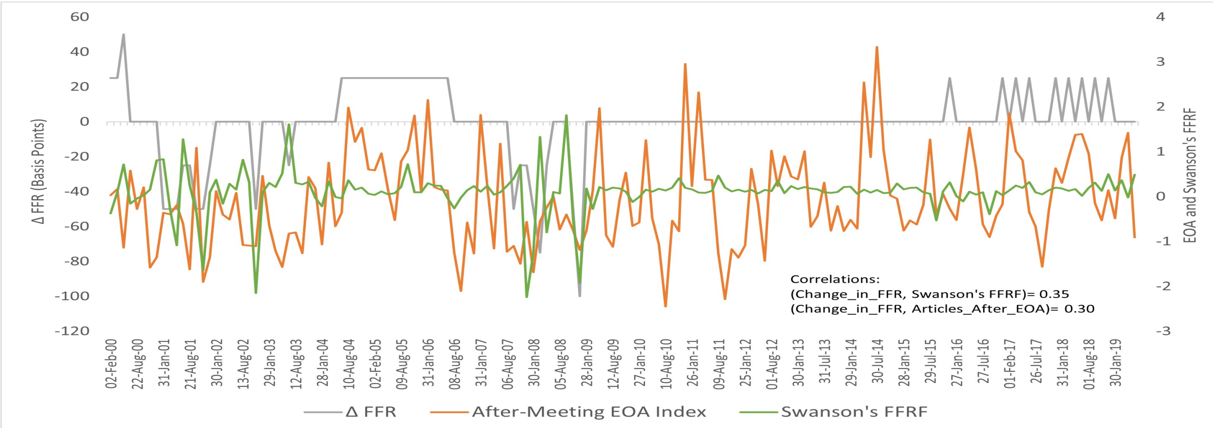

Figure 2.17: After-meeting EOA sentiment compared to Swanson's FFRF (Feb. 2000–Mar. 2019).

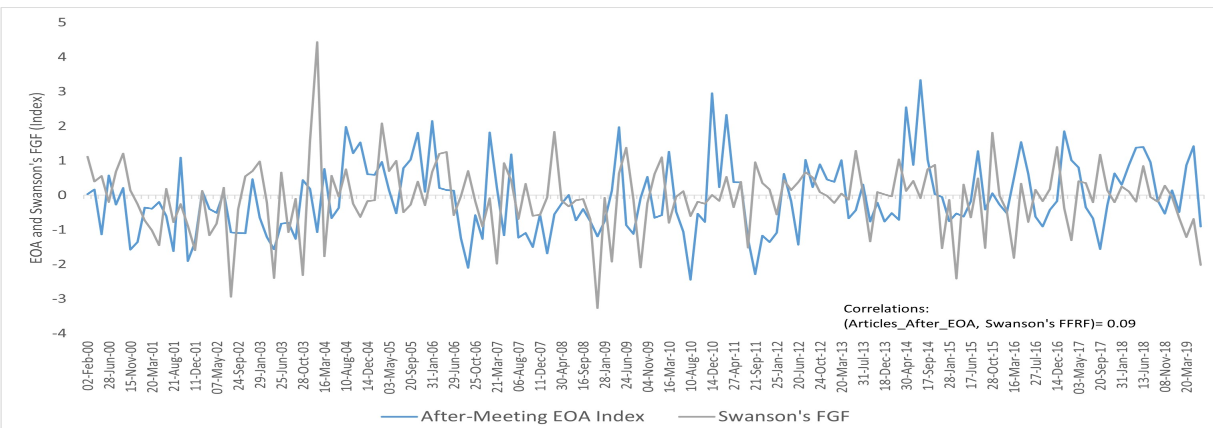

Figure 2.18: After-meeting EOA sentiment compared to Swanson's FGF (Feb. 2000–Mar. 2019).

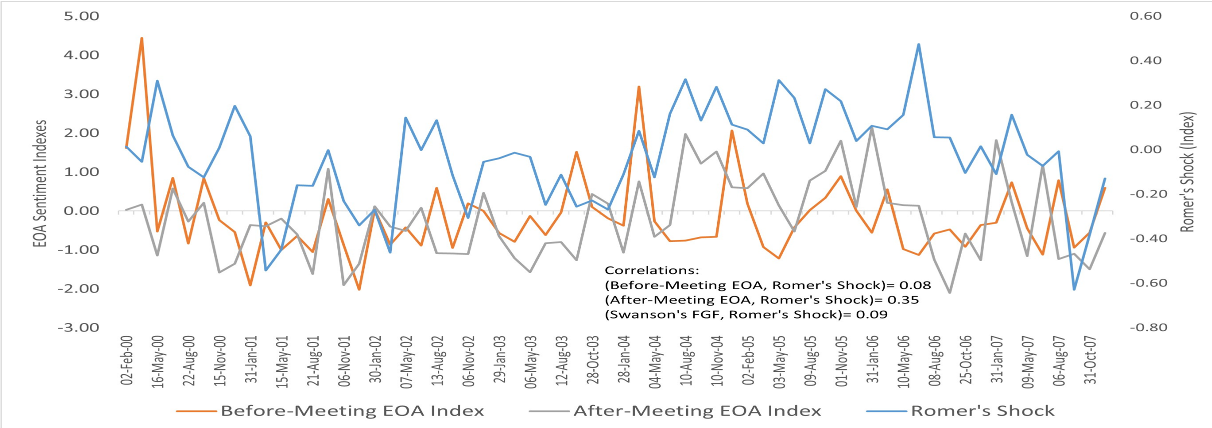

Figure 2.19: Romer's shock versus EOA sentiment indexes (Feb. 2000–Dec. 2007).

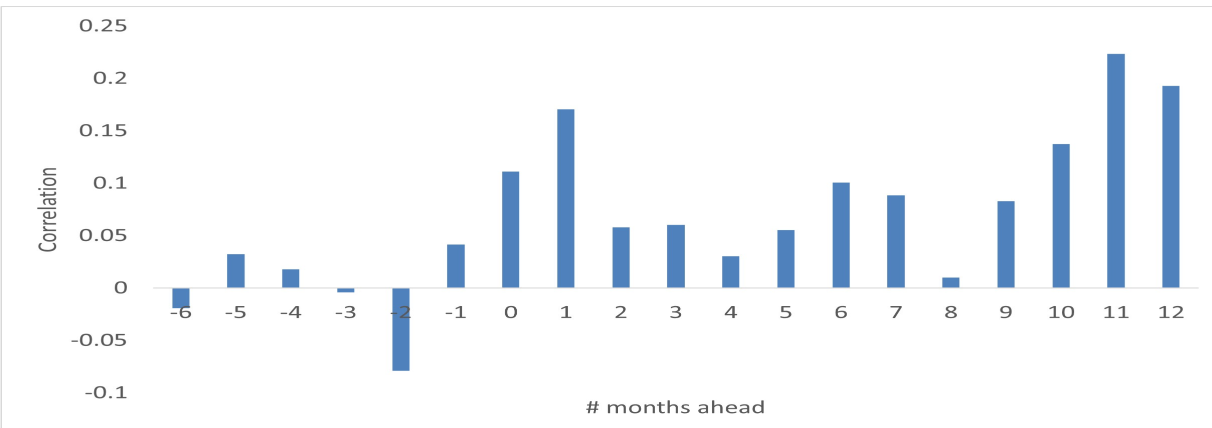

Figure 2.20: Cross-correlation between before-meeting EOA index and %ΔBS.

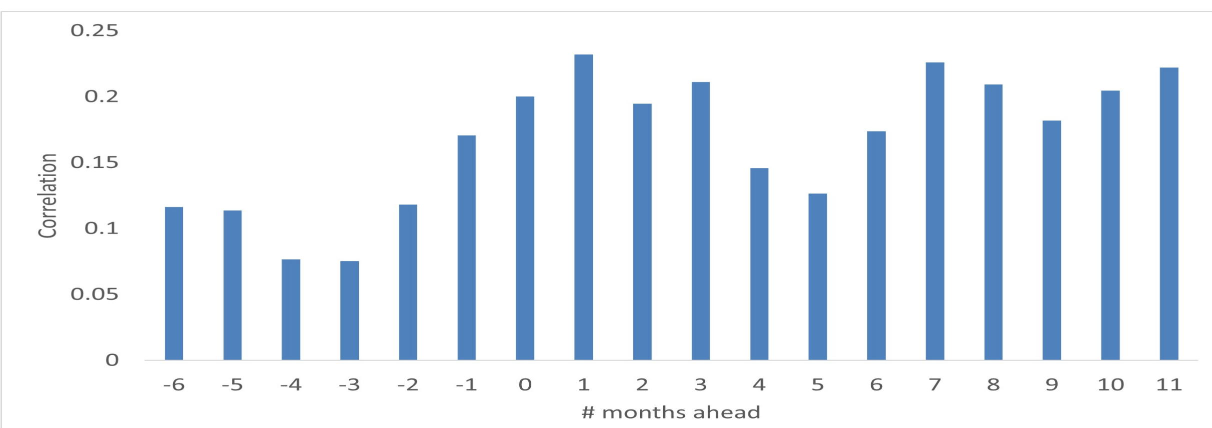

Figure 2.21: Cross-correlation between after-meeting EOA index and %ΔBS.

E. 4 Monetary Policy Sentiment Shocks

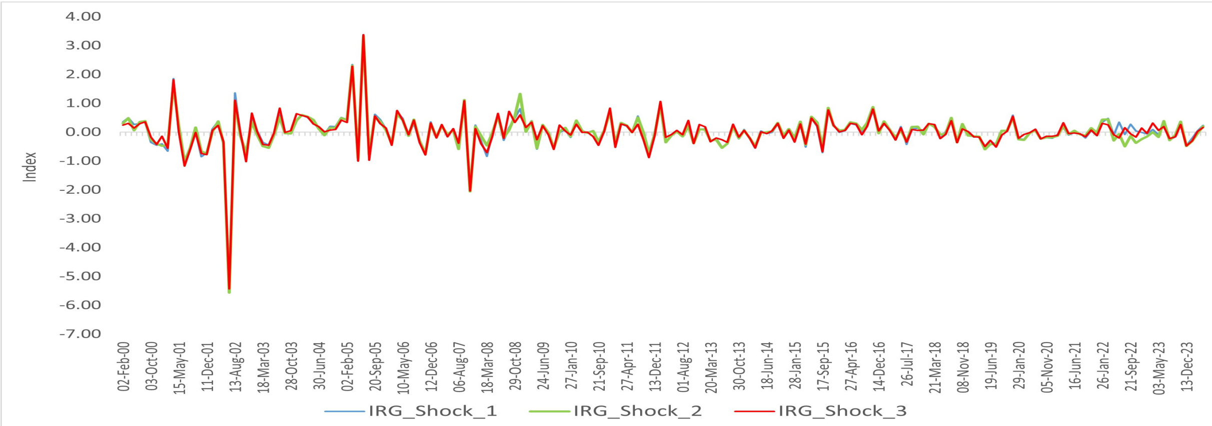

Figure 2.22: IRG shocks using specification 1, 2, and 3 (Feb. 2000–May 2024).

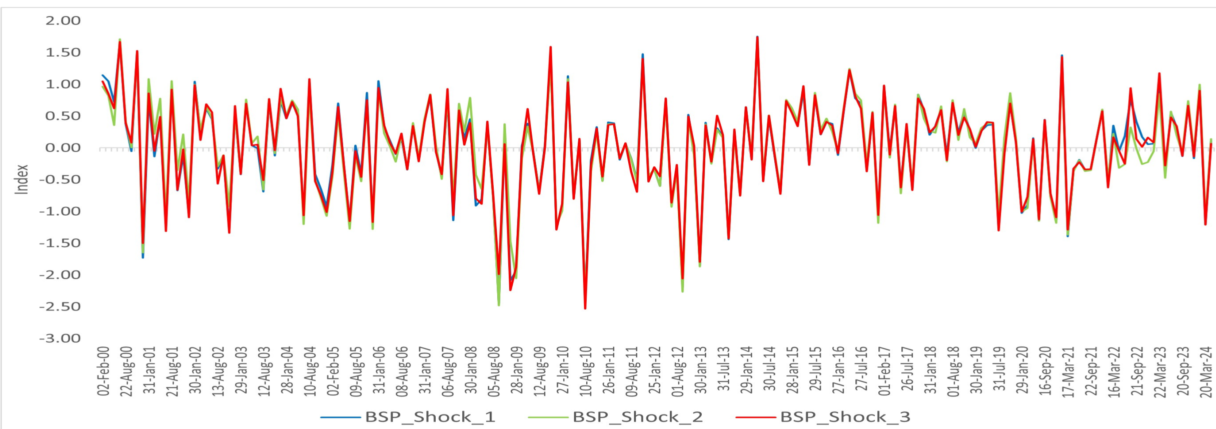

Figure 2.23: BSP shocks using specification 1, 2, and 3 (Feb. 2000–May 2024).

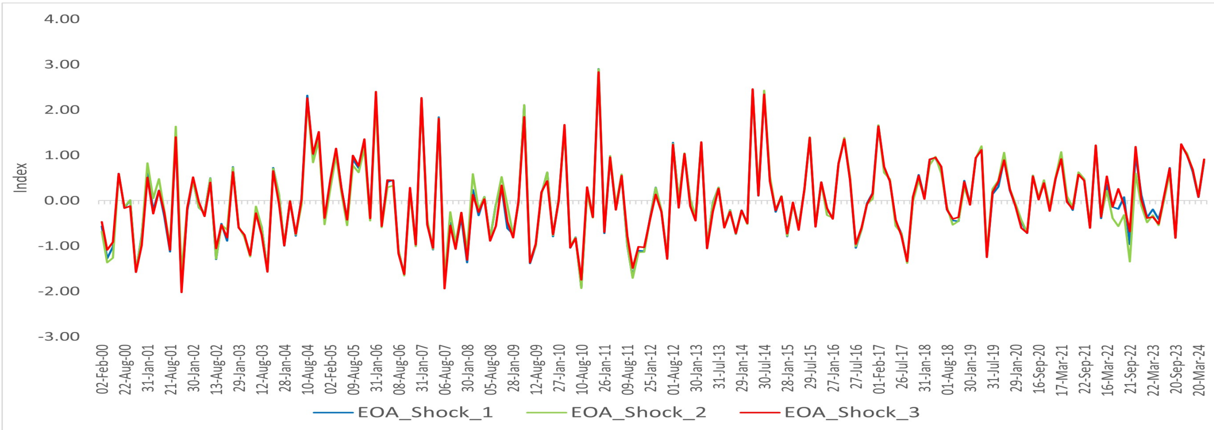

Figure 2.24: EOA shocks using specification 1, 2, and 3 (Feb. 2000–May 2024).

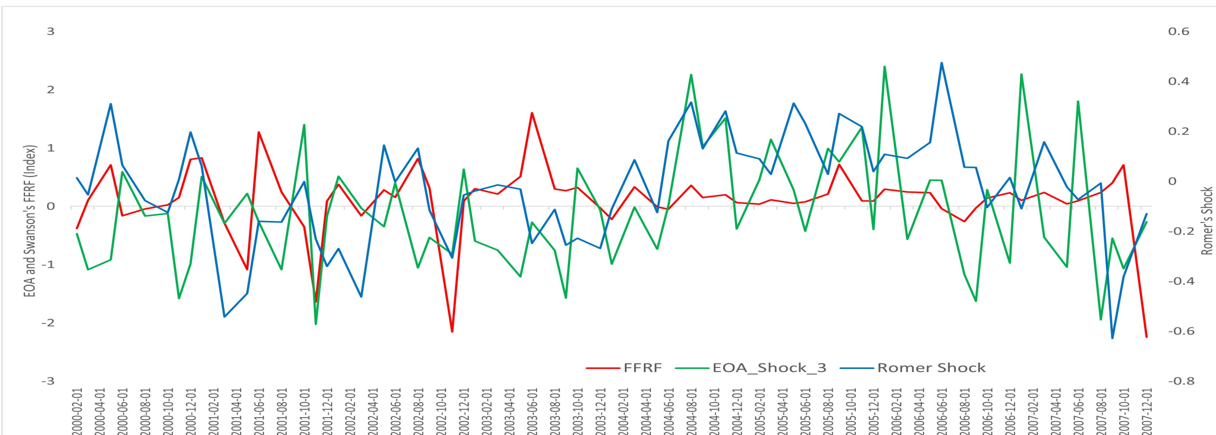

Figure 2.25: Romer's shock versus EOA shock and Swanson's FFRF (Feb. 2000–Dec. 2007).

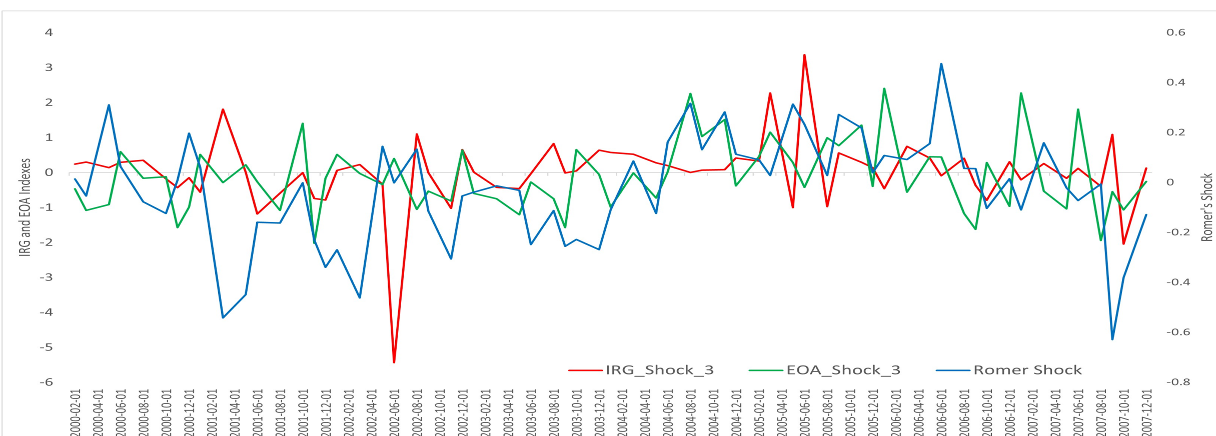

Figure 2.26: Romer's shock versus IRG and EOA shocks (Feb. 2000–Dec. 2007).

Appendix F: Tables

Table 2.11: FOMC scheduled meetings dates

2-Feb-00	13-Mar-12	28-Mar-06	2-May-18
21-Mar-00	25-Apr-12	10-May-06	13-Jun-18
16-May-00	20-Jun-12	29-Jun-06	1-Aug-18
28-Jun-00	1-Aug-12	8-Aug-06	26-Sep-18
22-Aug-00	13-Sep-12	20-Sep-06	8-Nov-18
3-Oct-00	24-Oct-12	25-Oct-06	19-Dec-18
15-Nov-00	12-Dec-12	12-Dec-06	30-Jan-19
19-Dec-00	30-Jan-13	31-Jan-07	20-Mar-19
31-Jan-01	20-Mar-13	21-Mar-07	1-May-19
20-Mar-01	1-May-13	9-May-07	19-Jun-19
15-May-01	19-Jun-13	28-Jun-07	31-Jul-19
27-Jun-01	31-Jul-13	7-Aug-07	18-Sep-19
21-Aug-01	18-Sep-13	18-Sep-07	30-Oct-19
2-Oct-01	30-Oct-13	31-Oct-07	11-Dec-19
6-Nov-01	18-Dec-13	11-Dec-07	29-Jan-20
11-Dec-01	29-Jan-14	30-Jan-08	29-Apr-20
30-Jan-02	19-Mar-14	18-Mar-08	10-Jun-20
19-Mar-02	30-Apr-14	30-Apr-08	29-Jul-20
7-May-02	18-Jun-14	25-Jun-08	16-Sep-20
26-Jun-02	30-Jul-14	5-Aug-08	5-Nov-20
13-Aug-02	17-Sep-14	16-Sep-08	16-Dec-20
24-Sep-02	29-Oct-14	29-Oct-08	27-Jan-21
6-Nov-02	17-Dec-14	16-Dec-08	17-Mar-21
10-Dec-02	28-Jan-15	28-Jan-09	28-Apr-21
29-Jan-03	18-Mar-15	18-Mar-09	16-Jun-21
18-Mar-03	29-Apr-15	29-Apr-09	28-Jul-21
6-May-03	17-Jun-15	24-Jun-09	22-Sep-21
25-Jun-03	29-Jul-15	12-Aug-09	3-Nov-21
12-Aug-03	17-Sep-15	23-Sep-09	15-Dec-21
16-Sep-03	28-Oct-15	4-Nov-09	26-Jan-22
28-Oct-03	16-Dec-15	16-Dec-09	16-Mar-22
9-Dec-03	27-Jan-16	27-Jan-10	4-May-22
28-Jan-04	16-Mar-16	16-Mar-10	15-Jun-22
16-Mar-04	27-Apr-16	28-Apr-10	27-Jul-22
4-May-04	15-Jun-16	23-Jun-10	21-Sep-22
30-Jun-04	27-Jul-16	10-Aug-10	2-Nov-22
10-Aug-04	21-Sep-16	21-Sep-10	14-Dec-22
21-Sep-04	2-Nov-16	3-Nov-10	1-Feb-23
10-Nov-04	14-Dec-16	14-Dec-10	22-Mar-23
14-Dec-04	1-Feb-17	26-Jan-11	3-May-23
2-Feb-05	15-Mar-17	15-Mar-11	14-Jun-23
22-Mar-05	3-May-17	27-Apr-11	26-Jul-23
3-May-05	14-Jun-17	22-Jun-11	20-Sep-23
30-Jun-05	26-Jul-17	9-Aug-11	1-Nov-23
9-Aug-05	20-Sep-17	21-Sep-11	13-Dec-23
20-Sep-05	1-Nov-17	2-Nov-11	31-Jan-24
1-Nov-05	13-Dec-17	13-Dec-11	20-Mar-24
13-Dec-05	31-Jan-18	25-Jan-12	1-May-24
31-Jan-06	21-Mar-18	13-Mar-12	**Total=194**

Table 2.12: Description of variables

Identifier	**Description**	**Source**	**Abbreviation**
SP500	S&P 500 INDEX (Bloomberg)	Bloomberg	$S\&P500$
INDU:IND	Dow Jones Industrial Average (Bloomberg)	Bloomberg	DJIA
VIX	CBOE Volatility Index: VIX	FRED	VIX
VXD	CBOE DJIA Volatility Index	FRED	DJVIX
DTB3	3-Month Treasury Bill Secondary Market Rate, Discount Basis, Percent, Daily, Not Seasonally Adjusted	FRED	DTB3
DTB6	6-Month Treasury Bill Secondary Market Rate, Discount Basis, Percent, Daily, Not Seasonally Adjusted	FRED	DTB6
DGS1	Market Yield on U.S. Treasury Securities at 1-Year Constant Maturity, Quoted on an Investment Basis	FRED	DGS1
DGS2	Market Yield on U.S. Treasury Securities at 2-Year Constant Maturity, Quoted on an Investment Basis, Percent, Daily, Not Seasonally Adjusted	FRED	DGS2
DGS5	Market Yield on U.S. Treasury Securities at 5-Year Constant Maturity, Quoted on an Investment Basis	FRED	DGS5
DGS30	Market Yield on U.S. Treasury Securities at 30-Year Constant Maturity, Quoted on an Investment Basis	FRED	DGS30
DEXUSEU	U.S. Dollars to Euro Spot Exchange Rate, U.S. Dollars to One Euro, Daily, Not Seasonally Adjusted	FRED	USDEUR
DAAA	Moody's Seasoned Aaa Corporate Bond Yield	FRED	DAAA
DBAA	Moody's Seasoned Baa Corporate Bond Yield	FRED	DBAA
BAMLCA0CM	ICE BofA US Corporate Index Option-Adjusted Spread, Percent, Daily, Not Seasonally Adjusted	FRED	CorpOAS
BAMLCC0A1AAATRIV	ICE BofA AAA US Corporate Index Total Return Index Value, Index, Daily, Not Seasonally Adjusted	FRED	AAART
USEPUINDXD	Economic Policy Uncertainty Index for United States, Index, Daily, Not Seasonally Adjusted	FRED	EUI

Table 2.13: Examples of sentence scoring

Category	Sentence	Sentiment	Source
IRG	**Before Meeting:** Investors are hoping that those releases or Mr. Powell's comments signal that Fed officials might $\underbrace{\text{slow}}_{\text{negation}}$ rate $\underbrace{\text{increases}}_{+}$ further in the new year.	Dovish	14 Dec 2022, WSJ
	After Meeting: Powell said he expects a couple more rate $\underbrace{\text{hikes}}_{+}$ still to go, and, given our outlook, I just $\underbrace{\text{don't}}_{\text{negation}}$ see us $\underbrace{\text{cutting}}_{-}$ rates this year.	Hawkish	14 Dec 2022, Reuters
	Overall Shock: This is a more hawkish set of communications than markets expected	**Hawkish**	14 Dec 2022, Reuters
	Comment: Investors had hoped for a slowdown in the pace of rate hikes, but Powell indicated that additional rate increases were likely.		
BSP	**Before Meeting:** The market rally came ahead of this week's FOMC meeting, which is being watched for indications the Fed will begin to $\underbrace{\text{cut}}_{-}$ or "$\underbrace{\text{taper}}_{-}$" its \$85bn monthly $\underbrace{\text{bond buying}}_{\text{Dovish}}$ program.	Hawkish	19 Sep 2013, FT
	After Meeting: Doug Cote, chief investment strategist for ING U.S. Investment Management, said this month's surprise decision $\underbrace{\text{not}}_{\text{negation}}$ to begin $\underbrace{\text{trimming}}_{-}$ $\underbrace{\text{stimulus}}_{\text{Dovish}}$ has weakened the central bank's credibility.	Dovish	19 Sep 2013, WSJ
	Overall Shock: It's surprising that the Fed telegraphed tapering and didn't do it...It's a pretty dovish statement.	**Dovish**	19 Sep 2013, WSJ
	Comment: The FOMC's unexpected decision to continue its asset purchase program led to significant market reactions.		
EOA	**Before Meeting:** Data released since mid-March show significantly $\underbrace{\text{more}}_{+}$ $\underbrace{\text{jobs}}_{\text{Hawkish}}$ have been $\underbrace{\text{added}}_{+}$ in recent months, though overall $\underbrace{\text{employment}}_{\text{Hawkish}}$ remains well $\underbrace{\text{short}}_{-}$ of levels seen a year ago. Meantime, $\underbrace{\text{inflation}}_{\text{Hawkish}}$ has been $\underbrace{\text{higher}}_{+}$ than economists had anticipated.	Hawkish	28 Apr 2021, FT
	After Meeting: The Fed underscored a $\underbrace{\text{lot}}_{+}$ of $\underbrace{\text{uncertainty}}_{\text{Dovish}}$ remains.	Dovish	28 Apr 2021, Reuters
	Overall Shock:	**Dovish**	
	Comment: An assertion of a pessimistic economic outlook.		

Table 2.14: Correlation analysis of sentiment indexes, Swanson's factors, FFR changes, and proxy funds rate

Variable 1	Variable 2	Correlation	95% Confidence Interval	P-Value
IRG^{Before}	BSP^{Before}	0.27	[0.13, 0.39]	0.0002
IRG^{Before}	EOA^{Before}	0.18	[0.04, 0.31]	0.0126
IRG^{Before}	IRG^{After}	0.72	[0.64, 0.78]	0.0000
IRG^{Before}	BSP^{After}	0.32	[0.18, 0.44]	0.0000
IRG^{Before}	EOA^{After}	0.24	[0.10, 0.37]	0.0007
IRG^{Before}	ΔFFR	0.70	[0.62, 0.77]	0.0000
IRG^{Before}	ΔPFR	0.16	[0.02, 0.29]	0.0260
BSP^{Before}	EOA^{Before}	-0.09	[-0.23, 0.05]	0.2116
BSP^{Before}	IRG^{After}	0.29	[0.15, 0.41]	0.0000
BSP^{Before}	BSP^{After}	0.53	[0.41, 0.62]	0.0000
BSP^{Before}	EOA^{After}	0.09	[-0.05, 0.23]	0.2026
BSP^{Before}	ΔFFR	0.29	[0.15, 0.41]	0.0000
BSP^{Before}	ΔPFR	0.04	[-0.10, 0.18]	0.5354
EOA^{Before}	IRG^{After}	0.14	[-0.00, 0.27]	0.0530
EOA^{Before}	BSP^{After}	-0.03	[-0.17, 0.11]	0.6719
EOA^{Before}	EOA^{After}	0.37	[0.24, 0.48]	0.0000
EOA^{Before}	ΔFFR	0.11	[-0.03, 0.25]	0.1224
EOA^{Before}	ΔPFR	0.02	[-0.12, 0.16]	0.7892
IRG^{After}	BSP^{After}	0.25	[0.11, 0.38]	0.0005
IRG^{After}	EOA^{After}	0.25	[0.11, 0.38]	0.0005
IRG^{After}	ΔFFR	0.61	[0.52, 0.69]	0.0000
IRG^{After}	ΔPFR	0.20	[0.06, 0.33]	0.0053
BSP^{After}	EOA^{After}	0.20	[0.06, 0.33]	0.0059
BSP^{After}	ΔFFR	0.32	[0.19, 0.44]	0.0000
BSP^{After}	ΔPFR	0.11	[-0.04, 0.24]	0.1403
EOA^{After}	ΔFFR	0.20	[0.06, 0.33]	0.0051
EOA^{After}	ΔPFR	-0.08	[-0.22, 0.06]	0.2664
IRG^{Before}	Swanson's FFRF	0.10	[-0.06, 0.26]	0.2044
IRG^{Before}	Swanson's LSAPF	0.15	[-0.01, 0.30]	0.0705
IRG^{Before}	Swanson's FGF	0.22	[0.07, 0.37]	0.0048
BSP^{Before}	Swanson's FFRF	0.01	[-0.15, 0.17]	0.9207
BSP^{Before}	Swanson's LSAPF	-0.17	[-0.32, -0.01]	0.0370
BSP^{Before}	Swanson's FGF	0.03	[-0.13, 0.18]	0.7502
EOA^{Before}	Swanson's FFRF	-0.01	[-0.17, 0.15]	0.8776
EOA^{Before}	Swanson's LSAPF	0.08	[-0.08, 0.24]	0.3076
EOA^{Before}	Swanson's FGF	0.03	[-0.13, 0.19]	0.6891
IRG^{After}	Swanson's FFRF	0.06	[-0.09, 0.22]	0.4336
IRG^{After}	Swanson's LSAPF	0.20	[0.05, 0.35]	0.0109
IRG^{After}	Swanson's FGF	0.22	[0.06, 0.36]	0.0061
BSP^{After}	Swanson's FFRF	0.05	[-0.11, 0.20]	0.5600
BSP^{After}	Swanson's LSAPF	-0.10	[-0.26, 0.05]	0.1972
BSP^{After}	Swanson's FGF	0.05	[-0.11, 0.21]	0.5217
EOA^{After}	Swanson's FFRF	0.08	[-0.08, 0.24]	0.3146
EOA^{After}	Swanson's LSAPF	-0.00	[-0.16, 0.15]	0.9746
EOA^{After}	Swanson's FGF	0.09	[-0.07, 0.24]	0.2836
IRG^{Before}	$\%\Delta BS$	-0.21	[-0.35, -0.07]	0.0050
BSP^{Before}	$\%\Delta BS$	-0.21	[-0.35, -0.07]	0.0051
EOA^{Before}	$\%\Delta BS$	-0.06	[-0.21, 0.09]	0.4492
IRG^{After}	$\%\Delta BS$	-0.12	[-0.26, 0.03]	0.1264
BSP^{After}	$\%\Delta BS$	-0.22	[-0.36, -0.07]	0.0043
EOA^{After}	$\%\Delta BS$	-0.02	[-0.17, 0.14]	0.8414
$Romer'sShock$	$Swanson'sFFRF$	0.22	[-0.08, 0.02]	0.0834
$Romer'sShock$	$Swanson'sLSAPF$	0.17	[-0.08, 0.02]	0.1817
$Romer'sShock$	$Swanson'sFGF$	0.09	[-0.08, 0.02]	0.4728
$Romer'sShock$	IRG^{Before}	0.67	[-0.08, 0.02]	0.0000
$Romer'sShock$	BSP^{Before}	0.33	[-0.08, 0.02]	0.0078
$Romer'sShock$	EOA^{Before}	0.08	[-0.08, 0.02]	0.5090
$Romer'sShock$	IRG^{After}	0.50	[-0.08, 0.02]	0.0000
$Romer'sShock$	BSP^{After}	0.21	[-0.08, 0.02]	0.0929
$Romer'sShock$	EOA^{After}	0.36	[-0.08, 0.02]	0.0040

Notes:
- First panel time frame: February 2000 to May 2024. Total observations: 194.
- Second panel time frame: February 2000 to June 2019. Total observations: 156.
- Third panel time frame: January 2003 to May 2024. Total observations: 170.
- Fourth Panel time frame: February 2000 to December 2007. Total observations: 64.

Table 2.15: Regressions for IRG shock under different specifications

Explanatory Variables		Specification		
		1	**2**	**3**
IRG_t^{Before}	Coefficient	0.5178***	0.4324***	0.4903***
	HAC S.E.	0.1021	0.0969	0.0997
IRG_{t-1}^{After}	Coefficient	0.2959***	0.2617***	0.3112***
	HAC S.E.	0.0863	0.0746	0.0806
ΔFFR_t	Coefficient		0.007**	
	HAC S.E.		0.0036	
ΔProxy_t	Coefficient			0.8528**
	HAC S.E.			0.3773
R-Squared		56.13%	57.29%	57.46%

- Dependent variable is IRG_t^{After}
- Standard errors in parentheses. *, **, *** denote significance at the 10% level, 5% level, and 1% level, respectively.
- HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000).

Table 2.16: Regressions for BSP shock under different specifications

Explanatory Variables		Specification		
		1	**2**	**3**
BSP_t^{Before}	Coefficient	0.32***	0.2921***	0.3206***
	HAC S.E.	0.0771	0.075	0.0755
BSP_{t-1}^{After}	Coefficient	0.389***	0.3643***	0.3819***
	HAC S.E.	0.0676	0.0619	0.066
ΔFFR_t	Coefficient		0.0066**	
	HAC S.E.		0.002	
ΔProxy_t	Coefficient			0.6667
	HAC S.E.			0.522
R-Squared		39.44%	41.34%	40.29%

- Dependent variable is BSP_t^{After}
- Standard errors in parentheses. *, **, *** denote significance at the 10% level, 5% level, and 1% level, respectively.
- HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000).

Table 2.17: Regressions for EOA shock under different specifications

Explanatory Variables		**Specification**		
		1	**2**	**3**
EOA_t^{Before}	Coefficient	0.3224***	0.3154***	0.3213***
	HAC S.E.	0.073	0.0747	0.0713
XX_{t-1}^{After}	Coefficient	0.2595***	0.2344***	0.2639***
	HAC S.E.	0.0663	0.0675	0.0683
ΔFFR_t	Coefficient		0.0052*	
	HAC S.E.		0.0027	
ΔProxy_t	Coefficient			−0.6751
	HAC S.E.			0.5176
R-Squared		20.21%	21.43%	21.07%

- Dependent variable is EOA_t^{After}
- Standard errors in parentheses. *, **, *** denote significance at the 10% level, 5% level, and 1% level, respectively.
- HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000).

Table 2.18: Correlation analysis of sentiment shocks, FFR changes, and PFR

Variable 1	Variable 2	Correlation	95% Confidence Interval	P-Value
IRG^{Shock1}	IRG^{Shock2}	0.99	[0.9823, 0.9899]	0.0000
IRG^{Shock1}	IRG^{Shock3}	0.98	[0.9795, 0.9883]	0.0000
IRG^{Shock1}	BSP^{Shock1}	-0.07	[-0.2084, 0.0721]	0.3355
IRG^{Shock1}	BSP^{Shock2}	-0.09	[-0.2257, 0.0539]	0.2244
IRG^{Shock1}	BSP^{Shock3}	-0.09	[-0.2283, 0.0512]	0.2103
IRG^{Shock1}	EOA^{Shock1}	0.03	[-0.1107, 0.1708]	0.6715
IRG^{Shock1}	EOA^{Shock2}	0.02	[-0.1216, 0.1600]	0.7864
IRG^{Shock1}	EOA^{Shock3}	0.05	[-0.0929, 0.1882]	0.5009
IRG^{Shock1}	ΔFFR	0.12	[-0.0254, 0.2526]	0.1077
IRG^{Shock1}	ΔPFR	0.18	[0.0362, 0.3093]	0.0140
IRG^{Shock2}	IRG^{Shock3}	0.97	[0.9667, 0.9810]	0.0000
IRG^{Shock2}	BSP^{Shock1}	-0.08	[-0.2172, 0.0628]	0.2749
IRG^{Shock2}	BSP^{Shock2}	-0.08	[-0.2153, 0.0648]	0.2872
IRG^{Shock2}	BSP^{Shock3}	-0.10	[-0.2350, 0.0442]	0.1770
IRG^{Shock2}	EOA^{Shock1}	0.03	[-0.1119, 0.1696]	0.6838
IRG^{Shock2}	EOA^{Shock2}	0.03	[-0.1085, 0.1729]	0.6493
IRG^{Shock2}	EOA^{Shock3}	0.05	[-0.0963, 0.1849]	0.5316
IRG^{Shock2}	ΔFFR	0.00	[-0.1385, 0.1433]	0.9731
IRG^{Shock2}	ΔPFR	0.15	[0.0141, 0.2892]	0.0313
IRG^{Shock3}	BSP^{Shock1}	-0.09	[-0.2259, 0.0537]	0.2232
IRG^{Shock3}	BSP^{Shock2}	-0.10	[-0.2408, 0.0380]	0.1513
IRG^{Shock3}	BSP^{Shock3}	-0.09	[-0.2264, 0.0532]	0.2206
IRG^{Shock3}	EOA^{Shock1}	0.05	[-0.0902, 0.1908]	0.4772
IRG^{Shock3}	EOA^{Shock2}	0.04	[-0.0989, 0.1824]	0.5552
IRG^{Shock3}	EOA^{Shock3}	0.05	[-0.0901, 0.1909]	0.4767
IRG^{Shock3}	ΔFFR	0.10	[-0.0422, 0.2368]	0.1686
IRG^{Shock3}	ΔPFR	0.01	[-0.1359, 0.1458]	0.9443
BSP^{Shock1}	BSP^{Shock2}	0.98	[0.9792, 0.9881]	0.0000
BSP^{Shock1}	BSP^{Shock3}	0.99	[0.9907, 0.9947]	0.0000
BSP^{Shock1}	EOA^{Shock1}	0.23	[0.0885, 0.3561]	0.0015
BSP^{Shock1}	EOA^{Shock2}	0.21	[0.0676, 0.3376]	0.0039
BSP^{Shock1}	EOA^{Shock3}	0.24	[0.1037, 0.3694]	0.0007
BSP^{Shock1}	ΔFFR	0.17	[0.0340, 0.3074]	0.0152
BSP^{Shock1}	ΔPFR	0.14	[-0.0058, 0.2709]	0.0601
BSP^{Shock2}	BSP^{Shock3}	0.98	[0.9745, 0.9855]	0.0000
BSP^{Shock2}	EOA^{Shock1}	0.21	[0.0701, 0.3398]	0.0035
BSP^{Shock2}	EOA^{Shock2}	0.21	[0.0705, 0.3401]	0.0034
BSP^{Shock2}	EOA^{Shock3}	0.22	[0.0819, 0.3502]	0.0020
BSP^{Shock2}	ΔFFR	0.01	[-0.1342, 0.1475]	0.9253
BSP^{Shock2}	ΔPFR	0.10	[-0.0374, 0.2414]	0.1489
BSP^{Shock3}	EOA^{Shock1}	0.24	[0.1032, 0.3690]	0.0007
BSP^{Shock3}	EOA^{Shock2}	0.22	[0.0847, 0.3527]	0.0018
BSP^{Shock3}	EOA^{Shock3}	0.24	[0.1056, 0.3710]	0.0006
BSP^{Shock3}	ΔFFR	0.16	[0.0148, 0.2899]	0.0306
BSP^{Shock3}	ΔPFR	0.02	[-0.1226, 0.1591]	0.7969
EOA^{Shock1}	EOA^{Shock2}	0.99	[0.9898, 0.9942]	0.0000
EOA^{Shock1}	EOA^{Shock3}	0.99	[0.9928, 0.9959]	0.0000
EOA^{Shock1}	ΔFFR	0.12	[-0.0250, 0.2530]	0.1063
EOA^{Shock1}	ΔPFR	-0.11	[-0.2473, 0.0311]	0.1258
EOA^{Shock2}	EOA^{Shock3}	0.98	[0.9793, 0.9882]	0.0000
EOA^{Shock2}	ΔFFR	0.00	[-0.1449, 0.1368]	0.9544
EOA^{Shock2}	ΔPFR	-0.13	[-0.2705, 0.0062]	0.0610
EOA^{Shock3}	ΔFFR	0.14	[-0.0053, 0.2713]	0.0593
EOA^{Shock3}	ΔPFR	-0.01	[-0.1480, 0.1338]	0.9203

Notes:
- Time frame: February 2000 to May 2024.
- Total number of observations: 194.

Table 2.19: Correlation analysis of sentiment shocks, Swanson's factors, FFR changes, and PFR (Cont'd)

Variable 1	Variable 2	Correlation	95% Confidence Interval	P-Value
Swanson's FFRF	Swanson's LSAPF	-0.03	[-0.1877, 0.1263]	0.6967
Swanson's FFRF	Swanson's FGF	0.09	[-0.0672, 0.2446]	0.2590
Swanson's FFRF	IRG^{Shock1}	-0.05	[-0.2015, 0.1121]	0.5702
Swanson's FFRF	IRG^{Shock2}	-0.10	[-0.2492, 0.0623]	0.2341
Swanson's FFRF	IRG^{Shock3}	-0.01	[-0.1635, 0.1508]	0.9355
Swanson's FFRF	BSP^{Shock1}	0.00	[-0.1573, 0.1570]	0.9987
Swanson's FFRF	BSP^{Shock2}	-0.06	[-0.2110, 0.1024]	0.4900
Swanson's FFRF	BSP^{Shock3}	0.03	[-0.1298, 0.1842]	0.7299
Swanson's FFRF	EOA^{Shock1}	0.10	[-0.0599, 0.2514]	0.2230
Swanson's FFRF	EOA^{Shock2}	0.06	[-0.0977, 0.2155]	0.4540
Swanson's FFRF	EOA^{Shock3}	0.08	[-0.0824, 0.2301]	0.3475
Swanson's FFRF	ΔFFR	0.35	[0.2028, 0.4797]	0.0000
Swanson's FFRF	ΔPFR	-0.26	[-0.3982, -0.1043]	0.0012
Swanson's LSAPF	Swanson's FGF	-0.06	[-0.2171, 0.0960]	0.4415
Swanson's LSAPF	IRG^{Shock1}	0.09	[-0.0666, 0.2451]	0.2559
Swanson's LSAPF	IRG^{Shock2}	0.08	[-0.0739, 0.2382]	0.2962
Swanson's LSAPF	IRG^{Shock3}	0.06	[-0.1012, 0.2121]	0.4811
Swanson's LSAPF	BSP^{Shock1}	-0.05	[-0.2063, 0.1072]	0.5292
Swanson's LSAPF	BSP^{Shock2}	-0.09	[-0.2450, 0.0667]	0.2565
Swanson's LSAPF	BSP^{Shock3}	-0.08	[-0.2318, 0.0807]	0.3364
Swanson's LSAPF	EOA^{Shock1}	-0.02	[-0.1774, 0.1368]	0.7966
Swanson's LSAPF	EOA^{Shock2}	-0.04	[-0.1986, 0.1151]	0.5959
Swanson's LSAPF	EOA^{Shock3}	0.00	[-0.1557, 0.1585]	0.9858
Swanson's LSAPF	ΔFFR	0.19	[0.0381, 0.3408]	0.0152
Swanson's LSAPF	ΔPFR	0.23	[0.0770, 0.3749]	0.0037
Swanson's FGF	IRG^{Shock1}	0.03	[-0.1268, 0.1872]	0.7008
Swanson's FGF	IRG^{Shock2}	0.03	[-0.1274, 0.1866]	0.7073
Swanson's FGF	IRG^{Shock3}	0.05	[-0.1041, 0.2093]	0.5036
Swanson's FGF	BSP^{Shock1}	0.04	[-0.1175, 0.1963]	0.6166
Swanson's FGF	BSP^{Shock2}	0.01	[-0.1502, 0.1640]	0.9302
Swanson's FGF	BSP^{Shock3}	0.06	[-0.1020, 0.2113]	0.4871
Swanson's FGF	EOA^{Shock1}	0.06	[-0.0982, 0.2149]	0.4582
Swanson's FGF	EOA^{Shock2}	0.04	[-0.1194, 0.1944]	0.6336
Swanson's FGF	EOA^{Shock3}	0.05	[-0.1104, 0.2032]	0.5555
Swanson's FGF	ΔFFR	0.22	[0.0683, 0.3673]	0.0051
Swanson's FGF	ΔPFR	-0.12	[-0.2696, 0.0405]	0.1443
ΔBS	IRG^{Shock1}	0.06	[-0.0927, 0.2073]	0.4478
ΔBS	IRG^{Shock2}	0.06	[-0.0914, 0.2086]	0.4373
ΔBS	IRG^{Shock3}	0.06	[-0.0878, 0.2120]	0.4106
ΔBS	BSP^{Shock1}	-0.08	[-0.2273, 0.0718]	0.3024
ΔBS	BSP^{Shock2}	-0.07	[-0.2194, 0.0801]	0.3560
ΔBS	BSP^{Shock3}	-0.08	[-0.2242, 0.0751]	0.3227
ΔBS	EOA^{Shock1}	0.03	[-0.1194, 0.1813]	0.6821
ΔBS	EOA^{Shock2}	0.05	[-0.1060, 0.1945]	0.5578
ΔBS	EOA^{Shock3}	0.03	[-0.1238, 0.1770]	0.7249
ΔBS	ΔFFR	-0.14	[-0.2835, 0.0118]	0.0707
ΔBS	ΔPFR	-0.05	[-0.1980, 0.1024]	0.5266
ΔBS	Swanson's FFRF	-0.02	[-0.1874, 0.1543]	0.8463
ΔBS	Swanson's LSAPF	0.34	[0.1771, 0.4809]	0.0001
ΔBS	Swanson's FGF	-0.21	[-0.3699, -0.0431]	0.0145
Romer's Shock	IRG^{Shock1}	0.06	[-0.1867, 0.3032]	0.6266
Romer's Shock	IRG^{Shock2}	0.05	[-0.2011, 0.2895]	0.7124
Romer's Shock	IRG^{Shock3}	0.06	[-0.1905, 0.2996]	0.6488
Romer's Shock	BSP^{Shock1}	0.03	[-0.2205, 0.2708]	0.8338
Romer's Shock	BSP^{Shock2}	-0.11	[-0.3444, 0.1418]	0.3967
Romer's Shock	BSP^{Shock1}	0.09	[-0.2378, 0.2538]	0.9466
Romer's Shock	EOA^{Shock1}	0.23	[-0.0138, 0.4527]	0.0641
Romer's Shock	EOA^{Shock2}	0.16	[-0.0905, 0.3895]	0.2099
Romer's Shock	EOA^{Shock3}	0.24	[-0.0025, 0.4617]	0.0525
Romer's Shock	Swanson's FFRF	0.22	[-0.0293, 0.4403]	0.0834
Romer's Shock	Swanson's LSAPF	0.17	[-0.0801, 0.3983]	0.1817
Romer's Shock	Swanson's FGF	0.09	[-0.1580, 0.3298]	0.4728
Romer's Shock	ΔFFR	0.71	[0.5668, 0.8160]	0.0000
Romer's Shock	ΔPFR	0.16	[-0.0838, 0.3951]	0.1915

Notes:
- First panel time frame: February 2000 to January 2019. Total observations: 156.
- Second panel time frame: January 2003 to May 2024. Total observations: 170.
- Third panel time frame: January 2003 to June 2019. Total observations: 132.
- Fourth panel time frame: February 2000 to December 2007. Total observations: 64.

Table 2.20: Descriptive statistics of main variables

Variable	Mean	Std. Dev.	Min	Max	Median	Skewness	Kurtosis
IRG^{Shock1}	0.0000	0.6637	-5.5724	3.3608	0.0041	-2.2347	29.2863
IRG^{Shock2}	0.0000	0.6548	-5.5725	3.3099	-0.0159	-2.3608	30.6280
IRG^{Shock3}	0.0000	0.6535	-5.4399	3.3669	0.0066	-2.1551	28.6416
BSP^{Shock1}	0.0000	0.7767	-2.4539	1.7544	0.1140	-0.6319	0.5549
BSP^{Shock2}	0.0000	0.7645	-2.4825	1.7177	0.1191	-0.5992	0.5758
BSP^{Shock3}	0.0000	0.8965	-1.9102	2.9060	-0.0596	0.5171	0.4438
EOA^{Shock1}	0.0000	1.0043	-4.2345	5.7658	-0.1001	-1.8659	8.6452
EOA^{Shock2}	0.0000	0.9862	-4.2031	5.5632	-0.0925	-1.7550	7.9854
EOA^{Shock3}	0.0000	0.9940	-4.2010	5.5311	-0.0956	-1.7426	7.9102
$\Delta SP500$	0.2488	1.2239	-2.9831	5.0085	0.0727	0.6490	1.9305
$\Delta DJIA$	0.2078	1.0828	-2.5192	4.1131	0.1401	0.4453	1.4725
$\Delta VIXCLS$	-2.3060	7.7263	-31.4140	48.0214	-2.0158	0.9827	9.9349
$\Delta VXDCLS$	-2.3222	7.6026	-42.6857	20.4020	-1.7243	-1.6316	8.0214
$\Delta DEXUSEU$	0.1061	0.4780	-1.2283	2.9615	0.0554	1.5217	8.0863
$\Delta DAAA$	-0.1505	1.2034	-4.2635	3.1561	-0.1894	0.0315	0.6028
$\Delta DBAA$	-0.1070	0.9271	-3.0654	2.4332	-0.1268	-0.1467	0.5874
ΔPFR	0.0189	0.1403	-0.6890	0.6729	0.0144	-0.0574	5.6261
ΔFFR	2.0619	22.0897	-100.0000	75.0000	0.0000	-0.3445	4.8870

Table 2.21: Ordered probit model results for predicting ΔFFR based on IRG^{Shock}

Spec.	IRG^{Shock}_{t-1}		ΔFFR_{t-1}		Pseudo R-squared
	Coefficient	S.E.	Coefficient	S.E.	
1	0.3265**	(0.1321)	0.0466***	(0.0047)	%29.85
2	0.4141***	(0.1322)	0.0484***	(0.0048)	%30.72
3	0.2538**	(0.1351)	0.0465***	(0.0047)	%29.24
4	0.4089**	(0.1324)	0.0483***	(0.0048)	%30.65
5	0.4161***	(0.1321)	0.0484***	(0.0048)	%30.74
6	0.3931***	(0.1336)	0.0482***	(0.0047)	%30.44
7	0.3769***	(0.1362)	0.0480***	(0.0047)	%30.21
8	0.2478*	(0.1355)	0.0465***	(0.0047)	%29.20
9	0.2548*	(0.1351)	0.0465***	(0.0047)	%29.25
10	0.2332*	(0.1365)	0.0464**	(0.0046)	%29.10
11	0.2197	(0.1388)	0.0464***	(0.0046)	%29.00

Dependent variable is ΔFFR_t
Standard errors in parentheses. *, **, *** denote significance at the 10% level, 5% level, and 1% level, respectively.

Table 2.22: Ordered probit model results for predicting ΔFFR changes based on EOA^{Shock}

Spec.	EOA^{Shock}_{t-1}		ΔFFR_{t-1}		Pseudo R-squared
	Coefficient	S.E.	Coefficient	S.E.	
1	0.1883*	(0.1059)	0.0463***	(0.0046)	%29.18
2	0.1935*	(0.1062)	0.0472***	(0.0047)	%29.22
3	0.2343**	(0.1071)	0.0462***	(0.0047)	%29.59
4	0.1832**	(0.1061)	0.0472***	(0.0047)	%29.13
5	0.1882*	(0.1068)	0.0472***	(0.0047)	%29.16
6	0.1841*	(0.1061)	0.0472***	(0.0047)	%29.14
7	0.1702	(0.1072)	0.0471***	(0.0047)	%29.02
8	0.2231**	(0.1068)	0.0463***	(0.0047)	%29.48
9	0.2247**	(0.1074)	0.0462***	(0.0047)	%29.49
10	0.2239**	(0.1069)	0.0463***	(0.0047)	%29.49
11	0.2155**	(0.1082)	0.0461***	(0.0047)	%29.38

Dependent variable is ΔFFR_t
Standard errors in parentheses. *, **, *** denote significance at the 10% level, 5% level, and 1% level, respectively.

Table 2.23: OLS regression results for predicting $\%\Delta BS$ based on BSP^{Shock}

Spec.	BSP^{Shock}_{t-1}		$\%\Delta BS_{t-1}$		R-squared
	Coefficient	HAC S.E.	Coefficient	HAC S.E.	
1	−0.4842*	(0.2717)	−0.1736	(0.1660)	%8.02
2	−0.5089*	(0.3024)	−0.1722	(0.1669)	%8.46
3	−0.4316*	(0.2378)	−0.1708	(0.1719)	%6.82
4	−0.5066*	(0.3045)	−0.1734	(0.1667)	%8.36
5	−0.5332	(0.3246)	−0.1725	(0.1634)	%8.98
6	−0.5073*	(0.3038)	−0.1738	(0.1668)	%8.36
7	−0.5072*	(0.3051)	−0.1728	(0.1672)	%8.32
8	−0.4294*	(0.2404)	−0.1718	(0.1717)	%6.73
9	−0.4463*	(0.2514)	−0.1709	(0.1694)	%7.05
10	−0.4288*	(0.2378)	−0.1724	(0.1721)	%6.70
11	−0.4263*	(0.2379)	−0.1711	(0.1728)	%6.62

Dependent variable is $\%\Delta BS_t$
Standard errors in parentheses. *, **, *** denote significance at the 10% level, 5% level, and 1% level, respectively.
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000).

Table 2.24: Capturing monetary policy sentiment shocks under different specifications

No.	Specification	Regression Equation
1	Basic	$XX_t^{After} = \gamma_0 + \gamma_1 XX_t^{Before} + \gamma_2 XX_{t-1}^{After} + XX_t^{Shock1}$
2	FFR	$XX_t^{After} = \gamma_0 + \gamma_1 XX_t^{Before} + \gamma_2 XX_{t-1}^{After} + \delta \Delta FFR_t + XX_t^{Shock2}$
3	PFR	$XX_t^{After} = \gamma_0 + \gamma_1 XX_t^{Before} + \gamma_2 XX_{t-1}^{After} + \lambda \Delta PFR_t + XX_t^{Shock3}$
4	EUI-FFR	$XX_t^{After} = \gamma_0 + \gamma_1 XX_t^{Before} + \gamma_2 XX_{t-1}^{After} + \delta \Delta FFR_t + \beta \Delta EUI_{t-1} + XX_t^{Shock4}$
5		$XX_t^{After} = \gamma_0 + \gamma_1 XX_t^{Before} + \gamma_2 XX_{t-1}^{After} + \delta \Delta FFR_t + \beta \Delta EUI_t + XX_t^{Shock5}$
6		$XX_t^{After} = \gamma_0 + \gamma_1 XX_t^{Before} + \gamma_2 XX_{t-1}^{After} + \delta \Delta FFR_t + \sum_{k=1}^{2} \beta_k \Delta EUI_{t-k} + XX_t^{Shock6}$
7		$XX_t^{After} = \gamma_0 + \gamma_1 XX_t^{Before} + \gamma_2 XX_{t-1}^{After} + \delta \Delta FFR_t + \sum_{k=1}^{3} \beta_k \Delta EUI_{t-k} + XX_t^{Shock7}$
8	EUI-PFR	$XX_t^{After} = \gamma_0 + \gamma_1 XX_t^{Before} + \gamma_2 XX_{t-1}^{After} + \lambda \Delta PFR_t + \beta \Delta EUI_{t-1} + XX_t^{Shock8}$
9		$XX_t^{After} = \gamma_0 + \gamma_1 XX_t^{Before} + \gamma_2 XX_{t-1}^{After} + \lambda \Delta PFR_t + \beta \Delta EUI_t + XX_t^{Shock9}$
10		$XX_t^{After} = \gamma_0 + \gamma_1 XX_t^{Before} + \gamma_2 XX_{t-1}^{After} + \lambda \Delta PFR_t + \sum_{k=1}^{2} \beta_k \Delta EUI_{t-k} + XX_t^{Shock10}$
11		$XX_t^{After} = \gamma_0 + \gamma_1 XX_t^{Before} + \gamma_2 XX_{t-1}^{After} + \lambda \Delta PFR_t + \sum_{k=1}^{3} \beta_k \Delta EUI_{t-k} + XX_t^{Shock11}$

Note: XX refers to IRG, BSP, or EOA.

Table 2.25: Regressions for IRG shock under different specifications - robustness check

Explanatory Variables		Specification 4	5	6	7	8	9	10	11
IRG_t^{Before}	Coefficient	0.4261***	0.4341***	0.4254***	0.4403***	0.4824***	0.4908***	0.4868***	0.501***
	HAC S.E.	0.0963	0.0972	0.0956	0.094	0.1002	0.1002	0.1003	0.0986
IRG_{t-1}^{After}	Coefficient	0.2677***	0.2588***	0.2675***	0.2644***	0.3176***	0.3103***	0.3181***	0.3133***
	HAC S.E.	0.0752	0.0739	0.0766	0.0756	0.0806	0.0801	0.0825	0.082
ΔFFR_t	Coefficient	0.007**	0.007**	0.0073**	0.0072**				
	HAC S.E.	0.0036	0.0036	0.0034	0.0033				
ΔProxy_t	Coefficient				0.8549**	0.8485**	0.8093**	0.7476**	
	HAC S.E.				0.376	0.3917	0.366	0.3537	
ΔEUI_{t-1}	Coefficient	−0.0006		0.000	−0.0006	−0.0007		−0.0001	−0.0007
	HAC S.E.	0.0006		0.0006	0.0006	0.0006		0.0007	0.0007
ΔEUI_t	Coefficient		−0.0003			−0.0001			
	HAC S.E.		0.0006			0.0007			
ΔEUI_{t-2}	Coefficient			0.0015**	0.0001		0.0012**	−0.0001	
	HAC S.E.			0.0007	0.0007		0.0006	0.0007	
ΔEUI_{t-3}	Coefficient				−0.0023**			−0.0021*	
	HAC S.E.				0.001			0.001	
R-Squared		57.38%	57.32%	58.11%	59.19%	57.58%	57.47%	58.04%	59.01%

- Dependent variable is IRG_t^{After}
- Standard errors in parentheses. *, **, *** denote significance at the 10% level, 5% level, and 1% level, respectively.
- HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000).

Table 2.26: Regressions for BSP shock under different specifications - robustness check

Explanatory Variables		Specification 4	5	6	7	8	9	10	11
BSP_t^{Before}	Coefficient	0.2892***	0.2839***	0.288***	0.2843***	0.3171***	0.3142***	0.3142***	0.3088***
	HAC S.E.	0.0733	0.0769	0.0734	0.0704	0.0733	0.0771	0.0729	0.0696
BSP_{t-1}^{After}	Coefficient	0.3608***	0.3712***	0.3614***	0.3654***	0.3779***	0.3895***	0.3784***	0.3832***
	HAC S.E.	0.061	0.0629	0.0613	0.0601	0.0656	0.0675	0.0653	0.0642
ΔFFR_t	Coefficient	0.0065***	0.007***	0.0064***	0.0063***				
	HAC S.E.	0.002	0.0019	0.002	0.002				
ΔProxy_t	Coefficient				0.6614	0.7796	0.6837	0.7053	
	HAC S.E.				0.5218	0.5282	0.5233	0.5286	
ΔEUI_{t-1}	Coefficient	-0.0012		-0.0013	-0.0011	-0.0012		-0.0015	-0.0012
	HAC S.E.	0.001		0.0011	0.0011	0.001		0.0011	0.001
ΔEUI_t	Coefficient		0.0023			0.0024**			
	HAC S.E.		0.0011			0.001			
ΔEUI_{t-2}	Coefficient			-0.0003	0.0001		-0.0007	0.0000	
	HAC S.E.			0.0001	0.0012		0.0011	0.0012	
ΔEUI_{t-3}	Coefficient				0.0008			0.001	
	HAC S.E.				0.0012			0.0012	
R-Squared		41.67%	42.85%	41.7%	41.83%	40.66%	41.86%	40.79%	41.01%

- Dependent variable is BSP_t^{After}
- Standard errors in parentheses. *, **, *** denote significance at the 10% level, 5% level, and 1% level, respectively.
- HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000).

Table 2.27: Regressions for EOA shock under different specifications - robustness check

Explanatory Variables		**Specification** 4	**5**	**6**	**7**	**8**	**9**	**10**	**11**
EOA_t^{Before}	Coefficient	0.3176^{***}	0.326^{***}	0.3183^{***}	0.3241^{***}	0.3234^{***}	0.3305^{***}	0.3241^{***}	0.3301^{***}
	HAC S.E.	0.0757	0.0746	0.0753	0.0743	0.0723	0.0712	0.0722	0.0711
EOA_{t-1}^{After}	Coefficient	0.2358^{***}	0.2372^{***}	0.2354^{***}	0.2379^{***}	0.2643^{***}	0.2667^{***}	0.2637^{***}	0.268^{***}
	HAC S.E.	0.0675	0.0674	0.0665	0.0614	0.0685	0.0684	0.0679	0.0624
ΔFFR_t	Coefficient	0.005^{*}	0.0054^{*}	0.0049^{*}	0.0052^{*}				
	HAC S.E.	0.0027	0.0028	0.0028	0.0028				
ΔProxy_t	Coefficient				-0.6856	-0.5969	-0.6818	-0.7558	
	HAC S.E.				0.5227	0.5253	0.5208	0.516	
ΔEUI_{t-1}	Coefficient	-0.0013		-0.0014	-0.0023^{*}	-0.0015		-0.0016	-0.0025^{*}
	HAC S.E.	0.001		0.0013	0.0013	0.0013		0.0013	0.0013
ΔEUI_t	Coefficient		0.0019^{*}			0.0016			
	HAC S.E.		0.0011			0.0011			
ΔEUI_{t-2}	Coefficient			-0.0001	-0.0022		-0.0001	-0.0022^{*}	
	HAC S.E.			0.0012	0.0013		0.0012	0.0013	
ΔEUI_{t-3}	Coefficient				-0.0032^{**}			-0.0032^{**}	
	HAC S.E.				0.0016			0.0016	
R-Squared		21.87%	22.46%	21.87%	24.04%	21.64%	21.79%	21.64%	23.9%

- Dependent variable is EOA_t^{After}
- Standard errors in parentheses. *, **, *** denote significance at the 10% level, 5% level, and 1% level, respectively.
- HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000).

Table 2.28: Estimated effects of IRG, BSP, and EOA shocks on DJIA

Specification	Shocks	Full Sample		Pre-ZLB		ZLB	
		Coefficient	(HAC S.E.)	Coefficient	(HAC S.E.)	Coefficient	(HAC S.E.)
1	IRG^{Shock}	−0.2109***	(0.0655)	−0.1977***	(0.0713)		
	BSP^{Shock}	−0.2218**	(0.1061)			−0.2401**	(0.1120)
	EOA^{Shock}	0.1138**	(0.0573)	0.0874	(0.0822)	0.1904**	(0.0805)
	R-Squared	47.63%		54.25%		63.84%	
	Controls			VXDCLS, DGS5, DJIA(-1), DJIA(-2)			
2	IRG^{Shock}	−0.1397**	(0.0670)	−0.1586**	(0.0724)		
	BSP^{Shock}	−0.1879*	(0.0972)			−0.2394**	(0.1120)
	EOA^{Shock}	0.1280**	(0.0603)	0.1012	(0.0894)	0.1887**	(0.0795)
	R-Squared	46.41%		53.32%		63.87%	
	Controls			VXDCLS, DGS5, DJIA(-1), DJIA(-2)			
3	IRG^{Shock}	−0.1754***	(0.0607)	−0.1894***	(0.0702)		
	BSP^{Shock}	−0.1950*	(0.1085)			−0.2190*	(0.1140)
	EOA^{Shock}	0.0917	(0.0580)	0.0746	(0.0786)	0.1807**	(0.0849)
	R-Squared	46.45%		53.84%		63.03%	
	Controls			VXDCLS, DGS5, DJIA(-1), DJIA(-2)			
4	IRG^{Shock}	−0.1465**	(0.0661)	−0.1609**	(0.0718)		
	BSP^{Shock}	−0.1963**	(0.0973)			−0.2348**	(0.1127)
	EOA^{Shock}	0.1216**	(0.0606)	0.0957	(0.0907)	0.1915**	(0.0789)
	R-Squared	46.53%		53.31%		63.85%	
	Controls			VXDCLS, DGS5, DJIA(-1), DJIA(-2)			
5	IRG^{Shock}	−0.1384**	(0.0672)	−0.1604**	(0.0724)		
	BSP^{Shock}	−0.1892**	(0.0951)			−0.2274*	(0.1140)
	EOA^{Shock}	0.1258**	(0.0616)	0.1126	(0.0936)	0.1911**	(0.0798)
	R-Squared	46.39%		53.48%		63.67%	
	Controls			VXDCLS, DGS5, DJIA(-1), DJIA(-2)			
6	IRG^{Shock}	−0.1561**	(0.0650)	−0.1579**	(0.0729)		
	BSP^{Shock}	−0.1952**	(0.0971)			−0.2337**	(0.1123)
	EOA^{Shock}	0.1218**	(0.0603)	0.0940	(0.0901)	0.1916**	(0.0789)
	R-Squared	46.60%		53.21%		63.81%	
	Controls			VXDCLS, DGS5, DJIA(-1), DJIA(-2)			
7	IRG^{Shock}	−0.1526**	(0.0647)	−0.1613**	(0.0738)		
	BSP^{Shock}	−0.1983**	(0.0970)			−0.2412**	(0.1173)
	EOA^{Shock}	0.1280**	(0.0626)	0.0930	(0.0897)	0.2041**	(0.0870)
	R-Squared	46.67%		53.27%		63.85%	
	Controls			VXDCLS, DGS5, DJIA(-1), DJIA(-2)			
8	IRG^{Shock}	−0.1828***	(0.0601)	−0.1920***	(0.0695)		
	BSP^{Shock}	−0.2037*	(0.1085)			−0.2148*	(0.1144)
	EOA^{Shock}	0.0853	(0.0586)	0.0683	(0.0794)	0.1844**	(0.0841)
	R-Squared	46.64%		53.85%		63.02%	
	Controls			VXDCLS, DGS5, DJIA(-1), DJIA(-2)			
9	IRG^{Shock}	−0.1748***	(0.0606)	−0.1900***	(0.0703)		
	BSP^{Shock}	−0.1964*	(0.1083)			−0.2034*	(0.1172)
	EOA^{Shock}	0.0899	(0.0589)	0.0837	(0.0819)	0.1818**	(0.0851)
	R-Squared	46.44%		53.93%		62.78%	
	Controls			VXDCLS, DGS5, DJIA(-1), DJIA(-2)			
10	IRG^{Shock}	−0.1952***	(0.0607)	−0.1924***	(0.0700)		
	BSP^{Shock}	−0.2004*	(0.1076)			−0.2117*	(0.1137)
	EOA^{Shock}	0.0853	(0.0583)	0.0667	(0.0785)	0.1841**	(0.0843)
	R-Squared	46.73%		53.83%		62.93%	
	Controls			VXDCLS, DGS5, DJIA(-1), DJIA(-2)			
11	IRG^{Shock}	−0.1950***	(0.0621)	−0.1969***	(0.0703)		
	BSP^{Shock}	−0.2010*	(0.1064)			−0.2154*	(0.1183)
	EOA^{Shock}	0.0854	(0.0600)	0.0622	(0.0779)	0.1926**	(0.0922)
	R-Squared	46.73%		53.90%		62.84%	
	Controls			VXDCLS, DGS5, DJIA(-1), DJIA(-2)			

Notes:
- Standard errors in parentheses. *, **, *** denote significance at the 10% level, 5% level, and 1% level, respectively. OLS estimation.
- HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000).
- Full sample, Feb. 2000 - May 2024, 194 observations.
- Pre-ZLB sample, Feb. 2000 ˘2013 Dec. 2008, 72 observations.
- ZLB sample, Jan. 2009 ˘2013 Oct. 2015, 56 observations.

Table 2.29: Estimated effects of IRG, BSP, and EOA shocks on SP500

Specification	Shocks	Full Sample Coefficient	Full Sample (HAC S.E.)	Pre-ZLB Coefficient	Pre-ZLB (HAC S.E.)	ZLB Coefficient	ZLB (HAC S.E.)
1	IRG^{Shock}	−0.1662***	(0.0607)	−0.1579**	(0.0710)		
	BSP^{Shock}	−0.2482*	(0.1278)			−0.2192*	(0.1139)
	EOA^{Shock}	0.0878	(0.0558)	0.0419	(0.0858)	0.1810**	(0.0702)
	R-Squared	49.06%		57.48%		62.29%	
	Controls	VXDCLS, DGS5, SP500(-1), SP500(-2)					
2	IRG^{Shock}	−0.0871	(0.0702)	−0.1177	(0.0747)		
	BSP^{Shock}	−0.2125*	(0.1180)			−0.2199*	(0.1150)
	EOA^{Shock}	0.1051*	(0.0580)	0.0578	(0.0909)	0.1823**	(0.0705)
	R-Squared	48.12%		56.85%		62.37%	
	Controls	VXDCLS, DGS5, SP500(-1), SP500(-2)					
3	IRG^{Shock}	−0.1244**	(0.0584)	−0.1500**	(0.0720)		
	BSP^{Shock}	−0.2181*	(0.1294)			−0.1931	(0.1158)
	EOA^{Shock}	0.0628	(0.0577)	0.0315	(0.0823)	0.1668**	(0.0716)
	R-Squared	48.16%		57.26%		61.64%	
	Controls	VXDCLS, DGS5, SP500(-1), SP500(-2)					
4	IRG^{Shock}	−0.0932	(0.0689)	−0.1190	(0.0741)		
	BSP^{Shock}	−0.2206*	(0.1190)			−0.2136*	(0.1164)
	EOA^{Shock}	0.0989*	(0.0582)	0.0545	(0.0914)	0.1859**	(0.0701)
	R-Squared	48.22%		56.85%		62.35%	
	Controls	VXDCLS, DGS5, SP500(-1), SP500(-2)					
5	IRG^{Shock}	−0.0855	(0.0708)	−0.1192	(0.0743)		
	BSP^{Shock}	−0.2154*	(0.1155)			−0.2018*	(0.1179)
	EOA^{Shock}	0.1009*	(0.0596)	0.0672	(0.0947)	0.1852**	(0.0715)
	R-Squared	48.11%		56.92%		62.19%	
	Controls	VXDCLS, DGS5, SP500(-1), SP500(-2)					
6	IRG^{Shock}	−0.1063	(0.0672)	−0.1212	(0.0757)		
	BSP^{Shock}	−0.2194*	(0.1189)			−0.2121*	(0.1162)
	EOA^{Shock}	0.0993*	(0.0578)	0.0536	(0.0905)	0.1859**	(0.0700)
	R-Squared	48.26%		56.87%		62.32%	
	Controls	VXDCLS, DGS5, SP500(-1), SP500(-2)					
7	IRG^{Shock}	−0.0902	(0.0673)	−0.1170	(0.0762)		
	BSP^{Shock}	−0.2276*	(0.1187)			−0.2248*	(0.1208)
	EOA^{Shock}	0.1173*	(0.0610)	0.0654	(0.0896)	0.2053**	(0.0802)
	R-Squared	48.41%		56.88%		62.52%	
	Controls	VXDCLS, DGS5, SP500(-1), SP500(-2)					
8	IRG^{Shock}	−0.1308**	(0.0574)	−0.1515**	(0.0713)		
	BSP^{Shock}	−0.2266*	(0.1301)			−0.1874	(0.1169)
	EOA^{Shock}	0.0567	(0.0580)	0.0277	(0.0823)	0.1716**	(0.0709)
	R-Squared	48.31%		57.28%		61.64%	
	Controls	VXDCLS, DGS5, SP500(-1), SP500(-2)					
9	IRG^{Shock}	−0.1237**	(0.0584)	−0.1505**	(0.0719)		
	BSP^{Shock}	−0.2211*	(0.1286)			−0.1703	(0.1204)
	EOA^{Shock}	0.0596	(0.0589)	0.0389	(0.0848)	0.1674**	(0.0715)
	R-Squared	48.16%		57.29%		61.43%	
	Controls	VXDCLS, DGS5, SP500(-1), SP500(-2)					
10	IRG^{Shock}	−0.1465**	(0.0580)	−0.1560**	(0.0724)		
	BSP^{Shock}	−0.2224*	(0.1293)			−0.1833	(0.1163)
	EOA^{Shock}	0.0569	(0.0576)	0.0269	(0.0812)	0.1709**	(0.0707)
	R-Squared	48.35%		57.34%		61.57%	
	Controls	VXDCLS, DGS5, SP500(-1), SP500(-2)					
11	IRG^{Shock}	−0.1356**	(0.0593)	−0.1536**	(0.0723)		
	BSP^{Shock}	−0.2294*	(0.1281)			−0.1930	(0.1207)
	EOA^{Shock}	0.0685	(0.0602)	0.0343	(0.0814)	0.1863**	(0.0807)
	R-Squared	48.39%		57.31%		61.66%	
	Controls	VXDCLS, DGS5, SP500(-1), SP500(-2)					

Notes:
- Standard errors in parentheses. *, **, *** denote significance at the 10% level, 5% level, and 1% level, respectively. OLS estimation.
- HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000).
- Full sample, Feb. 2000 - May 2024, 194 observations.
- Pre-ZLB sample, Feb. 2000 2̆013 Dec. 2008, 72 observations.
- ZLB sample, Jan. 2009 2̆013 Oct. 2015, 56 observations.

Table 2.30: Estimated effects of IRG, BSP, and EOA shocks on VXD

Specification	Shocks	Full Sample		Pre-ZLB		ZLB	
		Coefficient	(HAC S.E.)	Coefficient	(HAC S.E.)	Coefficient	(HAC S.E.)
1	IRG^{Shock}	−1.3086***	(0.3938)	−0.6796	(0.4831)		
	BSP^{Shock}	−0.5592	(0.4409)			−1.3741*	(0.7256)
	EOA^{Shock}	0.4292	(0.4178)	0.2930	(0.6010)	0.7521	(0.6084)
	R-Squared	45.22%		49.90%		59.39%	
	Controls	DJIA, DJIA(-1), DJIA(-2), DEXUSEU, DEXUSEU(-1)					
2	IRG^{Shock}	−0.9389**	(0.3719)	−0.5982	(0.4767)		
	BSP^{Shock}	−0.3417	(0.4203)			−1.3320*	(0.7139)
	EOA^{Shock}	0.5312	(0.4264)	0.2698	(0.5779)	0.7422	(0.6114)
	R-Squared	44.64%		49.58%		59.32%	
	Controls	DJIA, DJIA(-1), DJIA(-2), DEXUSEU, DEXUSEU(-1)					
3	IRG^{Shock}	−1.1336***	(0.3582)	−0.7265	(0.4723)		
	BSP^{Shock}	−0.4302	(0.4435)			−1.2432	(0.7702)
	EOA^{Shock}	0.3168	(0.4253)	0.3267	(0.5803)	0.6882	(0.6631)
	R-Squared	44.77%		50.12%		58.95%	
	Controls	DJIA, DJIA(-1), DJIA(-2), DEXUSEU, DEXUSEU(-1)					
4	IRG^{Shock}	−1.0030***	(0.3787)	−0.6181	(0.4821)		
	BSP^{Shock}	−0.4303	(0.4119)			−1.3118*	(0.7183)
	EOA^{Shock}	0.4656	(0.4319)	0.2035	(0.5526)	0.7399	(0.6155)
	R-Squared	44.70%		49.59%		59.29%	
	Controls	DJIA, DJIA(-1), DJIA(-2), DEXUSEU, DEXUSEU(-1)					
5	IRG^{Shock}	−0.9485**	(0.3708)	−0.6012	(0.4703)		
	BSP^{Shock}	−0.2585	(0.4295)			−1.2208	(0.7709)
	EOA^{Shock}	0.5554	(0.4260)	0.2828	(0.5595)	0.6854	(0.6704)
	R-Squared	44.66%		49.60%		58.92%	
	Controls	DJIA, DJIA(-1), DJIA(-2), DEXUSEU, DEXUSEU(-1)					
6	IRG^{Shock}	−1.0651***	(0.3834)	−0.5531	(0.4773)		
	BSP^{Shock}	−0.4219	(0.4129)			−1.2983*	(0.7197)
	EOA^{Shock}	0.4666	(0.4291)	0.1855	(0.5423)	0.7391	(0.6171)
	R-Squared	44.77%		49.37%		59.25%	
	Controls	DJIA, DJIA(-1), DJIA(-2), DEXUSEU, DEXUSEU(-1)					
7	IRG^{Shock}	−1.0172**	(0.4028)	−0.6370	(0.4873)		
	BSP^{Shock}	−0.4512	(0.4192)			−1.3265*	(0.7336)
	EOA^{Shock}	0.5132	(0.4618)	0.0562	(0.5473)	0.7646	(0.6624)
	R-Squared	44.76%		49.57%		59.23%	
	Controls	DJIA, DJIA(-1), DJIA(-2), DEXUSEU, DEXUSEU(-1)					
8	IRG^{Shock}	−1.2054***	(0.3707)	−0.7500	(0.4806)		
	BSP^{Shock}	−0.5249	(0.4348)			−1.2208	(0.7709)
	EOA^{Shock}	0.2500	(0.4336)	0.2586	(0.5529)	0.6854	(0.6704)
	R-Squared	44.91%		50.13%		58.92%	
	Controls	DJIA, DJIA(-1), DJIA(-2), DEXUSEU, DEXUSEU(-1)					
9	IRG^{Shock}	−1.1305***	(0.3603)	−0.7273	(0.4685)		
	BSP^{Shock}	−0.3457	(0.4523)			−1.0797	(0.8056)
	EOA^{Shock}	0.3289	(0.4236)	0.3319	(0.5694)	0.6876	(0.6741)
	R-Squared	44.73%		50.13%		58.66%	
	Controls	DJIA, DJIA(-1), DJIA(-2), DEXUSEU, DEXUSEU(-1)					
10	IRG^{Shock}	−1.2790***	(0.3855)	−0.7011	(0.4737)		
	BSP^{Shock}	−0.5031	(0.4339)			−1.1853	(0.7758)
	EOA^{Shock}	0.2509	(0.4312)	0.2435	(0.5439)	0.6791	(0.6751)
	R-Squared	45.01%		49.91%		58.83%	
	Controls	DJIA, DJIA(-1), DJIA(-2), DEXUSEU, DEXUSEU(-1)					
11	IRG^{Shock}	−1.2491***	(0.3869)	−0.7729	(0.4855)		
	BSP^{Shock}	−0.5220	(0.4448)			−1.1951	(0.7956)
	EOA^{Shock}	0.2668	(0.4429)	0.1298	(0.5500)	0.6844	(0.7301)
	R-Squared	44.97%		50.10%		58.76%	
	Controls	DJIA, DJIA(-1), DJIA(-2), DEXUSEU, DEXUSEU(-1)					

Notes:
- Standard errors in parentheses. *, **, *** denote significance at the 10% level, 5% level, and 1% level, respectively. OLS estimation.
- HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000).
- Full sample, Feb. 2000 - May 2024, 194 observations.
- Pre-ZLB sample, Feb. 2000 ˘2013 Dec. 2008, 72 observations.
- ZLB sample, Jan. 2009 ˘2013 Oct. 2015, 56 observations.

Table 2.31: Estimated effects of IRG, BSP, and EOA shocks on VIX

Specification	Shocks	Full Sample		Pre-ZLB		ZLB	
		Coefficient	(HAC S.E.)	Coefficient	(HAC S.E.)	Coefficient	(HAC S.E.)
1	IRG^{Shock}	−0.9318**	(0.4447)	−0.1943	(0.4627)		
	BSP^{Shock}	−0.3671	(0.6048)			−1.5988**	(0.7024)
	EOA^{Shock}	0.5575	(0.3867)	0.1159	(0.4995)	0.8451	(0.5103)
	R-Squared	54.45%		58.95%		76.36%	
	Controls	DJIA, DJIA(-1), DJIA(-2), DEXUSEU, DEXUSEU(-1)					
2	IRG^{Shock}	−0.6889	(0.4233)	−0.0751	(0.4683)		
	BSP^{Shock}	−0.2508	(0.5838)			−1.5656**	(0.6901)
	EOA^{Shock}	0.6513	(0.4050)	0.1553	(0.4797)	0.8204	(0.5142)
	R-Squared	54.29%		58.90%		76.30%	
	Controls	DJIA, DJIA(-1), DJIA(-2), DEXUSEU, DEXUSEU(-1)					
3	IRG^{Shock}	−0.8202*	(0.4282)	−0.2174	(0.4623)		
	BSP^{Shock}	−0.2843	(0.6196)			−1.6072**	(0.6957)
	EOA^{Shock}	0.4817	(0.3903)	0.1406	(0.4905)	0.8948	(0.5420)
	R-Squared	54.21%		58.98%		76.26%	
	Controls	DJIA, DJIA(-1), DJIA(-2), DEXUSEU, DEXUSEU(-1)					
4	IRG^{Shock}	−0.6994	(0.4243)	−0.0837	(0.4715)		
	BSP^{Shock}	−0.2678	(0.5847)			−1.5530**	(0.6885)
	EOA^{Shock}	0.6385	(0.4070)	0.1168	(0.4557)	0.8160	(0.5216)
	R-Squared	54.29%		58.88%		76.28%	
	Controls	DJIA, DJIA(-1), DJIA(-2), DEXUSEU, DEXUSEU(-1)					
5	IRG^{Shock}	−0.6973	(0.4238)	−0.0674	(0.4683)		
	BSP^{Shock}	−0.1754	(0.5915)			−1.4333**	(0.7096)
	EOA^{Shock}	0.6704	(0.4035)	0.1175	(0.4652)	0.8472	(0.5164)
	R-Squared	54.32%		58.87%		76.03%	
	Controls	DJIA, DJIA(-1), DJIA(-2), DEXUSEU, DEXUSEU(-1)					
6	IRG^{Shock}	−0.6973*	(0.4238)	−0.0957	(0.4607)		
	BSP^{Shock}	−0.1754	(0.5915)			−1.5420**	(0.6916)
	EOA^{Shock}	0.6704	(0.4035)	0.1180	(0.4501)	0.8161	(0.5228)
	R-Squared	54.32%		58.88%		76.24%	
	Controls	DJIA, DJIA(-1), DJIA(-2), DEXUSEU, DEXUSEU(-1)					
7	IRG^{Shock}	−0.8059*	(0.4257)	−0.1825	(0.4634)		
	BSP^{Shock}	−0.2409	(0.5700)			−1.6237**	(0.6874)
	EOA^{Shock}	0.5818	(0.4297)	−0.0163	(0.4482)	0.9086	(0.5653)
	R-Squared	54.31%		58.91%		76.38%	
	Controls	DJIA, DJIA(-1), DJIA(-2), DEXUSEU, DEXUSEU(-1)					
8	IRG^{Shock}	−0.8312*	(0.4301)	−0.2274	(0.4674)		
	BSP^{Shock}	−0.3038	(0.6199)			−1.5913**	(0.6932)
	EOA^{Shock}	0.4719	(0.3909)	0.1031	(0.4631)	0.8900	(0.5511)
	R-Squared	54.22%		58.97%		76.23%	
	Controls	DJIA, DJIA(-1), DJIA(-2), DEXUSEU, DEXUSEU(-1)					
9	IRG^{Shock}	−0.8162*	(0.4289)	−0.2131	(0.4613)		
	BSP^{Shock}	−0.2051	(0.6308)			−1.4575*	(0.7287)
	EOA^{Shock}	0.4899	(0.3881)	0.1079	(0.4801)	0.9052	(0.5440)
	R-Squared	54.21%		58.96%		75.94%	
	Controls	DJIA, DJIA(-1), DJIA(-2), DEXUSEU, DEXUSEU(-1)					
10	IRG^{Shock}	−0.8851**	(0.4341)	−0.2433	(0.4586)		
	BSP^{Shock}	−0.2894	(0.6155)			−1.5670**	(0.6999)
	EOA^{Shock}	0.4728	(0.3895)	0.1037	(0.4574)	0.8884	(0.5539)
	R-Squared	54.27%		58.99%		76.15%	
	Controls	DJIA, DJIA(-1), DJIA(-2), DEXUSEU, DEXUSEU(-1)					
11	IRG^{Shock}	−0.9467**	(0.4388)	−0.3230	(0.4648)		
	BSP^{Shock}	−0.2489	(0.6001)			−1.6697**	(0.6964)
	EOA^{Shock}	0.3902	(0.4119)	−0.0224	(0.4585)	0.9997	(0.6102)
	R-Squared	54.27%		59.07%		76.30%	
	Controls	DJIA, DJIA(-1), DJIA(-2), DEXUSEU, DEXUSEU(-1)					

Notes:
- Standard errors in parentheses. *, **, *** denote significance at the 10% level, 5% level, and 1% level, respectively. OLS estimation.
- HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000).
- Full sample, Feb. 2000 - May 2024, 194 observations.
- Pre-ZLB sample, Feb. 2000 2̆013 Dec. 2008, 72 observations.
- ZLB sample, Jan. 2009 2̆013 Oct. 2015, 56 observations.

Table 2.32: Estimated effects of IRG, BSP, and EOA shocks on DGS2

Specification	Shocks	Full Sample		Pre-ZLB		ZLB	
		Coefficient	(HAC S.E.)	Coefficient	(HAC S.E.)	Coefficient	(HAC S.E.)
1	IRG^{Shock}	−1.1570*	(0.6713)	−0.2492	(0.3572)		
	BSP^{Shock}	0.0400	(0.6615)			1.9885**	(0.8678)
	EOA^{Shock}	0.7740**	(0.3479)	0.7518**	(0.3089)	0.3645	(0.8618)
	R-Squared	23.59%		44.72%		60.46%	
	Controls	CORPOAS, DAAA, DEXUSEU, DGS2(-1), DGS2(-2), DGS2(-3)					
2	IRG^{Shock}	−1.2089*	(0.6614)	−0.2834	(0.3782)		
	BSP^{Shock}	0.0516	(0.6683)			1.9884**	(0.8669)
	EOA^{Shock}	0.7728**	(0.3468)	0.7287**	(0.3543)	0.3881	(0.8633)
	R-Squared	23.63%		44.43%		60.55%	
	Controls	CORPOAS, DAAA, DEXUSEU, DGS2(-1), DGS2(-2), DGS2(-3)					
3	IRG^{Shock}	−1.0152	(0.6740)	−0.2073	(0.3418)		
	BSP^{Shock}	0.1530	(0.6260)			1.9045**	(0.8565)
	EOA^{Shock}	0.6836**	(0.3236)	0.6932**	(0.2825)	0.4215	(0.8034)
	R-Squared	23.19%		44.31%		60.35%	
	Controls	CORPOAS, DAAA, DEXUSEU, DGS2(-1), DGS2(-2), DGS2(-3)					
4	IRG^{Shock}	−1.1941*	(0.6639)	−0.2802	(0.3814)		
	BSP^{Shock}	0.0747	(0.6724)			1.9318**	(0.8632)
	EOA^{Shock}	0.7853**	(0.3442)	0.7440**	(0.3546)	0.3497	(0.8728)
	R-Squared	23.65%		44.50%		60.35%	
	Controls	CORPOAS, DAAA, DEXUSEU, DGS2(-1), DGS2(-2), DGS2(-3)					
5	IRG^{Shock}	−1.2094*	(0.6585)	−0.2593	(0.3667)		
	BSP^{Shock}	0.0894	(0.7094)			1.8416**	(0.8546)
	EOA^{Shock}	0.7868**	(0.3357)	0.6215*	(0.3300)	0.3757	(0.8159)
	R-Squared	23.68%		43.78%		60.13%	
	Controls	CORPOAS, DAAA, DEXUSEU, DGS2(-1), DGS2(-2), DGS2(-3)					
6	IRG^{Shock}	−1.2624*	(0.6796)	−0.2217	(0.3683)		
	BSP^{Shock}	0.0829	(0.6718)			1.9411**	(0.8675)
	EOA^{Shock}	0.7843**	(0.3436)	0.7302**	(0.3570)	0.3406	(0.8698)
	R-Squared	23.77%		44.31%		60.35%	
	Controls	CORPOAS, DAAA, DEXUSEU, DGS2(-1), DGS2(-2), DGS2(-3)					
7	IRG^{Shock}	−1.0755	(0.6742)	−0.2024	(0.3750)		
	BSP^{Shock}	0.0082	(0.6704)			1.8273**	(0.8865)
	EOA^{Shock}	0.9448***	(0.3373)	0.7372**	(0.3474)	0.4876	(0.8502)
	R-Squared	23.78%		44.34%		60.32%	
	Controls	CORPOAS, DAAA, DEXUSEU, DGS2(-1), DGS2(-2), DGS2(-3)					
8	IRG^{Shock}	−0.9982	(0.6768)	−0.2026	(0.3440)		
	BSP^{Shock}	0.1771	(0.6303)			1.8416**	(0.8546)
	EOA^{Shock}	0.6967**	(0.3185)	0.7074**	(0.2832)	0.3757	(0.8159)
	R-Squared	23.21%		44.37%		60.13%	
	Controls	CORPOAS, DAAA, DEXUSEU, DGS2(-1), DGS2(-2), DGS2(-3)					
9	IRG^{Shock}	−1.0106	(0.6692)	−0.1968	(0.3358)		
	BSP^{Shock}	0.2054	(0.6606)			2.0473**	(0.8863)
	EOA^{Shock}	0.6967**	(0.3187)	0.6200**	(0.2710)	0.4114	(0.7849)
	R-Squared	23.26%		43.85%		60.63%	
	Controls	CORPOAS, DAAA, DEXUSEU, DGS2(-1), DGS2(-2), DGS2(-3)					
10	IRG^{Shock}	−1.0512	(0.6897)	−0.1553	(0.3335)		
	BSP^{Shock}	0.1970	(0.6310)			1.8558**	(0.8669)
	EOA^{Shock}	0.6936**	(0.3187)	0.6967**	(0.2856)	0.3586	(0.8090)
	R-Squared	23.31%		44.25%		60.13%	
	Controls	CORPOAS, DAAA, DEXUSEU, DGS2(-1), DGS2(-2), DGS2(-3)					
11	IRG^{Shock}	−0.8945	(0.6899)	−0.1398	(0.3393)		
	BSP^{Shock}	0.1024	(0.6310)			1.7026*	(0.9039)
	EOA^{Shock}	0.8516***	(0.3055)	0.7018**	(0.2662)	0.5340	(0.7857)
	R-Squared	23.35%		44.28%		60.08%	
	Controls	CORPOAS, DAAA, DEXUSEU, DGS2(-1), DGS2(-2), DGS2(-3)					

Notes:
- Standard errors in parentheses. *, **, *** denote significance at the 10% level, 5% level, and 1% level, respectively. OLS estimation.
- HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000).
- Full sample, Feb. 2000 - May 2024, 194 observations.
- Pre-ZLB sample, Feb. 2000 – Dec. 2008, 72 observations.
- ZLB sample, Jan. 2009 – Oct. 2015, 56 observations.

Table 2.33: Estimated effects of IRG, BSP, and EOA shocks on DGS30

Specification	Shocks	Full Sample		Pre-ZLB		ZLB	
		Coefficient	(HAC S.E.)	Coefficient	(HAC S.E.)	Coefficient	(HAC S.E.)
1	IRG^{Shock}	−0.1383***	(0.0514)	−0.1317***	(0.0492)		
	BSP^{Shock}	−0.1558*	(0.0860)			−0.40021**	(0.1876)
	EOA^{Shock}	0.1581*	(0.0884)	−0.0016	(0.0630)	0.42141*	(0.2257)
	R-Squared	73.03%		69.73%		84.44%	
	Controls			DGS2, DTB6, DAAA, DGS30(-1)			
2	IRG^{Shock}	−0.1637***	(0.0606)	−0.1398**	(0.0560)		
	BSP^{Shock}	−0.1742**	(0.0879)			−0.39036**	(0.1830)
	EOA^{Shock}	0.1572*	(0.0890)	0.0001	(0.0625)	0.42236*	(0.2234)
	R-Squared	73.21%		69.88%		84.42%	
	Controls			DGS2, DTB6, DAAA, DGS30(-1)			
3	IRG^{Shock}	−0.1217**	(0.0592)	−0.1416**	(0.0572)		
	BSP^{Shock}	−0.1456*	(0.0802)			−0.35728*	(0.1876)
	EOA^{Shock}	0.1488*	(0.0829)	0.0039	(0.0649)	0.40027*	(0.2298)
	R-Squared	71.76%		69.94%		83.74%	
	Controls			DGS2, DTB6, DAAA, DGS30(-1)			
4	IRG^{Shock}	−0.1670***	(0.0614)	−0.1409**	(0.0566)		
	BSP^{Shock}	−0.1789**	(0.0894)			−0.38603**	(0.1819)
	EOA^{Shock}	0.1534*	(0.0908)	−0.0029	(0.0637)	0.42431*	(0.2235)
	R-Squared	72.21%		69.90%		84.42%	
	Controls			DGS2, DTB6, DAAA, DGS30(-1)			
5	IRG^{Shock}	−0.1630***	(0.0603)	−0.1413**	(0.0571)		
	BSP^{Shock}	−0.1764*	(0.0921)			−0.38381**	(0.1818)
	EOA^{Shock}	0.1546*	(0.0896)	0.0094	(0.0642)	0.42514*	(0.2242)
	R-Squared	72.19%		69.91%		84.41%	
	Controls			DGS2, DTB6, DAAA, DGS30(-1)			
6	IRG^{Shock}	−0.1653***	(0.0618)	−0.1376**	(0.0539)		
	BSP^{Shock}	−0.1790**	(0.0893)			−0.38881**	(0.1816)
	EOA^{Shock}	0.1534*	(0.0909)	−0.0040	(0.0643)	0.42563*	(0.2234)
	R-Squared	72.13%		69.79%		84.44%	
	Controls			DGS2, DTB6, DAAA, DGS30(-1)			
7	IRG^{Shock}	−0.1580**	(0.0634)	−0.1349**	(0.0542)		
	BSP^{Shock}	−0.1810**	(0.0890)			−0.40792**	(0.1898)
	EOA^{Shock}	0.1584*	(0.0913)	0.0034	(0.0650)	0.44531*	(0.2351)
	R-Squared	72.21%		69.65%		84.37%	
	Controls			DGS2, DTB6, DAAA, DGS30(-1)			
8	IRG^{Shock}	−0.1253**	(0.0600)	−0.1431**	(0.0579)		
	BSP^{Shock}	−0.1504*	(0.0815)			−0.3540*	(0.1871)
	EOA^{Shock}	0.1447*	(0.0849)	0.0006	(0.0663)	0.4034*	(0.2303)
	R-Squared	71.76%		69.97%		83.75%	
	Controls			DGS2, DTB6, DAAA, DGS30(-1)			
9	IRG^{Shock}	−0.1214**	(0.0592)	−0.1421**	(0.0575)		
	BSP^{Shock}	−0.1454*	(0.0824)			−0.3457*	(0.1853)
	EOA^{Shock}	0.1474*	(0.0837)	0.0103	(0.0657)	0.4022*	(0.2303)
	R-Squared	71.75%		69.95%		83.71%	
	Controls			DGS2, DTB6, DAAA, DGS30(-1)			
10	IRG^{Shock}	−0.1232**	(0.0592)	−0.1397**	(0.0550)		
	BSP^{Shock}	−0.1511*	(0.0807)			−0.3580*	(0.1860)
	EOA^{Shock}	0.1447*	(0.0849)	−0.0007	(0.0666)	0.4064*	(0.2300)
	R-Squared	71.76%		69.86%		83.76%	
	Controls			DGS2, DTB6, DAAA, DGS30(-1)			
11	IRG^{Shock}	−0.1178*	(0.0616)	−0.1364**	(0.0547)		
	BSP^{Shock}	−0.1536*	(0.0799)			−0.3681*	(0.1943)
	EOA^{Shock}	0.1493*	(0.0845)	0.0071	(0.0679)	0.4173*	(0.2402)
	R-Squared	71.77%		69.72%		83.56%	
	Controls			DGS2, DTB6, DAAA, DGS30(-1)			

Notes:
- Standard errors in parentheses. *, **, *** denote significance at the 10% level, 5% level, and 1% level, respectively. OLS estimation.
- HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000).
- Full sample, Feb. 2000 - May 2024, 194 observations.
- Pre-ZLB sample, Feb. 2000 – Dec. 2008, 72 observations.
- ZLB sample, Jan. 2009 – Oct. 2015, 56 observations.

Table 2.34: Estimated effects of IRG, BSP, and EOA shocks on DAAA

Specification	Shocks	Full Sample		Pre-ZLB		ZLB	
		Coefficient	(HAC S.E.)	Coefficient	(HAC S.E.)	Coefficient	(HAC S.E.)
1	IRG^{Shock}	0.1607***	(0.0561)	0.1347***	(0.0440)		
	BSP^{Shock}	0.0905*	(0.0543)			0.1412*	(0.0742)
	EOA^{Shock}	−0.1127*	(0.0611)	−0.0626	(0.0483)	−0.1924	(0.1216)
	R-Squared	70.79%		69.32%		83.66%	
	Controls	DGS30, CORPOAS, DAAA(-1)					
2	IRG^{Shock}	0.1915***	(0.0562)	0.1473***	(0.0483)		
	BSP^{Shock}	0.1039*	(0.0536)			0.1291*	(0.0742)
	EOA^{Shock}	−0.1093*	(0.0618)	−0.0617	(0.0490)	−0.1964	(0.1219)
	R-Squared	71.08%		69.62%		83.67%	
	Controls	DGS30, CORPOAS, DAAA(-1)					
3	IRG^{Shock}	0.1704***	(0.0615)	0.1448***	(0.0502)		
	BSP^{Shock}	0.0990*	(0.0575)			0.1364*	(0.0776)
	EOA^{Shock}	−0.1184*	(0.0604)	−0.0696	(0.0492)	−0.1921	(0.1271)
	R-Squared	70.90%		69.83%		83.50%	
	Controls	DGS30, CORPOAS, DAAA(-1)					
4	IRG^{Shock}	0.1922***	(0.0571)	0.1479***	(0.0489)		
	BSP^{Shock}	0.1048*	(0.0546)			0.1284*	(0.0737)
	EOA^{Shock}	−0.1080*	(0.0626)	−0.0588	(0.0484)	−0.1971	(0.1233)
	R-Squared	71.08%		69.60%		83.67%	
	Controls	DGS30, CORPOAS, DAAA(-1)					
5	IRG^{Shock}	0.1904***	(0.0560)	0.1471***	(0.0482)		
	BSP^{Shock}	0.1106**	(0.0550)			0.1303*	(0.0721)
	EOA^{Shock}	−0.1057*	(0.0625)	−0.0587	(0.0495)	−0.1971	(0.1238)
	R-Squared	71.07%		69.56%		83.66%	
	Controls	DGS30, CORPOAS, DAAA(-1)					
6	IRG^{Shock}	0.1944***	(0.0608)	0.1473***	(0.0519)		
	BSP^{Shock}	0.1049*	(0.0543)			0.1293*	(0.0735)
	EOA^{Shock}	−0.1083*	(0.0627)	−0.0584	(0.0489)	−0.1974	(0.1233)
	R-Squared	71.08%		69.50%		83.67%	
	Controls	DGS30, CORPOAS, DAAA(-1)					
7	IRG^{Shock}	0.2043***	(0.0636)	0.1520***	(0.0560)		
	BSP^{Shock}	0.1006*	(0.0532)			0.1219	(0.0751)
	EOA^{Shock}	−0.0988	(0.0610)	−0.0525	(0.0466)	−0.1821	(0.1245)
	R-Squared	71.08%		69.57%		83.35%	
	Controls	DGS30, CORPOAS, DAAA(-1)					
8	IRG^{Shock}	0.1711***	(0.0626)	0.1456***	(0.0510)		
	BSP^{Shock}	0.0997*	(0.0586)			0.1359*	(0.0773)
	EOA^{Shock}	−0.1169	(0.0612)	−0.0666	(0.0488)	−0.1935	(0.1290)
	R-Squared	70.90%		69.81%		83.50%	
	Controls	DGS30, CORPOAS, DAAA(-1)					
9	IRG^{Shock}	0.1704***	(0.0614)	0.1448***	(0.0502)		
	BSP^{Shock}	0.1056*	(0.0588)			0.1378*	(0.0758)
	EOA^{Shock}	−0.1159*	(0.0608)	−0.0662	(0.0492)	−0.1920	(0.1280)
	R-Squared	70.91%		69.77%		83.50%	
	Controls	DGS30, CORPOAS, DAAA(-1)					
10	IRG^{Shock}	0.1701***	(0.0653)	0.1435***	(0.0526)		
	BSP^{Shock}	0.1002*	(0.0579)			0.1374*	(0.0770)
	EOA^{Shock}	−0.1169*	(0.0614)	−0.0659	(0.0493)	−0.1943	(0.1288)
	R-Squared	70.88%		69.68%		83.51%	
	Controls	DGS30, CORPOAS, DAAA(-1)					
11	IRG^{Shock}	0.1782***	(0.0669)	0.1467**	(0.0561)		
	BSP^{Shock}	0.0956*	(0.0566)			0.1230	(0.0784)
	EOA^{Shock}	−0.1084*	(0.0588)	−0.0617	(0.0470)	−0.1720	(0.1280)
	R-Squared	70.86%		69.72%		83.13%	
	Controls	DGS30, CORPOAS, DAAA(-1)					

Notes:
- Standard errors in parentheses. *, **, *** denote significance at the 10% level, 5% level, and 1% level, respectively. OLS estimation.
- HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000).
- Full sample, Feb. 2000 - May 2024, 194 observations.
- Pre-ZLB sample, Feb. 2000 – Dec. 2008, 72 observations.
- ZLB sample, Jan. 2009 – Oct. 2015, 56 observations.

Table 2.35: Estimated effects of IRG, BSP, and EOA shocks on DBAA

Specification	Shocks	Full Sample		Pre-ZLB		ZLB	
		Coefficient	(HAC S.E.)	Coefficient	(HAC S.E.)	Coefficient	(HAC S.E.)
1	IRG^{Shock}	0.1161***	(0.0395)	0.0781**	(0.0360)		
	BSP^{Shock}	0.0647*	(0.0374)			0.0692	(0.0824)
	EOA^{Shock}	−0.0557*	(0.0330)	−0.0293	(0.0430)	−0.0433	(0.0542)
	R-Squared	82.93%		78.32%		90.47%	
	Controls	DGS30, CORPOAS, DAAA(-1)					
2	IRG^{Shock}	0.1250***	(0.0398)	0.0875**	(0.0380)		
	BSP^{Shock}	0.0660*	(0.0382)			0.0738	(0.0799)
	EOA^{Shock}	−0.0553*	(0.0330)	−0.0280	(0.0433)	−0.0447	(0.0542)
	R-Squared	83.01%		78.57%		90.50%	
	Controls	DGS30, CORPOAS, DAAA(-1)					
3	IRG^{Shock}	0.1174***	(0.0412)	0.0807**	(0.0373)		
	BSP^{Shock}	0.0658*	(0.0400)			0.0757	(0.0859)
	EOA^{Shock}	−0.0560*	(0.0338)	−0.0303	(0.0438)	−0.0506	(0.0558)
	R-Squared	82.92%		78.44%		90.51%	
	Controls	DGS30, CORPOAS, DAAA(-1)					
4	IRG^{Shock}	0.1271***	(0.0403)	0.0877**	(0.0385)		
	BSP^{Shock}	0.0687*	(0.0389)			0.0743	(0.0792)
	EOA^{Shock}	−0.0535*	(0.0328)	−0.0273	(0.0428)	−0.0448	(0.0545)
	R-Squared	83.03%		78.57%		90.50%	
	Controls	DGS30, CORPOAS, DAAA(-1)					
5	IRG^{Shock}	0.1248***	(0.0397)	0.0869**	(0.0378)		
	BSP^{Shock}	0.0680*	(0.0376)			0.0653	(0.0784)
	EOA^{Shock}	−0.0550*	(0.0337)	−0.0234	(0.0438)	−0.0495	(0.0547)
	R-Squared	83.01%		78.50%		90.47%	
	Controls	DGS30, CORPOAS, DAAA(-1)					
6	IRG^{Shock}	0.1226***	(0.0422)	0.0833**	(0.0404)		
	BSP^{Shock}	0.0689*	(0.0390)			0.0754	(0.0793)
	EOA^{Shock}	−0.0530	(0.0331)	−0.0266	(0.0430)	−0.0452	(0.0546)
	R-Squared	82.97%		78.36%		90.51%	
	Controls	DGS30, CORPOAS, DAAA(-1)					
7	IRG^{Shock}	0.1183***	(0.0437)	0.0817*	(0.0429)		
	BSP^{Shock}	0.0709*	(0.0386)			0.0791	(0.0810)
	EOA^{Shock}	−0.0564*	(0.0331)	−0.0286	(0.0403)	−0.0501	(0.0561)
	R-Squared	82.96%		78.31%		90.52%	
	Controls	DGS30, CORPOAS, DAAA(-1)					
8	IRG^{Shock}	0.1198***	(0.0417)	0.0809**	(0.0379)		
	BSP^{Shock}	0.0684*	(0.0406)			0.0764	(0.0850)
	EOA^{Shock}	−0.0540*	(0.0336)	−0.0295	(0.0433)	−0.0509	(0.0562)
	R-Squared	82.94%		78.44%		90.52%	
	Controls	DGS30, CORPOAS, DAAA(-1)					
9	IRG^{Shock}	0.1176***	(0.0412)	0.0805**	(0.0373)		
	BSP^{Shock}	0.0676*	(0.0395)			0.0668	(0.0846)
	EOA^{Shock}	−0.0559	(0.0342)	−0.0265	(0.0439)	−0.0536	(0.0559)
	R-Squared	82.92%		78.39%		90.48%	
	Controls	DGS30, CORPOAS, DAAA(-1)					
10	IRG^{Shock}	0.1156***	(0.0429)	0.0767*	(0.0391)		
	BSP^{Shock}	0.0699*	(0.0406)			0.0789	(0.0852)
	EOA^{Shock}	−0.0538	(0.0338)	−0.0287	(0.0435)	−0.0521	(0.0564)
	R-Squared	82.83%		78.26%		90.53%	
	Controls	DGS30, CORPOAS, DAAA(-1)					
11	IRG^{Shock}	0.1117**	(0.0442)	0.0749*	(0.0412)		
	BSP^{Shock}	0.0728*	(0.0402)			0.0837	(0.0875)
	EOA^{Shock}	−0.0576*	(0.0336)	−0.0313	(0.0407)	−0.0585	(0.0582)
	R-Squared	82.93%		78.23%		90.55%	
	Controls	DGS30, CORPOAS, DAAA(-1)					

Notes:
- Standard errors in parentheses. *, **, *** denote significance at the 10% level, 5% level, and 1% level, respectively. OLS estimation.
- HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000).
- Full sample, Feb. 2000 - May 2024, 194 observations.
- Pre-ZLB sample, Feb. 2000 – Dec. 2008, 72 observations.
- ZLB sample, Jan. 2009 – Oct. 2015, 56 observations.

Table 2.36: Estimated effects of IRG, BSP, and EOA shocks on DEXUSEU

Specification	Shocks	Full Sample		Pre-ZLB		ZLB	
		Coefficient	(HAC S.E.)	Coefficient	(HAC S.E.)	Coefficient	(HAC S.E.)
1	IRG^{Shock}	−0.1206**	(0.0570)	−0.1197*	(0.0618)		
	BSP^{Shock}	0.0257	(0.0491)			0.21171*	(0.1198)
	EOA^{Shock}	0.0979**	(0.0453)	0.1301***	(0.0425)	−0.04464	(0.0873)
	R-Squared	13.99%		25.04%		18.99%	
	Controls	DEXUSEU, VXDCLS, DJIA(-1), DJIA(-2), DGS2					
2	IRG^{Shock}	−0.1062*	(0.0619)	−0.1137*	(0.0653)		
	BSP^{Shock}	0.0385	(0.0480)			0.20596*	(0.1216)
	EOA^{Shock}	0.1049**	(0.0484)	0.1520***	(0.0536)	−0.04109	(0.0886)
	R-Squared	14.19%		25.90%		18.41%	
	Controls	DEXUSEU, VXDCLS, DJIA(-1), DJIA(-2), DGS2					
3	IRG^{Shock}	−0.1059*	(0.0602)	−0.1321**	(0.0592)		
	BSP^{Shock}	0.0402	(0.0517)			0.23040*	(0.1226)
	EOA^{Shock}	0.0871*	(0.0450)	0.1299***	(0.0429)	−0.06510	(0.0947)
	R-Squared	13.03%		26.26%		20.66%	
	Controls	DEXUSEU, VXDCLS, DJIA(-1), DJIA(-2), DGS2					
4	IRG^{Shock}	−0.1069*	(0.0612)	−0.1158*	(0.0640)		
	BSP^{Shock}	0.0384	(0.0478)			0.20596*	(0.1201)
	EOA^{Shock}	0.1052**	(0.0490)	0.1504***	(0.0560)	−0.03975	(0.0892)
	R-Squared	14.21%		25.87%		18.55%	
	Controls	DEXUSEU, VXDCLS, DJIA(-1), DJIA(-2), DGS2					
5	IRG^{Shock}	−0.1054*	(0.0616)	−0.1129*	(0.0651)		
	BSP^{Shock}	0.0349	(0.0478)			0.2107*	(0.1224)
	EOA^{Shock}	0.1057**	(0.0487)	0.1471***	(0.0537)	−0.0395	(0.0884)
	R-Squared	13.96%		25.29%		18.82%	
	Controls	DEXUSEU, VXDCLS, DJIA(-1), DJIA(-2), DGS2					
6	IRG^{Shock}	−0.1066*	(0.0614)	−0.1153*	(0.0678)		
	BSP^{Shock}	0.0393	(0.0481)			0.2055*	(0.1203)
	EOA^{Shock}	0.1048**	(0.0489)	0.1490**	(0.0557)	−0.0399	(0.0894)
	R-Squared	14.16%		25.71%		18.41%	
	Controls	DEXUSEU, VXDCLS, DJIA(-1), DJIA(-2), DGS2					
7	IRG^{Shock}	−0.1024	(0.0630)	−0.1116	(0.0711)		
	BSP^{Shock}	0.0370	(0.0486)			0.2146*	(0.1268)
	EOA^{Shock}	0.1090**	(0.0509)	0.1512**	(0.0588)	−0.0530	(0.0997)
	R-Squared	14.22%		25.68%		18.84%	
	Controls	DEXUSEU, VXDCLS, DJIA(-1), DJIA(-2), DGS2					
8	IRG^{Shock}	−0.1067*	(0.0596)	−0.1343**	(0.0582)		
	BSP^{Shock}	0.0400	(0.0518)			0.2296*	(0.1212)
	EOA^{Shock}	0.0878*	(0.0459)	0.1290***	(0.0454)	−0.0637	(0.0958)
	R-Squared	13.06%		26.33%		20.73%	
	Controls	DEXUSEU, VXDCLS, DJIA(-1), DJIA(-2), DGS2					
9	IRG^{Shock}	−0.1057*	(0.0597)	−0.1318**	(0.0587)		
	BSP^{Shock}	0.0370	(0.0521)			0.2374*	(0.1235)
	EOA^{Shock}	0.0880*	(0.0450)	0.1248***	(0.0419)	−0.0647	(0.0940)
	R-Squared	12.89%		25.76%		21.35%	
	Controls	DEXUSEU, VXDCLS, DJIA(-1), DJIA(-2), DGS2					
10	IRG^{Shock}	−0.1078*	(0.0590)	−0.1339**	(0.0603)		
	BSP^{Shock}	0.0411	(0.0521)			0.2293*	(0.1218)
	EOA^{Shock}	0.0875*	(0.0458)	0.1281***	(0.0452)	−0.0640	(0.0961)
	R-Squared	13.10%		26.19%		20.48%	
	Controls	DEXUSEU, VXDCLS, DJIA(-1), DJIA(-2), DGS2					
11	IRG^{Shock}	−0.1054*	(0.0598)	−0.1305**	(0.0624)		
	BSP^{Shock}	0.0399	(0.0533)			0.2420*	(0.1287)
	EOA^{Shock}	0.0892*	(0.0471)	0.1289***	(0.0464)	−0.0817	(0.1065)
	R-Squared	13.08%		26.03%		21.26%	
	Controls	DEXUSEU, VXDCLS, DJIA(-1), DJIA(-2), DGS2					

Notes:
- Standard errors in parentheses. *, **, *** denote significance at the 10% level, 5% level, and 1% level, respectively. OLS estimation.
- HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000).
- Full sample, Feb. 2000 - May 2024, 194 observations.
- Pre-ZLB sample, Feb. 2000 – Dec. 2008, 72 observations.
- ZLB sample, Jan. 2009 – Oct. 2015, 56 observations.

Table 2.37: Regression results of lagged financial indicators on IRG shocks

Spec.	**Lag**	**Coef.**	$SP500$	VIX	$DGS2$	EUI
1	y_{t-1}	Coefficient	0.0236	0.0009	0.0053	−0.0007
		HAC S.E.	(0.0435)	(0.0038)	(0.0113)	(0.0007)
	y_{t-2}	Coefficient	0.2315	−0.0045	0.0027	0.0001
		HAC S.E.	(0.2788)	(0.0052)	(0.0130)	(0.0007)
	y_{t-3}	Coefficient	−0.1938	0.0033	0.0083	−0.0019*
		HAC S.E.	(0.2887)	(0.0040)	(0.0101)	(0.0010)
	R-Squared		1.07%	0.29%	0.47%	3.80%
2	y_{t-1}	Coefficient	0.0277	0.0008	0.0030	0.0006
		HAC S.E.	(0.044)	(0.0039)	(0.0112)	(0.0006)
	y_{t-2}	Coefficient	0.2214	−0.0047	0.0051	0.0003
		HAC S.E.	(0.2706)	(0.0052)	(0.0129)	(0.0007)
	y_{t-3}	Coefficient	−0.1823	0.0033	0.0048	−0.0019*
		HAC S.E.	(0.2809)	(0.0040)	(0.0099)	(0.0010)
	R-Squared		11.9%	0.35%	0.3%	4.0%
3	y_{t-1}	Coefficient	0.0177	0.0006	−0.0018	−0.0008
		HAC S.E.	(0.042)	(0.0039)	(0.0112)	(0.0007)
	y_{t-2}	Coefficient	0.2163	−0.0049	−0.0029	0.0000
		HAC S.E.	(0.2701)	(0.0052)	(0.0128)	(0.0007)
	y_{t-3}	Coefficient	−0.1938	0.0055	0.0047	−0.0017*
		HAC S.E.	(0.0041)	(0.0052)	(0.0099)	(0.0010)
	R-Squared		0.85%	0.50%	0.14%	3.20%

Notes:
- Each column in each panel presents OLS regression results for the three-day lagged values of SP500, VIX, DGS2, and EUI (separately) on IRG shocks across three specifications: (1) Basic, (2) FFR, and (3) Proxy.
- Standard errors in parentheses. *, **, *** denote significance at the 10% level, 5% level, and 1% level, respectively.
- HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000).

Table 2.38: Regression results of lagged financial indicators on BSP shocks

Spec.	**Lag**	**Coef.**	$SP500$	VIX	$DGS2$	EUI
1	y_{t-1}	Coefficient	0.0272	−0.0036	0.0155	−0.0012
		HAC S.E.	(0.0420)	(0.0097)	(0.0208)	(0.0010)
	y_{t-2}	Coefficient	−0.1171	0.0057	−0.0048	−0.0001
		HAC S.E.	(0.2841)	(0.0071)	(0.0190)	(0.0012)
	y_{t-3}	Coefficient	0.0145	0.0051	−0.0231	0.0006
		HAC S.E.	(0.2938)	(0.0079)	(0.0154)	(0.0009)
	R-Squared		2.58%	0.74%	3.15%	0.92%
2	y_{t-1}	Coefficient	0.0325	−0.0024	0.0138	−0.0011
		HAC S.E.	(0.0430)	(0.0096)	(0.0199)	(0.0011)
	y_{t-2}	Coefficient	−0.1332	0.0060	−0.011	0.0005
		HAC S.E.	(0.2925)	(0.0068)	(0.0174)	(0.0011)
	y_{t-3}	Coefficient	0.0343	0.0049	−0.0224	0.0005
		HAC S.E.	(0.302)	(0.0077)	(0.015)	(0.0009)
	R-Squared		2.7%	0.7%	3.4%	0.7%
3	y_{t-1}	Coefficient	0.0246	−0.0037	0.0102	−0.0012
		HAC S.E.	(0.042)	(0.0087)	(0.0188)	(0.0010)
	y_{t-2}	Coefficient	−0.1292	0.0055	−0.0094	−0.0001
		HAC S.E.	(0.2653)	(0.0070)	(0.0184)	(0.0012)
	y_{t-3}	Coefficient	0.2008	0.0067	−0.0255	0.0007
		HAC S.E.	(0.277)	(0.0077)	(0.0155)	(0.0009)
	R-Squared		2.83%	0.93%	3.43%	1.05%

Notes:
- Each column in each panel presents OLS regression results for the three-day lagged values of SP500, VIX, DGS2, and EUI (separately) on BSP shocks across three specifications: (1) Basic, (2) FFR, and (3) Proxy.
- Standard errors in parentheses. *, **, *** denote significance at the 10% level, 5% level, and 1% level, respectively.
- HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000).

Table 2.39: Regression results of lagged financial indicators on EOA shocks

Spec.	**Lag**	**Coef.**	$SP500$	VIX	$DGS2$	EUI
1	y_{t-1}	Coefficient	0.0125	−0.0084	−0.0136	−0.0025
		HAC S.E.	(0.0465)	(0.0081)	(0.0122)	(0.0013)
	y_{t-2}	Coefficient	0.2800	0.0096	0.0042	−0.0020
		HAC S.E.	(0.1929)	(0.0075)	(0.0162)	(0.0013)
	y_{t-3}	Coefficient	−0.2313	−0.0062	0.0051	−0.0026*
		HAC S.E.	(0.1859)	(0.0085)	(0.0109)	(0.0014)
	R-Squared		0.79%	1.02%	0.66%	2.92%
2	y_{t-1}	Coefficient	0.0101	−0.0077	−0.0172	−0.0023
		HAC S.E.	(0.0472)	(0.0091)	(0.0124)	(0.0013)
	y_{t-2}	Coefficient	0.2606	0.0096	0.0007	−0.0019
		HAC S.E.	(0.1895)	(0.0075)	(0.0169)	(0.0013)
	y_{t-3}	Coefficient	−0.2026	−0.0058	0.0052	−0.0027*
		HAC S.E.	(0.1838)	(0.0085)	(0.0111)	(0.0014)
	R-Squared		0.8%	1.0%	0.8%	2.9%
3	y_{t-1}	Coefficient	0.0034	−0.0083	−0.0079	−0.0025
		HAC S.E.	(0.0463)	(0.0079)	(0.0128)	(0.0014)
	y_{t-2}	Coefficient	0.2950	0.0098	0.0090	−0.0020
		HAC S.E.	(0.1911)	(0.0074)	(0.0154)	(0.0014)
	y_{t-3}	Coefficient	−0.2399	0.0058	0.0075	−0.0028*
		HAC S.E.	(0.1859)	(0.0085)	(0.0104)	(0.0014)
	R-Squared		0.93%	1.12%	0.60%	3.17%

Notes:
- Each column in each panel presents OLS regression results for the three-day lagged values of SP500, VIX, DGS2, and EUI (separately) on EOA shocks across three specifications: (1) Basic, (2) FFR, and (3) Proxy.
- Standard errors in parentheses. *, **, *** denote significance at the 10% level, 5% level, and 1% level, respectively.
- HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000).

Table 2.40: Regression results of lagged financial indicators on IRG, BSP, and EOA shocks

Lagged Values	**Coefficient**	**IRG**			**BSP**			**EOA**		
		1	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
$SP500_{t-1}$	Coefficient	0.0756	0.0840	0.0604	0.0343	0.0569	0.0266	−0.0450	−0.0195	−0.0393
	HAC S.E.	(0.0689)	(0.0692)	(0.0674)	(0.0415)	(0.0407)	(0.0417)	(0.0802)	(0.0815)	(0.0820)
$SP500_{t-2}$	Coefficient	0.3560	0.3480	0.3030	−0.0506	−0.0678	−0.0917	0.1492	0.1257	0.1937
	HAC S.E.	(0.3397)	(0.3289)	(0.3363)	(0.2790)	(0.2872)	(0.2699)	(0.2325)	(0.2268)	(0.2231)
$SP500_{t-3}$	Coefficient	−0.2780	−0.2526	−0.2168	−0.1033	−0.0909	−0.0599	−0.0738	−0.0421	−0.1224
	HAC S.E.	(0.3240)	(0.3132)	(0.3211)	(0.2946)	(0.3057)	(0.2834)	(0.2110)	(0.2070)	(0.2016)
VIX_{t-1}	Coefficient	0.0150	0.0151	0.0105	0.0034	0.0069	0.0006	−0.0153	−0.0124	−0.0127
	HAC S.E.	(0.0099)	(0.0100)	(0.0098)	(0.0116)	(0.0113)	(0.0113)	(0.0146)	(0.0143)	(0.0147)
VIX_{t-2}	Coefficient	0.0023	0.0017	−0.0003	0.0059	0.0058	0.0040	0.0130	0.0126	0.0151
	HAC S.E.	(0.0060)	(0.0058)	(0.0059)	(0.0074)	(0.0075)	(0.0075)	(0.0074)	(0.0073)	(0.0074)
VIX_{t-3}	Coefficient	0.0160	0.0182	0.0184	−0.0149	−0.0155	−0.0135	0.0049	0.0062	0.0031
	HAC S.E.	(0.0157)	(0.0155)	(0.0152)	(0.0121)	(0.0125)	(0.0117)	(0.0137)	(0.0137)	(0.0134)
$DGS2_{t-1}$	Coefficient	0.0079	0.0049	−0.0011	0.0143	0.0116	0.0074	−0.0141	−0.0192	−0.0066
	HAC S.E.	(0.0081)	(0.0079)	(0.0087)	(0.0222)	(0.0210)	(0.0207)	(0.0149)	(0.0148)	(0.0150)
$DGS2_{t-2}$	Coefficient	0.0044	0.0006	−0.0031	−0.0054	−0.0121	−0.0117	0.0066	0.0010	0.0131
	HAC S.E.	(0.0094)	(0.0079)	(0.0089)	(0.0202)	(0.0189)	(0.0199)	(0.0169)	(0.0174)	(0.0168)
$DGS2_{t-3}$	Coefficient	0.0040	0.0023	0.0014	−0.0170	−0.0164	−0.0186	−0.0015	−0.0017	0.0001
	HAC S.E.	(0.0054)	(0.0052)	(0.0056)	(0.0170)	(0.0167)	(0.0170)	(0.0130)	(0.0132)	(0.0122)
EUI_{t-1}	Coefficient	−0.0007	−0.0006	−0.0008	−0.0012	−0.0011	−0.0013	−0.0025	−0.0023	−0.0025
	HAC S.E.	(0.0007)	(0.0007)	(0.0007)	(0.0011)	(0.0011)	(0.0010)	(0.0015)	(0.0014)	(0.0015)
EUI_{t-2}	Coefficient	0.0003	0.0004	0.0000	0.0002	0.0003	0.0000	−0.0020	−0.0018	−0.0018
	HAC S.E.	(0.0008)	(0.0008)	(0.0008)	(0.0011)	(0.0011)	(0.0011)	(0.0015)	(0.0014)	(0.0015)
EUI_{t-3}	Coefficient	−0.0018*	−0.0018*	−0.0017*	0.0001	−0.0001	0.0001	−0.0028*	−0.0030*	−0.0029*
	HAC S.E.	(0.0010)	(0.0009)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0014)	(0.0014)	(0.0014)
R-Squared		6.59%	7.11%	5.73%	6.32%	6.9%	6.5%	5.85%	5.89%	6.00%

Notes:
- Each column presents OLS regression results for the three-day lagged values of SP500, VIX, DGS2, and EUI on monetary policy sentiment shocks (IRG, BSP, and EOA) across three specifications: (1) Basic, (2) FFR, and (3) Proxy.
- Standard errors in parentheses. *, **, *** denote significance at the 10% level, 5% level, and 1% level, respectively.
- HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000).

Table 2.41: Regression results of forecasted RGDP, inflation, and unemployment on IRG, BSP, and EOA shocks

Lagged Values	**Coefficient**	**IRG**			**BSP**			**EOA**		
		1	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
$RGDP_{q-1}$	Coefficient	−0.0277	−0.0192	−0.0202	−0.0107	−0.0087	−0.0053	−0.0813	−0.0790	−0.0865
	HAC S.E.	(0.0580)	(0.0569)	(0.0576)	(0.0332)	(0.0335)	(0.0338)	(0.0570)	(0.0568)	(0.0551)
$RGDP_q$	Coefficient	0.0878	0.0872	0.0672	0.0087	0.0112	−0.0049	−0.1063	−0.1110	−0.0912
	HAC S.E.	(0.0803)	(0.0758)	(0.0787)	(0.0718)	(0.0771)	(0.0735)	(0.1298)	(0.1302)	(0.1278)
$RGDP_{q+1}$	Coefficient	−0.0065	−0.0260	−0.0214	0.1967	0.1283	0.1822	0.2683	0.2188	0.2821*
	HAC S.E.	(0.1249)	(0.1157)	(0.1156)	(0.1303)	(0.1235)	(0.1317)	(0.1651)	(0.1655)	(0.1595)
$RGDP_{q+2}$	Coefficient	0.0370	0.0473	0.0604	0.1254	0.1065	0.1361	−0.1086	−0.1099	−0.1198
	HAC S.E.	(0.2506)	(0.2262)	(0.2402)	(0.2456)	(0.2529)	(0.2471)	(0.3279)	(0.3323)	(0.3187)
$RGDP_{q+3}$	Coefficient	−0.1082	−0.1407	−0.1064	−0.2231	−0.1791	−0.2128	−0.1363	−0.1242	−0.1454
	HAC S.E.	(0.2257)	(0.2091)	(0.2188)	(0.2137)	(0.2143)	(0.2141)	(0.2520)	(0.2591)	(0.2504)
INF_{q-1}	Coefficient	0.0188	0.0236	0.0145	−0.0199	−0.0055	−0.0220	0.0171	0.0294	0.0189
	HAC S.E.	(0.0291)	(0.0276)	(0.0283)	(0.0252)	(0.0287)	(0.0256)	(0.0538)	(0.0541)	(0.0545)
INF_q	Coefficient	−0.0405	−0.0444	−0.0285	−0.0404	−0.0448	−0.0310	0.0585	0.0550	0.0493
	HAC S.E.	(0.0317)	(0.0317)	(0.0310)	(0.0377)	(0.0375)	(0.0345)	(0.0419)	(0.0412)	(0.0431)
INF_{q+1}	Coefficient	0.0374	0.0285	0.0359	0.0501	0.0492	0.0470	−0.0401	−0.0383	−0.0374
	HAC S.E.	(0.0480)	(0.0466)	(0.0484)	(0.0613)	(0.0618)	(0.0585)	(0.0679)	(0.0662)	(0.0674)
INF_{q+2}	Coefficient	−0.1657	−0.1672	−0.1900	0.3201	0.2904	0.2943	0.4456	0.4258	0.4696
	HAC S.E.	(0.2268)	(0.2300)	(0.2412)	(0.2978)	(0.2960)	(0.2824)	(0.3404)	(0.3402)	(0.3242)
INF_{q+3}	Coefficient	−0.0438	−0.0660	0.0150	−0.5211	−0.5783	−0.4743	−0.8183*	−0.8810*	−0.8610*
	HAC S.E.	(0.3595)	(0.3490)	(0.3830)	(0.4208)	(0.4221)	(0.3939)	(0.4828)	(0.4613)	(0.4811)
$UNEMP_{q-1}$	Coefficient	0.0245	0.0114	−0.0829	−0.1628	−0.1653	−0.2484	−0.0726	−0.0812	0.0167
	HAC S.E.	(0.3283)	(0.3249)	(0.3436)	(0.4021)	(0.3980)	(0.3927)	(0.3836)	(0.3736)	(0.3920)
$UNEMP_q$	Coefficient	0.2987	0.2434	0.6067	0.9260	0.8275	1.1629	1.4338*	1.3708*	1.1842
	HAC S.E.	(0.7267)	(0.7232)	(0.6862)	(0.9256)	(0.9433)	(0.9253)	(0.8055)	(0.8048)	(0.7917)
$UNEMP_{q+1}$	Coefficient	−0.6411	−0.6405	−0.6722	−2.1558	−2.1064	−2.1738	−1.8648	−1.8276	−1.8298
	HAC S.E.	(1.4426)	(1.3781)	(1.4058)	(1.5089)	(1.5745)	(1.5017)	(1.5181)	(1.5138)	(1.5016)
$UNEMP_{q+2}$	Coefficient	−0.2715	−0.0060	−0.5698	1.7765	1.9822	1.5103	0.1287	0.2691	0.3844
	HAC S.E.	(1.6503)	(1.5833)	(1.6475)	(1.6838)	(1.6508)	(1.7085)	(2.3077)	(2.2560)	(2.2755)
$UNEMP_{q+3}$	Coefficient	0.5789	0.3747	0.7137	−0.5179	−0.6987	−0.3824	0.2745	0.1567	0.1405
	HAC S.E.	(0.8313)	(0.8050)	(0.8390)	(0.8835)	(0.8734)	(0.9194)	(1.2085)	(1.1730)	(1.1809)
R-Squared		5.07%	5.14%	4.02%	18.82%	15.13%	18.28%	8.21%	6.88%	8.39%

Notes:
- Each column presents OLS regression results of forecasted RGDP, Inflation, and Unemployment on IRG, BSP, and EOA shocks across three specifications.
- Standard errors in parentheses. *, **, *** denote significance at the 10% level, 5% level, and 1% level, respectively.
- HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000).
- From February 2000 to December 2018.

Chapter 3

U.S. Monetary Policy and Commodity Prices: An Empirical Analysis

3.1 Introduction

In the wake of the COVID-19 pandemic, commodity prices have once again taken center stage in global economic discussions. As inflation surged to multi-decade highs, the rapid increase in commodity prices became a focal point for policymakers, investors, and market participants. Between 2020 and 2022, the global commodity price index nearly doubled, driven by unprecedented monetary stimulus measures, including substantial reductions in policy rates and large-scale asset purchases (see Figure 3.8). These developments have underscored both the fragility of global supply chains and the heightened sensitivity of commodity markets to macroeconomic policies. The sharp rise in the cost of raw materials, alongside mounting inflationary pressures, has prompted renewed scrutiny of the role that monetary policy plays in driving commodity price dynamics.

Commodity markets serve as key channels through which international economic shocks are transmitted. Fluctuations in commodity prices significantly affect real economic activity, influencing both producer costs and consumer prices. Given their critical role in shaping inflationary expectations and their weight in the CPI, understanding the macroeconomic factors behind commodity price movements is crucial. For policymakers, being able to anticipate and mitigate such fluctuations is essential for stabilizing inflation and ensuring economic resilience. For market participants, including investors and traders, understanding the relationship between monetary policy and commodity prices is vital for making informed trading and hedging decisions, as monetary policy shifts often trigger significant commodity price volatility.

This study seeks to understand the impact of U.S. monetary policy on commodity prices by addressing the following research questions: How do U.S. conventional and unconventional monetary policies influence commodity prices, and are these effects significant and persistent? To what extent can the recent surge in commodity prices be attributed to unconventional monetary policy shocks?

The relationship between monetary policy and commodity prices remains a subject of active debate and exploration. While the impact of conventional monetary policy on commodity prices has been widely studied, the findings are inconclusive, with some studies suggesting that contractionary policy decreases prices (e.g., Christiano et al., 1994; Frankel, 2008; Anzuini et al., 2013) and others indicating the opposite (e.g., Hammoudeh et al., 2015; Aliyev and Kočenda, 2023). Research on the effects of unconventional monetary measures, such as large-scale asset purchases (LSAPs) and forward guidance, is scarce and less developed. Moreover, existing proxies for unconventional policy often fail to capture its qualitative dimensions, particularly the multifaceted nature of forward guidance, which includes guidance on interest rates, balance sheets, and economic outlooks. Additionally, the unprecedented reliance on unconventional monetary measures during the COVID-19 pandemic, coupled with the sharp rise in commodity prices, highlights the need to examine their impact. However, no study has yet investigated this period, and incorporating it into the analysis would provide a valuable contribution to the existing literature.

This study revisits the relationship between conventional monetary policy and commodity prices while contributing to the understanding of the impact of unconventional monetary tools. For the first time, this study utilizes a Vector Error Correction Model (VECM) to explore the long-run dynamics between monetary policy—both conventional and unconventional—and commodity prices. The study also employs a structural vector autoregressive (SVAR) model to identify monetary policy shocks and their propagation effects on commodity prices. Furthermore, this study is the first to apply sentiment-driven monetary policy shocks, constructed from media coverage surrounding Federal Open Market Committee (FOMC) meetings, to analyze their effects on commodity prices. These shocks focus on three distinct types of forward guidance: interest rate guidance (IRG), balance sheet policy (BSP) guidance, and economic outlook assessment (EOA) guidance. By integrating these methodologies, this study provides a comprehensive analysis of the channels through which monetary policy shapes commodity price dynamics. Additionally, an extended dataset encompassing the COVID-19 pandemic period is incorporated to capture the unique monetary policy challenges of that time.

To better distinguish the effects of conventional and unconventional monetary policies and address overlaps often overlooked in prior research, the analysis is divided into three distinct periods: pre-Zero Lower Bound (pre-ZLB), ZLB, and post-ZLB. The pre-ZLB period is marked by the exclusive use of conventional monetary policy tools, such as adjustments to the federal funds rate. The ZLB period reflects a reliance on unconventional tools like quantitative easing and forward guidance, which were necessitated by the ZLB constraint. The post-ZLB period combines the use of both conventional and unconventional tools. During the post-ZLB period, the impacts of each policy type are further isolated by applying shocks to one policy while controlling for the other, allowing for a clearer analysis of their individual contributions.

The findings reveal that monetary policy has significant and differentiated impacts on commodity prices, with variations in magnitude and direction depending on the policy tool and mechanism. Conventional monetary tightening, represented by a one-percentage-point (pp) increase in the effective federal funds rate (EFFR), is associated with a 3.66 percent long-term decline in commodity prices, reflecting reduced borrowing, investment, and persistent contractionary effects on aggregate demand. A contractionary conventional monetary policy shock, represented by a 1 pp rise in the EFFR, causes a persistent 5 percent decline in commodity prices in the short run, consistent with Frankel (2008), Anzuini et al. (2013), and Belke et al. (2014), while diverging from Hammoudeh et al. (2015) and Aliyev and Kočenda (2023), who report price increases under similar conditions.

On the other hand, unconventional monetary policy measures, represented by a 1 pp reduction in the proxy federal funds rate (PFR), yield strong expansionary effects, driving a 47.65 percent rise in commodity prices in the long term. Balance sheet policies, including a 5 percent expansion in the monetary base (MB), further underscore the liquidity-enhancing effects of LSAPs, leading to a 5 percent long-term increase in commodity prices. Expansionary unconventional shock, represented by a 1 pp decrease in the PFR, causes a 20 percent rise in commodity prices within six months. Notably, unconventional measures significantly influenced commodity price trajectories during the pandemic by amplifying credit availability and speculative demand. The analysis also highlights the role of monetary policy sentiment shocks, particularly hawkish interest rate guidance, in shaping commodity price dynamics. This finding aligns with Rosa (2014) and Scrimgeour (2015), who report that surprise federal funds rate (FFR) hikes reduce commodity prices.

The paper is structured as follows: Section 2 reviews the literature, Section 3 describes the data, and Section 4 outlines the methodologies. Section 5 analyzes the transmission mechanism, while Section 6 presents the SVAR and VECM results. Section 7 discusses the variance and historical decomposition results. Section 8 covers the event study findings, Section 9 addresses robustness checks, and Section 10 concludes with key findings and policy implications.

3.2 Literature Review

The relationship between conventional monetary policy and commodity prices is well-established in the literature, with foundational insights provided by Jeffrey Frankel. Frankel (1984) argues that expansionary monetary policy lowers real interest rates by reducing nominal rates and increasing inflation expectations. This encourages a shift from interest-bearing assets to commodities, driving up prices. Empirical evidence from Frankel and Hardouvelis (1985) demonstrates that monetary surprises negatively impact commodity prices, reflecting anticipated economic contractions. Frankel (1986) uses Dornbusch's exchange rate overshooting model to show that commodity prices adjust more quickly than consumer goods prices, causing them to initially exceed their long-term equilibrium after an increase in the nominal money supply. Furthermore, Frankel (2008) identifies three key channels—inventory costs, resource extraction timing, and speculative activity—through which monetary policy affects commodity markets, finding a negative correlation between real interest rates and commodity demand, particularly for oil.

This study aligns closely with previous research utilizing VAR models to examine the effects of monetary policy on commodity prices. While these studies generally agree on the overshooting behavior of commodity prices in response to U.S. monetary policy shocks (e.g., Frankel, 1986; Anzuini et al., 2013; Cabrales et al., 2014), they differ in their evaluations of the magnitude and persistence of these effects. For instance, Christiano et al. (1994) identifies a pronounced and enduring impact of conventional U.S. monetary policy, whereas Reicher and Utlaut (2013) notes a similarly sharp but less sustained response. Studies such as Leeper and Zha (2003), Anzuini et al. (2013), and Cabrales et al. (2014) report smaller yet more persistent effects. In contrast, Mallick and Sousa (2012) finds minimal and short-lived impacts, illustrating the variability in outcomes across the existing literature.

Research on the impact of unconventional monetary policy on commodity prices is limited. Hammoudeh et al. (2015) briefly address this using changes in central bank reserves to represent unconventional policy, focusing on LSAP implementation while neglecting announcements and tools like forward guidance. They find that contractionary conventional monetary policy raises commodity prices, potentially due to aggregation bias, inflation expectations, and overshooting. In contrast, Apergis et al. (2020) employ an EGARCH-X model and show that unconventional monetary policy, proxied by short-term shadow rates, has a stronger impact on both commodity returns and volatility, regardless of region or commodity type.

This study deepens the understanding of the relationship between monetary policy, particularly unconventional measures, and commodity prices by employing both recursive and non-recursive identification strategies within the SVAR model and utilizing the VECM framework to examine often-overlooked long-run relationships. By leveraging multiple time horizons and more accurately isolating the effects of conventional and unconventional monetary policies, this study offers a refined perspective on their influence on commodity markets. In addition, this study builds on the literature by shedding light on the impact of monetary policy on commodity prices utilizing an extended dataset encompassing the COVID-19 pandemic period.

Another closely related branch of literature comprises event studies that utilize high-frequency data to robustly identify monetary policy shocks. For example, Gürkaynak et al. (2005) analyze the impact of FOMC forward guidance on asset prices, identifying two key factors that drive asset price responses: changes in the current federal funds rate and adjustments to the expected future policy path. Expanding on this approach, Rosa (2014) investigate the determinants of oil price fluctuations during the 2008 financial crisis, leveraging intraday data to identify monetary policy "surprises" associated with target rates, forward guidance, and asset purchases. Their results indicate that such surprises generally place downward pressure on oil prices. Similarly, Scrimgeour (2015) use high-frequency financial data to explore the effects of U.S. monetary policy surprises on commodity prices, finding that a 10-basis-point surprise in interest rates leads to a 0.6 percent decline in commodity prices.

This study is the first to apply sentiment-driven monetary policy shocks to examine their effects on commodity prices. By leveraging media-based sentiment measures and a dataset encompassing the COVID-19 period, it uncovers unexpected elements of monetary policy communication and their effects on market behavior. The analysis disentangles the role of forward guidance categories, shedding light on the interplay between sentiment-driven shocks, commodity price dynamics, and market conditions during uncertain times.

3.3 Data

Table 3.6 presents a detailed overview of the data used in the analysis, including their sources and descriptions. Before discussing the specifics of the dataset, I outline the process for determining the suitable time series econometric model for the analysis. In line with standard practices, I begin by evaluating the stationarity properties of the variables. This step is essential to ensure the reliability of regression results and the validity of statistical inferences, as non-stationary data can lead to spurious outcomes.

To evaluate stationarity, I employ two widely recognized unit root tests: the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test. The findings, summarized in Table 3.7, indicate that all endogenous variables are non-stationary at the level but become stationary after first differencing, indicating they are integrated of order 1 (I(1)). This conclusion is supported by the inability to reject the null hypothesis of a unit root at conventional significance levels.[1]

Given the presence of non-stationarity, the next step investigates the potential for cointegration among these I(1) variables. The Johansen cointegration test, a robust methodology for detecting long-run equilibrium relationships, is employed for this purpose.[2] The test results, based on the "Trace" and "Maximum Eigenvalue" statistics (see Table 3.8), confirm at least one cointegration relationship. This finding suggests that, despite their individual non-stationary nature, the variables share a long-run equilibrium path.

The presence of cointegration warrants the use of a VECM for analyzing the dynamic interactions among the variables. The VECM framework, as introduced by Engle and Granger (1987), effectively captures both short-term dynamics and long-term equilibrium adjustments. Lag selection criteria, presented in Table 3.9, indicate the use of one lag for the pre-ZLB model, two lags for the ZLB model, and one lag for the post-ZLB model. Diagnostic checks, detailed in Table 3.10, confirm that the VECM specifications meet essential assumptions, including normality, homoscedasticity, and the absence of autocorrelation.

In addition, we employ the SVAR model to analyze dynamic relationships among variables and identify structural shocks. The SVAR framework, grounded in economic theory, allows for contemporaneous interactions and causal effects through theoretically derived restrictions, ensuring interpretable and meaningful shocks. It is widely recognized that VAR models specified in differences lead to misspecification issues when cointegration is present. Therefore, we estimate the SVAR in levels rather than differencing, following the

[1] Details of the unit root testing procedures are provided in Appendix A.1.
[2] For a detailed explanation of the Johansen test, refer to in Appendix A.2.

recommendations of Ramaswamy and Sloek (1998). This approach ensures consistent estimates and preserves long-term dynamics, as emphasized by Sims (1980), who caution that differencing may obscure critical relationships. The focus on dynamic interactions over precise parameter estimates further supports this choice, consistent with the methodologies of Anzuini et al. (2013), Hammoudeh et al. (2015), and Belongia and Ireland (2016).

The SVAR models are estimated with one lag, as determined by the lag selection tests shown in Table 3.11.[3] Impulse response functions are computed with confidence intervals spanning two standard deviations (95 percent), and responses are deemed statistically significant if their confidence intervals exclude zero.[4] This methodology ensures a robust and theoretically consistent analysis of the variables' dynamic interactions and the underlying structural shocks.[5]

For both VECM and SVAR analyses, I use monthly data spanning three distinct monetary policy periods: the pre-ZLB period (July 1976–October 2008), the ZLB period (November 2008–November 2015), and the post-ZLB period (January 2015–June 2024). For conventional U.S. monetary policy, I use the EFFR, following Anzuini et al. (2013) and Hammoudeh et al. (2015). For unconventional monetary policy, I employ three proxies: MB, PFR, and the shadow rate (SR).

LSAPs directly expand MB by increasing central bank liabilities through reserve credits to financial institutions, reflecting the scale of these programs. The SR, introduced by Wu and Xia (2016), commonly used in empirical studies (e.g., Krippner, 2013; Christensen and Rudebusch, 2015; Bauer and Rudebusch, 2016; Wu and Xia, 2016; Von Borstel et al., 2016; Wu and Xia, 2020), captures monetary policy shocks, especially during periods of near-zero interest rates. It represents the nominal interest rate that would prevail if the ZLB did not exist and is typically derived from a financial model that assumes a shadow yield curve. Unlike the central bank's actual target rate, the SR reflects the implied short-term interest rate based on the entire term structure. Its main advantage, as noted by Rossi (2021), lies in its ability to account for various financial conditions, including private interest rates, the Fed's balance sheet, and the Taylor rule, making it a robust measure of unconventional monetary policy. The SR is particularly useful during ZLB periods, as it can take negative values to capture additional easing measures by the Fed. However, its availability extends only until February 2022.

[3] The results remain robust when two lags are used.

[4] Confidence intervals are generated using the "analytic (asymptotic)" method.

[5] In line with Glaister (1991), the VAR stability condition must be satisfied before performing impulse response analysis. To ensure stability, I confirm that the modulus of each eigenvalue of the matrix polynomial is strictly less than one. Once stability is verified, impulse response functions are generated.

The PFR, developed by Doh et al. (2016), provides another measure of the broader stance of U.S. monetary policy. This proxy incorporates 12 financial indicators, such as Treasury and mortgage rates, to gauge overall financial conditions. Using principal component analysis, these conditions are mapped to a hypothetical FFR, which tracks the actual rate until 2008. Afterward, it diverges, reflecting how financial conditions respond to additional tools like forward guidance and balance sheet actions. The PFR estimates the hypothetical FFR that would produce comparable financial conditions, assuming it were the sole monetary policy instrument in use.

For commodity prices, I use the Commodity Research Bureau (CRB) Spot Commodity Price Index, which tracks price trends across 19 major commodities and is widely referenced in studies on monetary policy and commodity markets (e.g., Frankel, 2008; Browne and Cronin, 2010; Anzuini et al., 2013; Belke et al., 2014; Cabrales et al., 2014). It is made up of agriculture commodities (41 percent), energy commodities (39 percent), industrial metals (13 percent), and precious metals (7 percent). The CRB index is designed to separate out and reflect the general direction of price movement in commodity trades. One advantage of using commodity groups rather than individual commodity prices is that idiosyncratic factors affecting individual commodity markets should have far less impact at the level of a broadly based index (Browne and Cronin, 2010).

In addition to the previously mentioned variables, both models incorporate the industrial production index (IPI), private sector final consumption expenditure (PCE), consumer price index (CPI), real money stock (M1), and the yield spread between 10-year and 2-year Treasury securities (Y10M2Y). Including these variables aligns with standard practice in empirical studies utilizing VAR models to assess the effects of monetary policy shocks on economic indicators (e.g., Kim, 1999; Anzuini et al., 2013; Reicher and Utlaut, 2013; Hammoudeh et al., 2015). While most variables are expressed in natural logarithms, exceptions include EFFR, SR, PFR, and Y10M2Y, as these are rates for which logarithmic transformation is not applicable.

In the SVAR model, I also use the Federal Government Current Expenditures (GCE) variable to validate the robustness of the results when incorporating a proxy for fiscal policy. Since this variable is available only at a quarterly frequency, I converted it to monthly data using forward-filling. This method involves filling missing months by carrying forward the most recent value from the previous quarter, ensuring each month has a value without creating new data, by repeating the last observed value until the next quarter.

In the VECM framework, I also include the Dow Jones Industrial Average (DJIA) and the real broad effective exchange rate (REER) for the United States to capture additional dimensions of economic and financial dynamics. The DJIA serves as a proxy for stock market performance, reflecting investor sentiment and broader economic expectations. Meanwhile, the REER measures the value of the U.S. dollar against a basket of currencies, adjusted for inflation differentials, providing insights into the competitiveness of U.S. goods and services in global markets. These variables enrich the analysis by integrating both domestic financial market conditions and international trade competitiveness into the model.

For the event study regression, this study utilizes the monetary policy sentiment shocks extracted in Chapter 2. These sentiment shocks were derived through a detailed analysis of newspaper articles surrounding FOMC meetings. This data aims to assess the relationship between these sentiment-driven monetary policy shocks and commodity market fluctuations. It spans all scheduled FOMC meetings from February 2000 to May 2024, comprising a total of 194 observations.

The event study regression utilizes a set of control variables—the Japanese Yen to U.S. Dollar exchange rate (DEXJPUS), the ICE BofA US High Yield Index Option-Adjusted Spread (HYIELD), the Market Yield on U.S. Treasury Securities at 5-Year Constant Maturity (DGS5), and Moody's Seasoned Aaa Corporate Bond Yield (DAAA)—each expressed as the log daily change from the prior day's closing price to the FOMC statement release day. Including these controls improve the model's explanatory power and ensures that the observed effects of sentiment shocks are robust and reliable.[6]

3.4 Empirical Methodologies

The empirical methodology in this study combines robust econometric techniques to analyze the dynamic interactions among key variables and uncover structural relationships. Initially, stationarity and cointegration tests guide the use of a VECM to capture long-term relationships. To delve deeper into structural shocks, this study employs an SVAR model, utilizing both recursive (e.g., Sims, 1980; Hammoudeh et al., 2015; Belongia and Ireland, 2016) and non-recursive identification strategies (e.g., Kim, 2003; Anzuini et al., 2013; Belongia and Ireland, 2016). Building on this, this study integrates an event study approach, leveraging sentiment-driven monetary policy shocks to address one of the most elusive qualitative aspects of unconventional monetary policy—forward guidance. This

[6]The results remain consistent even when additional controls, such as stock market prices and volatility indices, are included.

forward guidance framework is further dissected into three critical components: IRG, BSP, and EOA, ensuring a comprehensive understanding of its multifaceted impact.

3.4.1 Vector Error Correction Model (VECM)

The VECM is a specialized version of the VAR model developed to address non-stationary time series that exhibit cointegration. It ensures that the long-term behavior of endogenous variables aligns with their cointegrating relationships while maintaining flexibility in capturing short-term dynamics. Empirical and simulation studies consistently demonstrate the superior forecasting performance of the VECM compared to standard VAR models (e.g., Engle and Yoo (1987)). The cointegration term, known as the Error Correction Term (ECT), captures deviations from the long-run equilibrium, which are gradually corrected through partial short-term adjustments.

The general form of a VECM is expressed as:

$$\Delta y_t = \beta_0 + \sum_{i=0}^{p} \Gamma_i \Delta x_{t-i} + \sum_{i=0}^{p} \mu_i \Delta y_{t-i} - \lambda ECT_{t-1} + \varepsilon_t \tag{3.1}$$

where:

$$ECT_{t-1} = y_{t-1} - \alpha - \beta x_{t-1} \tag{3.2}$$

Here, $y_t = \alpha + \beta x_t$ represents the long-run cointegrating relationship between two variables, and λ denotes the error correction parameter, capturing the speed of adjustment back to equilibrium.

During the pre-ZLB period, when conventional monetary policy was the primary tool, the VECM specification is as follows:

$$\begin{aligned} \Delta CRB_t = \beta_0 &+ \sum_{i=0}^{p} \delta_i \Delta CRB_{t-i} + \sum_{i=0}^{p} \gamma_i \Delta IPI_{t-i} + \sum_{i=0}^{p} \eta_i \Delta CPI_{t-i} \\ &+ \sum_{i=0}^{p} \pi_i \Delta EFFR_{t-i} + \sum_{i=0}^{p} \nu_i \Delta REER_{t-i} + \sum_{i=0}^{p} \theta_i \Delta Y10M2Y_{t-i} + \sum_{i=0}^{p} \sigma_i \Delta DJIA_{t-i} - \lambda ECT_{t-1} + \varepsilon_t \end{aligned} \tag{3.3}$$

where:

$$\begin{aligned} ECT_{t-1} = CRB_{t-1} - \alpha - \beta_1 IPI_{t-1} - \beta_2 CPI_{t-1} - \beta_3 EFFR_{t-1} \\ - \beta_4 REER_{t-1} - \beta_5 Y10M2Y_{t-1} - \beta_6 DJIA_{t-1} \end{aligned} \tag{3.4}$$

During the ZLB period, when unconventional monetary policy tools were utilized, the VECM specification is as follows:

$$\Delta CRB_t = \beta_0 + \sum_{i=0}^{p} \delta_i \Delta CRB_{t-i} + \sum_{i=0}^{p} \gamma_i \Delta IPI_{t-i} + \sum_{i=0}^{p} \eta_i \Delta CPI_{t-i} \\ + \sum_{i=0}^{p} \pi_i \Delta PFR_{t-i} + \sum_{i=0}^{p} \nu_i \Delta REER_{t-i} + \sum_{i=0}^{p} \theta_i \Delta Y10M2Y_{t-i} + \sum_{i=0}^{p} \sigma_i \Delta DJIA_{t-i} - \lambda ECT_{t-1} + \varepsilon_t \quad (3.5)$$

where:

$$ECT_{t-1} = CRB_{t-1} - \alpha - \beta_1 IPI_{t-1} - \beta_2 CPI_{t-1} - \beta_3 PFR_{t-1} \\ - \beta_4 REER_{t-1} - \beta_5 Y10M2Y_{t-1} - \beta_6 DJIA_{t-1} \quad (3.6)$$

In the post-ZLB period, where both conventional and unconventional monetary policies are employed, the VECM specification is as follows:

$$\Delta CRB_t = \beta_0 + \sum_{i=0}^{p} \delta_i \Delta CRB_{t-i} + \sum_{i=0}^{p} \gamma_i \Delta IPI_{t-i} + \sum_{i=0}^{p} \eta_i \Delta CPI_{t-i} \\ + \sum_{i=0}^{p} \pi_i \Delta EFFR_{t-i} + \sum_{i=0}^{p} \varsigma_i \Delta MB_{t-i} + \sum_{i=0}^{p} \nu_i \Delta REER_{t-i} \\ + \sum_{i=0}^{p} \theta_i \Delta Y10M2Y_{t-i} + \sum_{i=0}^{p} \sigma_i \Delta DJIA_{t-i} - \lambda ECT_{t-1} + \varepsilon_t \quad (3.7)$$

where:

$$ECT_{t-1} = CRB_{t-1} - \alpha - \beta_1 IPI_{t-1} - \beta_2 CPI_{t-1} - \beta_3 EFFR_{t-1} \\ - \beta_4 MB_{t-1} - \beta_5 REER_{t-1} - \beta_6 Y10M2Y_{t-1} - \beta_7 DJIA_{t-1} \quad (3.8)$$

3.4.2 Structural Vector Autoregressive (SVAR) Model

A key limitation of standard VAR models lies in their inability to capture contemporaneous relationships between the variables under analysis. This limitation becomes particularly problematic in impulse response analysis, where understanding the immediate effects of an economic shock is crucial. A viable alternative is the use of SVAR models, which directly model the interactions between contemporaneous variables, providing a more accurate depiction of these relationships:

$$\mathbf{A(L)Z_t = A_0Z_t + A_1Z_{t-1} + ... + A_{\rho}Z_{t-\rho} = c} + \epsilon_\mathbf{t} \tag{3.9}$$

$$\mathbf{u_t = A_0^{-1}}\epsilon_\mathbf{t} \tag{3.10}$$

In this framework, $\boldsymbol{Z_t}$ represents the vector of endogenous variables at time t, while $\boldsymbol{A_0}$ denotes the contemporaneous coefficient matrix. The term $\boldsymbol{A(L)}$ refers to an $n \times n$ polynomial matrix in the lag operator L, and $\boldsymbol{c}$ is a vector of constants. Additionally, $\boldsymbol{\epsilon_t}$ captures the vector of shocks to economic fundamentals, $\boldsymbol{u_t}$ represents the vector of VAR innovations, and n corresponds to the number of variables in the system.

This study uses the SVAR model with two different identification strategies to the monetary policy shocks. One popular approach follows Sims (1980) by requiring the contemporaneous matrix to be lower triangular. This approach is well-known as the recursive SVAR approach. The second approach follows Kim (2003) and Anzuini et al. (2013), which is based on non-recursive restrictions.

The approach of using these two identification strategies is similar to that of Belongia and Ireland (2016), who investigated the impact of monetary policy shocks on some macroeconomic variables by employing recursive and non-recursive structural VAR models, where the results show important differences, in general, across the model estimated with the triangular identification scheme and the model estimated with the interest rate-money rule for monetary policy.

Recursive Structural VAR

The first identification strategy employed to examine the impact of U.S. monetary policy shocks, both conventional and unconventional, on commodity prices is the recursive approach. This method relies on a predetermined ordering of variables, where certain variables, such as interest rates, are adjusted first, while other economic variables respond with a lag. The recursive approach assumes a hierarchical structure in which monetary policy changes, primarily through interest rates, influence the broader economy sequentially.

In the recursive identification scheme, the variables in vector $\mathbf{Z_t}$ can be separated into 3 groups: (i) slow-moving variables ($\mathbf{X_{1t}}$): a subset of $n1$ variables that do not respond contemporaneously to the monetary policy shock; (ii) i_t: the monetary policy instrument; and (iii) fast-moving variables ($\mathbf{X_{2t}}$): a subset of $n2$ variables that respond contemporaneously to the monetary policy shock. Therefore, the recursive assumptions can be summarized by $\mathbf{Z_t = [X_{1t}, i_t, X_{2t}]'}$ and

$$\boldsymbol{A_0} = \begin{bmatrix} \underbrace{\boldsymbol{A_{11}}}_{n1*n1} & \underbrace{\mathbf{0}}_{n1*1} & \underbrace{\mathbf{0}}_{n1*n2} \\ \underbrace{\boldsymbol{A_{21}}}_{1*n1} & \underbrace{\boldsymbol{A_{22}}}_{1*1} & \underbrace{\mathbf{0}}_{1*n2} \\ \underbrace{\boldsymbol{A_{31}}}_{n2*n1} & \underbrace{\boldsymbol{A_{32}}}_{n2*1} & \underbrace{\boldsymbol{A_{33}}}_{n2*n2} \end{bmatrix} \tag{3.11}$$

For the recursive approach, the slow-moving variables ($\mathbf{X_{1t}}$) include IPI, PCE, and CPI, in that order. The policy instrument is represented by one of the following: EFFR, PFR, SR, or MB. The fast-moving variables ($\mathbf{X_{2t}}$) consist of RM1, Y10M2Y, and CRB, also in that order, under the assumption that commodity prices respond contemporaneously to all sources of shocks. Consequently, the vector of endogenous variables can be expressed as:

$$\mathbf{Z_t} = [\overbrace{IPI_t, PCE_t, CPI_t}^{\boldsymbol{X_{1t}}}, \overbrace{Policy\ Instrument_t}^{\boldsymbol{i_t}}, \overbrace{RM1_t, Y10M2Y, CRB_t}^{\boldsymbol{X_{2t}}}]' \tag{3.12}$$

Non-recursive Structural VAR

Unlike the recursive approach, the non-recursive method does not impose a strict sequence or ordering of variables, allowing for a broader range of interactions between monetary policy tools and the overall economy. Following Kim (2003) and Anzuini et al. (2013), the vector of endogenous variables, $\mathbf{Z_t}$, and the contemporaneous coefficient matrix, $\mathbf{A_0}$ is as follows:

$$\mathbf{Z_t} = [Policy\ Instrument_t, RM1_t, CPI_t, IPI_t, CRB_t]' \tag{3.13}$$

where the contemporaneous matrix is:

$$\boldsymbol{A_0} = \begin{bmatrix} 1 & a_{12} & 0 & 0 & a_{15} \\ a_{21} & 1 & a_{23} & a_{24} & 0 \\ 0 & 0 & 1 & a_{34} & 0 \\ 0 & 0 & 0 & 1 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & 1 \end{bmatrix} \tag{3.14}$$

According to Anzuini et al. (2013), the first row represents the money supply equation, which models the reaction function of the monetary authority. It is assumed that the monetary authorities do not have contemporaneous access to current levels of prices and output. The second row represents a money demand equation, where the demand for money depends on the real income and the interest rate.

The third and fourth rows in the matrix capture key macroeconomic assumptions: the third row reflects price stickiness, indicating that CPI adjusts contemporaneously only to real activity (IPI) due to rigidities like contracts or menu costs, while the fourth row represents adjustment costs, suggesting that real activity responds gradually to monetary policy and other shocks due to production and investment frictions. The last row captures the arbitrage equation which describes equilibrium in the commodity market as financial market equilibrium. It is assumed again that the commodity prices respond contemporaneously to all variables in the model.

3.4.3 Event Study

The event study regression is specified as follows:

$$\Delta CRB_t = \beta_0 + \beta_1 IRG_t^{Shock} + \beta_2 BSP_t^{Shock} + \beta_3 EOA_t^{Shock} + \beta_5 \text{Controls}_t + \varepsilon_t \tag{3.15}$$

This regression evaluates the impact of monetary policy sentiment shocks, as derived in Chapter 2, on commodity prices. Specifically, three types of shocks—IRG, BSP, and EOA—are considered.[7] These shocks are extracted by analyzing shifts in media sentiment surrounding FOMC meetings, comparing "before-meeting" sentiment, which reflects pre-meeting expectations, to "after-meeting" sentiment, which captures post-announcement reactions. A dictionary-based sentiment analysis, employing tailored lexicons, identifies hawkish or dovish signals within media narratives. The shocks, represented by the residuals, capture unexpected changes introduced during FOMC meetings, disaggregated into the three forward guidance components to provide nuanced insights into their distinct impacts on public and market sentiment.

IRG captures the Federal Reserve's forward-looking communication about the future trajectory of interest rates. It reflects expectations regarding policy adjustments, such as rate hikes or cuts, and serves as a tool to guide market perceptions about the central bank's stance on inflation and economic conditions. The sentiment associated with interest rate

[7] The shocks are derived using the FFR specification, regressing the after-meeting sentiment index on the before-meeting sentiment index, controlling for the previous after-meeting index and the actual change in the FFR. The residuals from this regression represent the monetary policy sentiment shocks. Details of the exogeneity tests for these shocks are provided in Appendix C of Chapter 2.

guidance is critical in shaping immediate market expectations, particularly borrowing costs and bond yields, by providing a clearer outlook on monetary policy intentions.

BSP capture the Federal Reserve's stance on its asset holdings and liquidity management. These policies communicate the central bank's intentions regarding quantitative easing or tightening, which significantly affect liquidity in financial markets. Sentiment surrounding balance sheet policies indicates the anticipated direction of liquidity changes, with tightening reducing liquidity and signaling a restrictive stance, while easing suggests an expansionary approach. This dimension of monetary policy has far-reaching implications for long-term asset prices and market stability.

EOA captures the Federal Reserve's evaluation of economic conditions, encompassing growth, employment, and inflation. The sentiment reflects broader expectations about the economy's health and resilience, influencing market confidence and stock prices. Optimistic economic outlook sentiment aligns with expectations of stability and growth, whereas pessimistic sentiment raises concerns about economic downturns, unemployment, or inflationary pressures. This assessment provides a broader perspective on the Fed's view of economic conditions and its potential policy responses.

The regression incorporates key control variables—DEXJPUS, HYIELD, DGS5, and DAAA—each expressed as the log daily change from the prior day's closing price to the FOMC statement release day. DEXJPUS accounts for currency fluctuations that influence the prices of globally traded commodities, typically denominated in U.S. dollars. HYIELD reflects credit market conditions and changes in investor risk appetite or liquidity, which can indirectly impact commodity demand. DGS5 captures variations in medium-term interest rates, signaling shifts in broader economic expectations. DAAA serves as a proxy for corporate borrowing costs, with higher yields indicating tighter financial conditions that could suppress industrial and commodity-related activities. These controls ensure that the analysis isolates the effects of monetary policy shocks on commodity prices while accounting for significant financial market influences.

The inclusion of these controls based on studies on the impact of monetary policy surprises on financial indicators (e.g., Baker et al., 2016, Strohsal et al., 2016, Swanson, 2021, Tadle, 2022, Gorodnichenko et al., 2023, and others) and to ensure that the effects of sentiment shocks on commodity prices are accurately isolated by accounting for other relevant financial indicators and historical data.

3.5 Transmission Channels

Monetary policy affects commodity prices through well-established transmission mechanisms, as documented extensively in the literature. Frankel (2008) identifies three primary channels: the inventory channel, the supply channel, and the financial market channel.

The inventory channel explains how monetary policy impacts the opportunity cost of holding inventories. When interest rates are low, as under expansionary monetary policy, the cost of holding inventory decreases, encouraging firms to accumulate more stock. This increased demand for commodities like oil drives prices upward. Empirical evidence by Anzuini et al. (2013) supports this channel, finding that real interest rates are significantly and negatively correlated with oil prices, even after controlling for industrial production, risk indices, and the spot-future price spread.

The supply channel highlights the impact of interest rates on resource extraction decisions. Low interest rates reduce the incentive for producers to extract oil immediately, as the opportunity cost of leaving resources in the ground decreases. This deferral of extraction reduces current supply, putting upward pressure on prices. This behavior aligns with the Hotelling rule (Hotelling, 1931), which demonstrates how extraction rates are influenced by the cost of capital and expected future prices. Anzuini et al. (2013) find that loose monetary policy encourages delayed extraction, thereby constraining supply and elevating commodity prices.

The financial market channel reflects the reallocation of investments prompted by monetary policy. Lower interest rates encourage investors to shift from fixed-income securities to commodities as alternative investments or hedges against inflation. This increased speculative demand raises futures prices, which, through arbitrage, also elevate spot prices. As Rosa (2014) demonstrate, monetary policy surprises, including unexpected rate changes and asset purchase announcements, have significant effects on crude oil prices by altering investor behavior in futures markets.

Building on these channels, monetary policy sentiment shocks provide an additional dimension for understanding the transmission of monetary policy to commodity prices. These shocks are categorized into IRG, BSP, and EOA shocks. IRG shocks represent shifts in the central bank's future policy stance, influencing expectations of borrowing costs and economic conditions. Hawkish IRG shocks, signaling higher future interest rates, suppress borrowing and reduce commodity demand, thereby lowering prices. Conversely, dovish IRG shocks stimulate borrowing and economic activity, increasing demand and raising prices. These effects are consistent with the findings of Frankel (1984), who demonstrate that lower interest rates reallocate investor preferences toward commodities, boosting their prices.

BSP shocks operate through liquidity and risk-taking channels. Expansionary BSP measures, such as quantitative easing, increase liquidity and reduce credit spreads, encouraging speculative and hedging activities that elevate commodity prices. Contractionary BSP measures, like quantitative tightening, restrict liquidity, diminishing speculative investments and lowering prices. This channel also alters broader financial market conditions, including risk premia, further influencing commodity markets (Anzuini et al., 2013).

EOA shocks capture sentiment regarding future economic conditions and directly influence commodity demand expectations. Positive EOA shocks, reflecting optimism about economic growth, raise expectations of future commodity demand, driving prices upward. Conversely, negative EOA shocks, signaling weaker economic prospects, suppress demand expectations and reduce prices. This underscores the critical role of expectations in shaping commodity price dynamics (Rosa, 2014).

3.6 Empirical Results: VECM and SVAR

This section presents the findings from the VECM and SVAR analyses. I begin with the VECM results, which explore the cointegration relationships to illuminate the long-term equilibrium dynamics among the variables. Next, I present the SVAR model results, highlighting its ability to capture dynamic relationships and contemporaneous interactions among variables through theoretically derived structural shocks.

In both models, the EFFR represents conventional monetary policy, while MB, SR, and PFR serve as proxies for unconventional monetary policy. In the SVAR model, a positive shock to the EFFR signifies a contractionary stance, whereas a negative shock indicates an expansionary stance. For unconventional policies, positive shocks to SR and PFR imply a contractionary stance, while negative shocks suggest an expansionary stance. Conversely, a positive shock to MB reflects an expansionary stance, while a negative shock indicates a contractionary stance. Table 3.12 provides a detailed summary of the exercises conducted within the SVAR framework.

A comparative summary of the estimated effects across policies is provided in Table 3.1, which outlines both long-run and short-run responses of commodity prices to conventional and unconventional monetary policy shocks.

Table 3.1: Summary of long-run (LR) and short-run (SR) effects of conventional and unconventional monetary policy shocks on commodity prices across different periods.

Period	Conventional MP		Unconventional MP		Shock
	LR	SR	LR	SR	
Pre-ZLB	↓ 3.66%	↓ 5% (persistent)	-	-	1 pp ↑ EFFR
ZLB	-	-	↑ 47.65%	↑ 20% (6 mos, lasts 2 ys)	1 pp ↓ PFR
Post-ZLB	↓ 2.61%	↓ 4% (3 ys)	-	-	1 pp ↑ EFFR (MB const.)
	-	-	↑ 4.3%	↑ 5%	5% ↓ MB (EFFR const.)

3.6.1 Pre-ZLB Period

I begin by evaluating the impact of conventional monetary policy on commodity prices and other macroeconomic variables during the pre-ZLB period. For the VECM results, the error correction term (ECT), which measures the speed of adjustment towards long-run equilibrium, is negative and statistically significant (-0.21 with t-statistics of -4.567). This indicates the existence of a long-run causal relationship. The ECT coefficient implies that approximately 21 percent of the deviation of the commodity price index from its long-term equilibrium is corrected every month. Consequently, it takes slightly more than four months for the commodity price index to return close to its long-term equilibrium, assuming a linear adjustment process.

Based on the results listed in Table 3.13, the long-run relationship equation can be written as:[8]

$$\begin{aligned} CRB_t = \underset{(0.7534)}{4.1271}\, IPI_t + \underset{(0.4396)}{2.7318}\, CPI_t - \underset{(0.0180)}{0.0366}\, EFFR_t + \underset{(0.3703)}{1.7564}\, REER_t \\ + \underset{(0.0234)}{0.0936}\, Y10M2Y_t + \underset{(0.0960)}{0.6296}\, DJ_t - 41.32C \end{aligned} \tag{3.16}$$

The results show that the EFFR has a statistically significant negative long-run relationship with CRB, where a 1 pp increase in EFFR corresponds to a 3.66 percent decrease in CRB. Higher interest rates reduce borrowing, increase the opportunity cost of holding inventories, strengthen the dollar (making commodities costlier globally), and deter speculative activity, all of which lower commodity prices. The IPI and CPI exhibit strong positive long-run elasticities with CRB. A 1 percent increase in IPI is associated with a 4.13 percent increase in CRB, while a 1 percent increase in CPI is linked to a 2.73 percent

[8]The VECM is estimated using the Maximum Likelihood method within the Johansen cointegration framework, typically under the assumption of normally distributed error terms.

rise in CRB. These results highlight the procyclical nature of commodity prices, driven by expanding economic activity and inflationary pressures. This also highlight the sensitivity of commodity prices to inflation, which reinforces their role in macroeconomic stability. As economic output grows (via IPI), the demand for raw materials rises, boosting commodity prices. Similarly, higher CPI reflects increased production costs and inflationary expectations, which directly and indirectly elevate commodity prices, consistent with their role as both economic inputs and inflation hedges.

The REER shows a positive long-run elasticity with the CRB, where a 1 percent increase in REER corresponds to a 1.76 percent rise in CRB. This reflects the strong link between REER and commodity prices, as many commodities are priced in dollars. A stronger REER signals robust demand, higher currency purchasing power, and global liquidity, driving up commodity prices. The 1.76 percent elasticity highlights the close interplay between exchange rates, trade, and commodity markets.

Additionally, the DJIA exhibits a significant positive relationship with CRB, reflecting the interconnectedness of financial markets and commodity prices. A robust equity market, as indicated by a rising DJIA, often signals strong economic growth, which drives higher commodity demand. Lastly, the term spread (Y10M2Y) has a positive, albeit modest, impact on CRB, with growth expectations (captured by an upward-sloping yield curve) supporting commodity price increases in the long run.

For the SVAR results, Figure 3.1 illustrates the impulse response functions (IRFs) for a conventional monetary policy shock, defined as a 1 pp increase in the EFFR, estimated using the recursive approach over a 50-month horizon (July 1976–October 2008). The CRB index shows a significant and persistent decline, reaching a trough of 5 percent after two years, indicating that higher interest rates reduce borrowing, consumer spending, and industrial demand for commodities like energy, metals, and agriculture. This prolonged decline, with prices remaining below pre-shock levels even after four years, highlights the lasting contractionary effects of tighter monetary policy on commodity markets. These results align with the findings of Anzuini et al. (2013) but contrast with Hammoudeh et al. (2015), who report a positive effect of contractionary policy. They also reinforce the broader perspective of strong and persistent monetary policy impacts on commodity markets, as noted by Frankel (2008) and Anzuini et al. (2013).

Following the monetary policy shock, IPI shows a sharp decline, reaching a trough of 2 percent after two years before gradually recovering, highlighting the contractionary effects of higher interest rates on economic activity. PCE also declines, though less severely, stabilizing after approximately 15 months as consumption adjusts more gradually. The

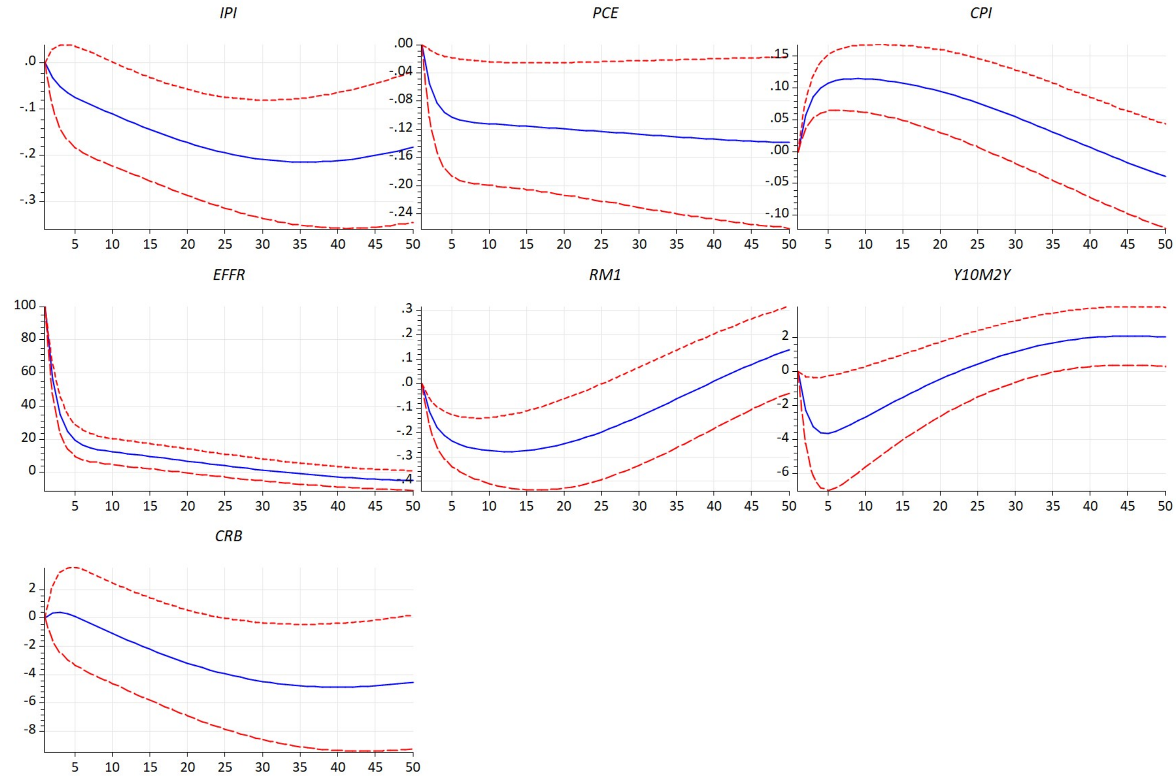

Figure 3.1: IRFs to a 100-basis-point increase in the EFFR using a recursive approach during pre-ZLB period. The solid line shows the impulse response, while the dashed lines represent the 95 percent confidence interval computed using the analytic (asymptotic) method.

CPI exhibits a delayed response, with a slight initial rise followed by a gradual decline, reflecting short-term price stickiness and a later contraction in aggregate demand. The RM1 decreases sharply and remains low, indicating reduced demand for money due to higher interest rates. Lastly, the Y10M2Y flattens, suggesting expectations of slower future growth or eventual rate cuts as long-term rates rise less dramatically than short-term rates.

These IRFs align with conventional macroeconomic theory, showing that a contractionary monetary policy shock leads to reduced economic activity, lower inflation, and falling commodity prices. While real variables such as IPI and PCE experience long-lasting negative effects, financial indicators adjust more rapidly in response to the policy shift.

3.6.2 ZLB Period

The VECM results reveal that the ECT is negative and statistically significant (-0.0963, t-statistic: -6.324), confirming the existence of a long-run causal relationship. The ECT coefficient indicates that around 9.63 percent of the deviation of the CRB Index from its long-term equilibrium is corrected each month. As a result, the commodity price index requires just over 10 months to approach its long-term equilibrium, assuming a linear adjustment process.

Based on the results in Table 3.14, the long-run relationship equation can be written as:

$$
\begin{aligned}
CRB_t = \underset{(1.7826)}{1.4441}\, IPI_t - \underset{(1.5456)}{9.2256}\, CPI_t - \underset{(0.0521)}{0.4765}\, PFR_t + \underset{(0.6654)}{1.4990}\, REER_t \\
- \underset{(0.0497)}{0.3303}\, Y10M2Y_t + \underset{(0.4316)}{0.4917}\, DJ_t + 38.8885C \qquad (3.17)
\end{aligned}
$$

The PFR exhibits a statistically significant negative long-run relationship with the CRB, with a 1 percentage point decrease in the PFR associated with a substantial 47.65 percent increase in the CRB. This result underscores the powerful expansionary effects of unconventional monetary policy during the ZLB period. The pronounced response highlights the role of liquidity injections and lowered borrowing costs in stimulating speculative and fundamental demand for commodities. A 1 percent rise in IPI increases CRB by 1.44 percent, while a 1 percent rise in CPI decreases CRB by 9.23 percent, reflecting inflation driven by non-commodity sectors and subdued commodity demand. The REER has a positive elasticity, with a 1 percent rise increasing CRB by 1.50 percent, while the DJIA shows a modest 0.49 percent increase in CRB for a 1 percent rise. Finally, the Y10M2Y exhibits a negative relationship, where a 1 percent increase reduces CRB by 0.33 percent, signaling the influence of growth expectations and market sentiment on commodity prices.

During the pre-ZLB period, the faster adjustment speed (ECT: -0.21) and stronger elasticities underscore the effectiveness of conventional monetary policy tools, such as interest rate adjustments, in stabilizing commodity prices. The procyclical relationship between economic activity and commodity demand is evident, as variables like industrial production and inflation exhibit positive elasticities with commodity prices. Inflationary pressures and growth expectations during this period directly drove commodity prices upward, reflecting the stability and predictability of conventional monetary mechanisms in a well-understood macroeconomic environment.

In contrast, the ZLB period reveals the challenges of unconventional monetary tools like quantitative easing and forward guidance, reflected in slower adjustment speeds (ECT: -0.0963) and weakened or reversed elasticities. These tools operate through indirect and less predictable channels, such as liquidity injections and market expectations. Notably, CPI displayed a negative relationship with commodity prices, likely due to subdued economic growth and weaker purchasing power, while the term spread (Y10M2Y) exhibited a negative elasticity, signaling heightened market uncertainty. The shift in the term spread's impact from positive in the pre-ZLB period to negative in the ZLB period highlights the evolving dynamics of monetary policy transmission, where unconventional tools altered market sentiment and expectations about economic recovery and policy effectiveness.

Figure 3.2 illustrates the IRFs resulting from an expansionary unconventional monetary policy shock, defined as a 1 pp reduction in the PFR, during the ZLB period (November 2008 to November 2015). The CRB index exhibits a pronounced response, rising sharply to a peak of 20 percent within six months before gradually normalizing. The impact of the PFR shock on IPI and PCE shows a strong positive response. Both experience a steady increase, with IPI reflecting the boost to industrial output from improved credit conditions and heightened demand, while PCE indicates enhanced consumer spending due to lower borrowing costs. The CPI also responds positively, with inflationary effects becoming evident as aggregate demand increases, demonstrating the gradual pass-through of expansionary policies to prices. The yield spread (Y10M2Y) flattens significantly, reflecting a substantial rise in short-term rates relative to long-term rates. This suggests market expectations of subdued future growth or a prolonged period of monetary accommodation.

3.6.3 Post-ZLB Period

The VECM results reveal a negative and statistically significant ECT coefficient (-0.0440, t-statistic: -3.574), confirming the existence of a long-run causal relationship. This coefficient indicates that about 4.4 percent of the deviation of the CRB from its long-term equilibrium is corrected monthly. As a result, the commodity price index requires just over 22 months to approach its equilibrium, assuming a linear adjustment process.

Based on the results in Table 3.15, the long-run relationship equation can be written as:

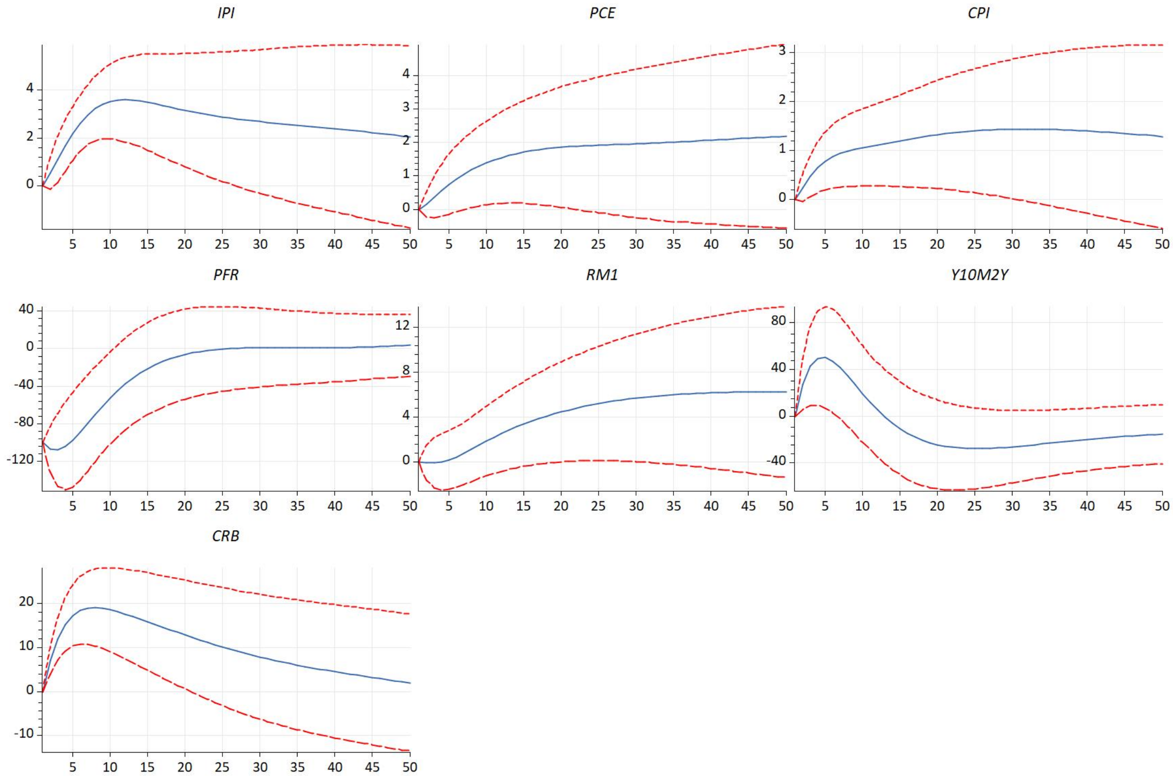

Figure 3.2: IRFs to a 100-basis-point decrease in the PFR by applying the recursive approach during ZLB period. The solid line shows the impulse response, while the dashed lines represent the 95 percent confidence interval computed using the analytic (asymptotic) method.

$$
\begin{aligned}
CRB_t = \underset{(1.0866)}{3.1043}\, IPI_t - \underset{(1.5114)}{6.7289}\, CPI_t - \underset{(0.0339)}{0.0261}\, EFFR_t + \underset{(0.1526)}{0.8574}\, MB_t \\
+ \underset{(0.9544)}{2.7350}\, REER_t - \underset{(0.0529)}{0.2804}\, Y10M2Y_t + \underset{(0.2215)}{0.8280}\, DJ_t - 4.0883C \quad (3.18)
\end{aligned}
$$

The MB exhibits a statistically significant positive long-run relationship with the CRB, with a 1 percent increase in MB leading to a 0.86 percent rise in CRB. This finding suggests that balance sheet expansions bolster commodity prices by enhancing liquidity and raising inflationary expectations. The IPI and CPI display contrasting elasticities with the CRB. A 1 percent rise in IPI corresponds to a 3.10 percent increase in CRB, while a 1 percent rise in CPI results in a 6.73 percent decrease in CRB, suggesting that inflation during this period disproportionately affected non-commodity sectors, reducing real demand for commodities.

The contrasting relationship between CPI and CRB in the post-ZLB period, where inflation negatively impacts commodity prices, likely stems from structural changes in commodity markets and the shifting dynamics of monetary policy transmission after the ZLB period. Unlike the pre-ZLB period, where inflation positively influenced commodity prices through demand-driven pressures, the post-ZLB period was characterized by unique economic conditions. During this time, inflation may have been less reflective of robust economic activity and more indicative of cost-push factors, such as supply chain disruptions or rising energy costs, which disproportionately impacted non-commodity sectors. This dynamic could have constrained real income and purchasing power, reducing overall demand for commodities.

Additionally, the post-ZLB period saw a partial return to conventional monetary policies alongside the continuation of balance sheet policies, creating a mixed-policy environment. Conventional interest rate hikes, aimed at containing inflation, may have tightened financial conditions more broadly, dampening speculative and demand-driven investments in commodities. The combination of these structural market shifts and policy dynamics highlights how inflation's influence evolved, transitioning from a driver of commodity demand in the pre-ZLB period to a suppressor in the post-ZLB period. These results underscore the importance of contextualizing economic relationships within the broader framework of changing monetary regimes and market structures.

The REER shows a positive long-run elasticity with the CRB, where a 1 percent increase in REER leads to a 2.74 percent rise in CRB. Similarly, the DJIA exhibits a statistically significant positive relationship, with a 1 percent increase in DJIA associated with a 0.83 percent rise in CRB. In contrast, the term spread (Y10M2Y) has a statistically significant negative relationship, where a 1 percent increase in Y10M2Y results in a 0.28 percent decrease in CRB.

In the post-ZLB period, the adjustment speed (ECT: -0.044) was the slowest across all periods, reflecting the complexities of managing a mixed-policy environment with both conventional and unconventional tools and highlighting lingering uncertainties in policy effectiveness. While the procyclical relationship between IPI and commodity prices partially recovered (3.10 percent) compared to the ZLB period (1.44 percent), it remained below the pre-ZLB level (4.13 percent), reflecting weaker economic activity. CPI elasticity, shifting from positive (2.73 percent) in the pre-ZLB period to negative (-6.73 percent) in the post-ZLB period, indicates ongoing subdued commodity demand under inflationary pressures. The term spread (Y10M2Y) exhibited a consistent negative relationship (-0.28 percent), signaling market uncertainties, while REER's influence grew significantly (2.74 percent), emphasizing the increased sensitivity of commodity prices to exchange rate fluctuations. These shifts underscore the evolving dynamics of monetary policy transmission and their implications for commodity price behavior across different economic regimes.

In the SVAR model for the post-ZLB period, I incorporate proxies for both conventional (represented by EEFR) and unconventional (represented by MB) monetary policies within the same system. I begin by imposing a conventional monetary policy shock (EFFR) while holding the unconventional shock (MB) and other shocks in the system constant. Next, I reverse the approach by imposing an unconventional monetary policy shock (MB), keeping the conventional shock (EFFR) and all other shocks in the system constant.

Figure 3.3 illustrates a significant decline in the CRB index following an EFFR increase, reaching a trough of 5 percent two years after the shock before gradually recovering. This pattern aligns with findings from the pre-ZLB period. Similarly, variables like IPI and PCE show substantial declines, reflecting a broader economic slowdown triggered by monetary tightening. The MB and yield spread (Y10M2Y) also decrease, highlighting the contraction in liquidity and tighter financial conditions.

Figure 3.4 illustrates the dynamic responses of key economic variables to a 5 percent contractionary shock in the MB during the post-ZLB period. This shock is imposed while holding the EFFR shock constant, ensuring that the observed responses isolate the effects of the unconventional monetary policy measure. The contractionary MB shock results in a substantial drop in the CRB, with a trough occurring around six months after the shock. This response reflects reduced demand for commodities, consistent with the observed decline in economic activity. Interestingly, the CRB begins to recover after its initial decline, suggesting that commodity prices adjust to new equilibrium levels over the medium term.

The monetary tightening also leads an immediate decline in IPI, with the effect intensifying in the first few months following the shock. This contraction reflects the adverse impact of reduced monetary base liquidity on production and economic activity. Similarly, PCE declines following the shock, indicating reduced consumer spending, likely driven by tighter credit conditions and diminished economic confidence. Over time, both IPI and PCE exhibit a slow recovery, suggesting the temporary nature of the shock's impact. Inflationary dynamics, captured by the CPI, reveal an initial downward pressure on prices. The CPI response suggests that the monetary tightening reduces aggregate demand, exerting a deflationary effect. However, the CPI begins to stabilize after approximately 10 months, reflecting potential price-level adjustments as the economy adapts to the shock. The yield spread (Y10M2Y) initially narrows following the shock, reflecting increased de-

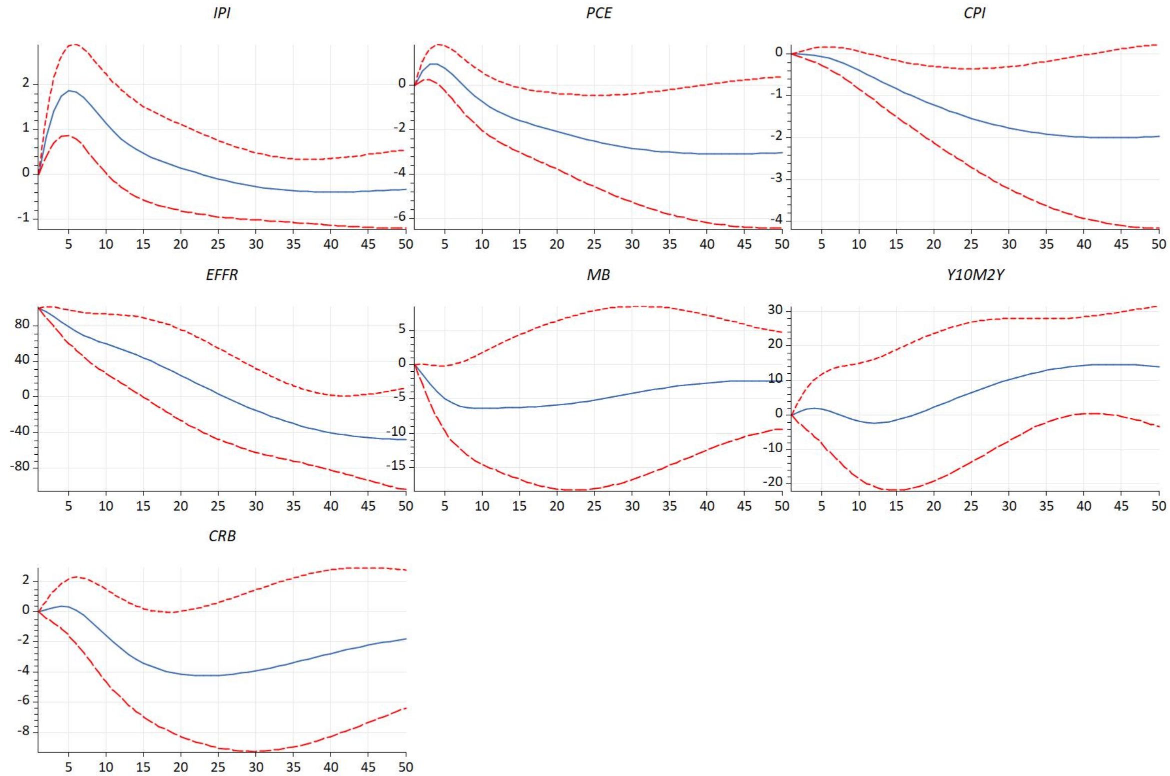

Figure 3.3: IRFs to a 100-basis-point increase in the EFFR by applying the recursive approach during post-ZLB period. The solid line shows the impulse response, while the dashed lines represent the 95 percent confidence interval computed using the analytic (asymptotic) method.

mand for short-term securities as market participants adjust their expectations. Over time, the yield spread stabilizes, indicating a normalization of the yield curve.

3.7 Monetary Policy and Commodity Prices Fluctuations

A forecast-error-variance decomposition breaks down the total variance of forecast errors into contributions from different shocks, providing a clear measure of the influence of each shock over a specific time horizon. This approach is particularly useful for understanding the relative impact of monetary policy shocks on overall commodity price fluctuations by quantifying the proportion of variability in commodity prices that can be attributed to these shocks.

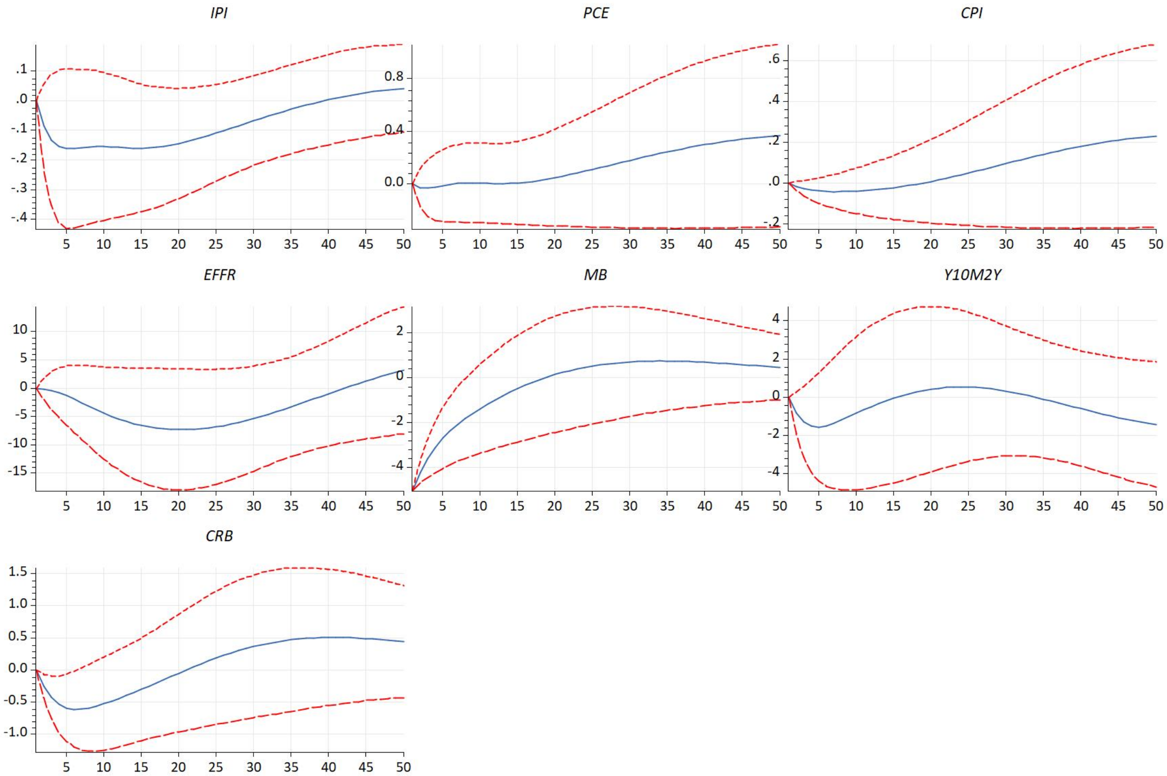

Figure 3.4: IRFs to a 5 percent decrease in the MB by applying the recursive approach during post-ZLB period. The solid line shows the impulse response, while the dashed lines represent the 95 percent confidence interval computed using the analytic (asymptotic) method.

3.7.1 Forecast-Error-Variance Decomposition

Pre-ZLB Period

In Table 3.2, I report the forecast-error-variance decomposition of the commodity price index with respect to the conventional monetary policy shock (EFFR) and other system variables during the pre-ZLB period. The forecast-error-variance decomposition reveals the dynamics of commodity price fluctuations and the evolving impact of different shocks over time. In the short term, the variance of the CRB is predominantly driven by its own dynamics, accounting for over 92 percent of the variance within the first five periods. This indicates that commodity price movements are largely self-sustained in the immediate aftermath of shocks. External factors, such as monetary policy shocks (EFFR), have a minimal influence initially, contributing less than 1 percent.

Over longer horizons, the role of external factors becomes more significant. The contribution of monetary policy shocks grows steadily, reaching 5.5 percent by the 50th period,

Table 3.2: Variance decomposition of CRB - recursive model (1976M07-2008M10)

Period	S.E.	IPI	PCE	CPI	EFFR	RM1	Y10M2Y	CRB
1	0.006583	2.868959	0.131239	3.398666	0.506565	0.1873	0.499642	92.40763
2	0.009264	2.683527	0.264274	3.11953	0.648878	0.209131	0.484232	92.59043
3	0.011291	2.497062	0.427458	2.849019	0.717211	0.228497	0.485638	92.79512
4	0.012976	2.313671	0.617709	2.593426	0.733539	0.245892	0.495066	93.0007
5	0.014436	2.136015	0.833722	2.355808	0.716518	0.261581	0.507406	93.18895
				...				
46	0.040687	4.672181	19.56379	2.743968	4.948682	0.412875	0.688891	66.96961
47	0.04122	4.808837	19.96998	2.801972	5.093846	0.447095	0.715374	66.1629
48	0.041752	4.938734	20.36719	2.857196	5.232117	0.484029	0.741038	65.37969
49	0.042282	5.061601	20.75551	2.909649	5.363366	0.523626	0.76573	64.62052
50	0.042808	5.177219	21.13502	2.959356	5.487515	0.565819	0.789318	63.88575

highlighting the lagged transmission of monetary policy effects on commodity prices. This results is consistent with Anzuini et al. (2013). Similarly, PCE emerge as a critical driver, accounting for nearly 21 percent of the variance by the 50th period, reflecting the growing importance of aggregate demand conditions. Meanwhile, variables like IPI, CPI, RM1, and the yield spread (Y10M2Y) play relatively minor roles throughout the forecast horizon, each contributing less than 5 percent.

ZLB Period

The forecast-error-variance decomposition of the CRB index during the ZLB period, as shown in Table 3.3, highlights the shifting dynamics in commodity price fluctuations under unconventional monetary policy conditions. Unlike the pre-ZLB period, where CRB's own variance was overwhelmingly dominant, the ZLB period demonstrates a more distributed influence across system variables, reflecting the altered monetary policy environment.

In the short term, CRB still accounts for a significant share of the forecast-error variance, with 71.6 percent in the first period. However, this dominance diminishes more rapidly compared to the pre-ZLB period, declining to 40.8 percent by the fifth period and just 18.3 percent by the 50th period. This indicates that external factors play a larger role in driving commodity price fluctuations during the ZLB period. Notably, PCE have a substantial impact, contributing 20.9 percent in the first period and growing to 32.4 percent by the 50th period. This underscores the heightened sensitivity of commodity prices to aggregate demand conditions during a period of unconventional monetary policy.

The influence of unconventional monetary policy shocks, represented by PFR, is also more pronounced during the ZLB period. Starting at 3.2 percent in the first period, the

Table 3.3: Variance decomposition of CRB - recursive model (2008M11-2015M11) - PFR shock

Period	S.E.	IPI	PCE	CPI	PFR	Y10M2Y	CRB
1	0.004598	0.305812	20.98026	3.856522	3.193305	0.01981	71.64429
2	0.005922	0.340375	19.45880	2.090533	9.93215	4.220045	63.95809
3	0.006811	0.264581	16.69884	1.497823	16.13048	10.66416	54.74411
4	0.007627	0.192665	13.96126	1.495382	20.77409	16.72877	46.84784
5	0.008489	0.187695	11.67787	1.674716	24.04078	21.62237	40.79657
			...				
46	0.025159	0.853086	28.71561	6.082373	18.44378	27.32148	18.58367
47	0.025305	0.835998	29.63424	6.121846	18.10650	26.78781	18.51360
48	0.025449	0.819287	30.54858	6.155822	17.77834	26.25963	18.43834
49	0.025590	0.802939	31.45753	6.184694	17.45890	25.73827	18.35767
50	0.025730	0.786937	32.35999	6.208817	17.14787	25.22492	18.27147

impact of PFR grows to a peak of 24 percent by the fifth period before stabilizing around 17 percent by the 50th period. This suggests that unconventional monetary policy measures have a stronger and more immediate effect on commodity prices compared to conventional policy shocks in the pre-ZLB period. Furthermore, the yield spread (Y10M2Y) gains significance over time, contributing 25.2 percent by the 50th period, highlighting the role of long-term interest rate expectations in influencing commodity prices.

Post-ZLB Period

The forecast-error-variance decomposition of the CRB index during the post-ZLB period, presented in Table 3.4, highlights the changing dynamics of commodity price fluctuations in an environment where conventional and unconventional monetary policies coexist. The decomposition provides insights into the influence of the EFFR and MB shocks, alongside other macroeconomic variables, on commodity price movements during this period.

In the short term, the variance of the CRB remains substantial, accounting for nearly 70 percent in the first period. However, this dominance gradually declines over time, reaching about 53 percent by the fifth period and 27 percent by the 50th period. This reduction reflects an increasing role for external factors in explaining commodity price fluctuations as the horizon extends. Among these, PCE contribute significantly, starting at 16.5 percent in the first period and rising to 36 percent by the fifth period. This underscores the importance of aggregate demand conditions in driving commodity price dynamics in the post-ZLB environment.

Table 3.4: Variance decomposition of CRB - recursive model (2015M01-2024M07) - EFFR and MB shocks

Period	S.E.	IPI	PCE	CPI	EFFR	MB	Y10M2Y	CRB
1	0.015119	9.230189	16.45373	2.372313	0.015392	1.295946	0.783813	69.84862
2	0.019278	8.821599	22.93618	1.253538	0.012288	2.433840	0.459502	64.08305
3	0.021557	6.824834	28.70465	0.853091	0.008828	3.544218	0.322944	59.74144
4	0.023079	5.106934	33.16122	0.737544	0.008986	4.513255	0.275857	56.19621
5	0.024256	4.609442	36.09263	0.693741	0.025059	5.293257	0.315396	52.97048
				...				
46	0.031129	16.20184	10.85454	3.463354	20.18206	4.390946	18.06654	26.84072
47	0.031187	16.14344	10.83224	3.500112	20.18299	4.474747	17.99637	26.87010
48	0.031239	16.09326	10.81864	3.534253	20.18131	4.554382	17.93338	26.88478
49	0.031287	16.04986	10.81321	3.565895	20.17737	4.629491	17.87764	26.88654
50	0.031330	16.01189	10.81548	3.595169	20.17151	4.699815	17.82899	26.87715

The impact of monetary policy shocks is also notable in this period. EFFR shocks, while negligible in the short term, become more prominent over longer horizons, accounting for approximately 20 percent of the variance by the 50th period. This highlights the reassertion of conventional monetary policy as a key driver of commodity price fluctuations after the ZLB period. Similarly, MB shocks exhibit a growing influence, contributing 1.3 percent in the first period and increasing to about 4.7 percent by the 50th period. This indicates that unconventional monetary policy measures, though secondary to conventional policy, still play a meaningful role in shaping commodity price movements.

3.7.2 Historical Decomposition

Historical decomposition, based on methodologies like Kilian (2008), provides a detailed assessment of the cumulative contributions of various shocks, including monetary policy, to commodity price movements over time. By distinguishing between systematic and non-systematic shocks, it offers valuable insights into the role of monetary policy in driving fluctuations in the CRB index. The analysis spans three distinct periods—pre-ZLB, ZLB, and post-ZLB—capturing the cumulative impact of monetary policy shocks and total stochastic influences on commodity prices, as illustrated in the figures below.

Pre-ZLB Period

During the pre-ZLB period, monetary policy shocks, represented by the red line for EFFR as shown in Figure 3.5, contributed moderately to fluctuations in the CRB index. While the overall trend of the CRB index (blue area) shows significant variability, the EFFR share demonstrates a generally limited role in driving these fluctuations. Notably, from the early 2000s onward, monetary policy shocks contributed positively to the run-up in commodity prices, particularly during 2006 and 2007. However, their influence diminished as commodity prices peaked in mid-2008. This pattern suggests that while monetary policy played a supporting role in commodity price increases, other factors, such as supply disruptions and global demand shocks, were likely more dominant drivers during this period.

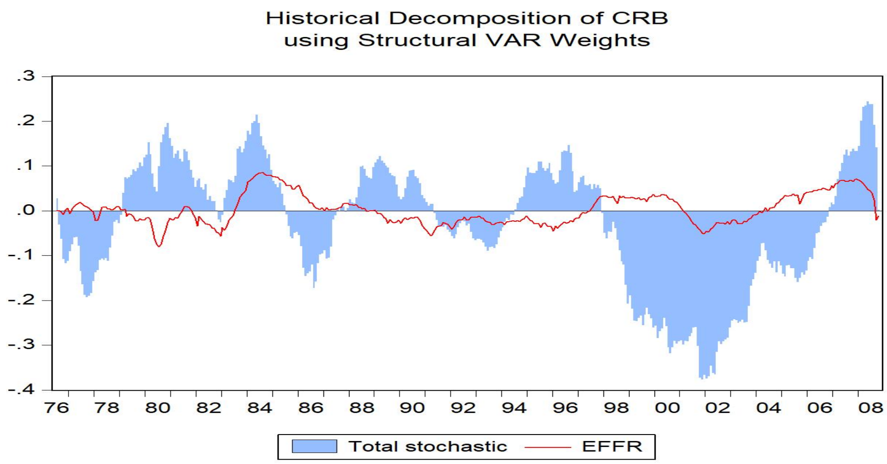

Figure 3.5: Historical decomposition of CRB by applying the recursive approach during the pre-ZLB period. EEFR share.

ZLB Period

The ZLB period is marked by unconventional monetary policy measures and the historical decomposition reflects this shift. Here, monetary policy shocks, represented by PFR, exhibit a more prominent role in driving CRB fluctuations compared to the pre-ZLB period, as shown in Figure 3.6. For example, the positive contributions of monetary policy shocks are particularly visible during 2011–2013, coinciding with the implementation of aggressive monetary easing. These policies likely amplified demand-side pressures on commodity prices. However, as the PFR contribution declines toward the end of the period, this suggests a weakening influence of monetary easing or an increasing role of other macroeconomic factors in driving commodity price movements.

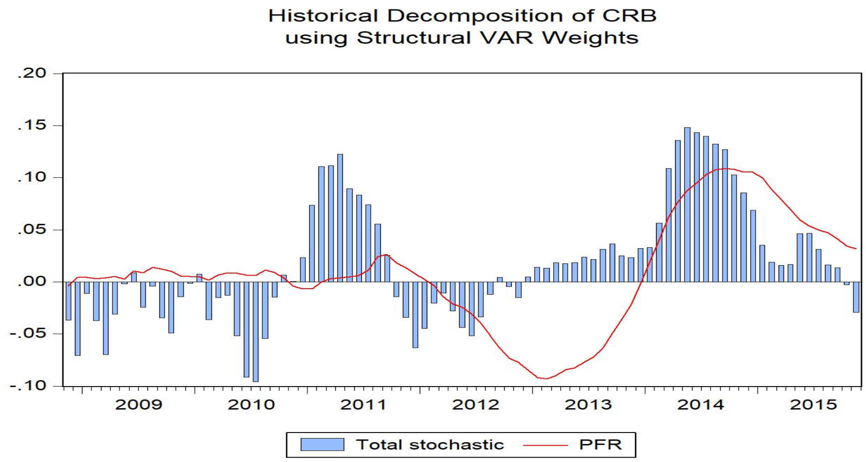

Figure 3.6: Historical decomposition of CRB by applying the recursive approach during the ZLB period. PFR share.

Post-ZLB Period

In the post-ZLB period, as monetary policy transitioned back toward normalization, the roles of both conventional (EFFR) and unconventional (MB) shocks become apparent. The EFFR share, shown in the left panel of Figure 3.7, reasserts itself as a significant driver of CRB fluctuations, particularly during periods of rate hikes, reflecting the renewed importance of conventional monetary tools. Meanwhile, the MB share, depicted in the right panel, highlights the continued but reduced influence of balance sheet policies. During 2020–2021, MB shocks made a substantial contribution to CRB fluctuations, likely tied to pandemic-related policy measures, but their influence fades as policies normalize. Overall, the post-ZLB period underscores the evolving interplay between conventional and unconventional monetary policy in shaping commodity prices.

3.8 Event Study Results

The regression results in Table 3.5 provide key insights into the impact of monetary policy sentiment shocks—IRG, BSP, and EOA—on commodity prices, as measured by the (daily change in) CRB Index. The coefficient for the IRG shock is statistically significant and negative (-0.1865), suggesting that a hawkish IRG shock reduces commodity prices. This aligns with expectations that hawkish monetary policy, often associated with higher future interest rates, raises the cost of financing and holding commodity inventories, thereby

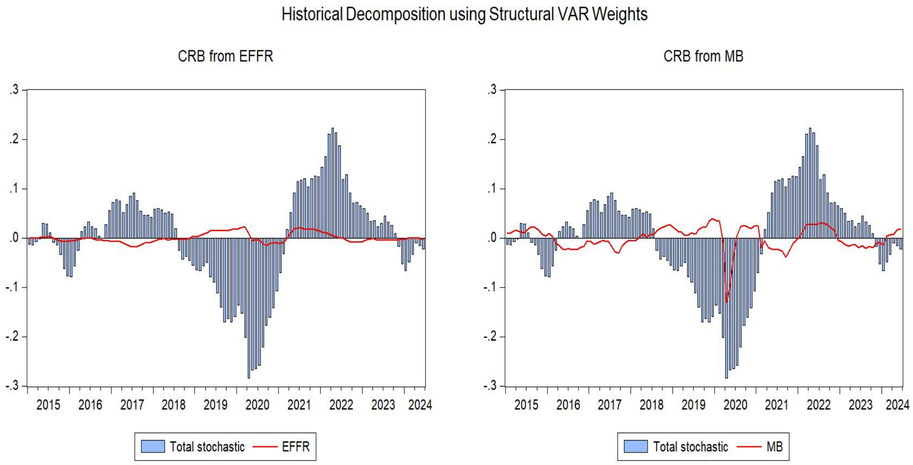

Figure 3.7: Historical decomposition of CRB by applying the recursive approach during the post-ZLB period. EFFR and MB shares.

lowering demand. Additionally, tighter policy slows economic growth, reducing demand for raw materials. The magnitude of this effect is considerable, highlighting the significant implications of IRG shocks for commodity markets. This result aligns with Rosa (2014), who find that unanticipated FFR hikes reduce crude oil prices.

Table 3.5: Regression results for CRB

Variable	Coefficient	HAC Std. Error	p-value
IRG^{Shock}	-0.1865^{*}	(0.1000)	0.0639
BSP^{Shock}	-0.0477	(0.0926)	0.6068
EOA^{Shock}	0.1336^{*}	(0.0776)	0.0869
R-squared	**0.1291**		

Notes:
- Standard errors in parentheses. *, **, *** denote significance at the 10 percent level, 5 percent level, and 1 percent level, respectively. OLS estimation.
- HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000).
- Sample, Feb. 2000 - May 2024, 194 observations.

By contrast, the BSP shock has a small negative coefficient (-0.0477) that is statistically insignificant. While BSP policies like quantitative easing or tightening are crucial monetary tools, their influence on commodities appears indirect. A possible explanation is that BSP shocks predominantly affect financial markets—bond yields and equity prices—through liquidity and risk premium channels. Commodities may react more strongly to macroeconomic expectations and interest rate guidance than to balance sheet adjustments. This finding highlights the differentiated transmission mechanisms of monetary policy tools and suggests that BSP shocks do not significantly affect commodity prices in this context.

The EOA shock, however, has a statistically significant positive coefficient (0.1336), indicating that a more optimistic economic outlook raises commodity prices. This underscores the critical role of broader economic sentiment in driving commodity markets. Improved economic expectations often lead to stronger industrial production and consumption growth, boosting demand for raw materials. The magnitude of the EOA shock effect emphasizes its importance as a key driver of commodity price dynamics.

3.9 Robustness

In addition to dividing the analysis into three distinct periods—pre-ZLB, ZLB, and post-ZLB—to more effectively distinguish the impacts of conventional and unconventional monetary policies while addressing overlaps often overlooked in previous studies, I also perform several additional robustness checks.

I run the SVAR model with shocks reversed in sign. The resulting IRFs, shown in Figures 3.9, 3.12, 3.19, and 3.22, symmetrically reverse the direction of the main scenarios depicted in Figures 3.1, 3.2, 3.3, and 3.4.

To evaluate the robustness of the findings against variations in the identification strategy, I implement a non-recursive SVAR approach, following Kim (2003), Anzuini et al. (2013), and Belongia and Ireland (2016). The IRFs derived from the non-recursive approach under contractionary shocks are presented in Figures 3.10, 3.13, 3.20, and 3.24, corresponding to the recursive IRFs in Figures 3.1, 3.2, 3.3, and 3.4. Similarly, the IRFs derived under expansionary shocks using the non-recursive approach are shown in Figures 3.11, 3.14, 3.21, and 3.23. The results indicate a high level of consistency between the recursive and non-recursive identification methods, with only minor differences observed in the magnitude and timing of the responses.

For the ZLB period, I use the SR as an alternative proxy for unconventional monetary policy. The resulting IRFs are shown in Figures 3.15, 3.16, 3.17, and 3.18. Figures 3.15 and 3.16 display the IRFs obtained using the recursive approach under contractionary and expansionary shocks, respectively, while Figures 3.17 and 3.18 show the IRFs derived using the non-recursive approach for contractionary and expansionary shocks, respectively. The findings remain robust across the different proxies for unconventional monetary policy.

For the post-ZLB period, both the PFR and the SR are used to evaluate the impact of monetary policy. The IRFs for PFR are presented in Figures 3.25, 3.26, 3.27, and 3.28. Under the recursive approach, shown in Figures 3.25 (contractionary shocks) and 3.26 (expansionary shocks), contractionary PFR shocks lead to a gradual decline in CRB, IPI, and PCE, with CRB reaching its lowest point approximately 25 months after the shock and recovering slowly afterward. The non-recursive approach, depicted in Figures 3.27 (contractionary shocks) and 3.28 (expansionary shocks), captures a sharper and more immediate decline in CRB and IPI, with faster adjustments across all variables.

The analysis is extended by replacing PFR with the SR as a proxy for monetary policy, with results presented in Figures 3.29, 3.30, 3.31, and 3.32. For contractionary shocks, Figures 3.29 (recursive approach) and 3.31 (non-recursive approach) reveal consistent patterns, with CRB, IPI, and PCE responding negatively. The non-recursive approach again shows more immediate effects compared to the recursive method. For expansionary shocks, Figures 3.30 (recursive approach) and 3.32 (non-recursive approach) depict symmetric positive impacts, highlighting the supportive role of monetary policy.

To ensure the robustness of the findings, I incorporate fiscal policy into the analysis by including GCE as a control variable. This addition is particularly relevant during the COVID-19 pandemic, a period marked by unprecedented fiscal stimulus, including direct government spending and transfer payments, which significantly influenced aggregate demand and the broader economy. By accounting for GCE, I aim to isolate the specific effects of monetary policy shocks on commodity prices, ensuring they are not confounded by concurrent fiscal interventions.

The results remain robust, confirming that both conventional and unconventional monetary policy shocks significantly influence commodity prices. The inclusion of GCE does not substantially alter the persistence or magnitude of these effects, demonstrating the reliability of the identified monetary policy channels. Figures 3.33, 3.34, and 3.35 illustrate these findings, highlighting that the transmission of monetary policy to commodity markets remains consistent, even when accounting for fiscal policy measures. This analysis reinforces the distinct and significant role of monetary policy, particularly during economic crises, in shaping commodity price dynamics.

The robustness checks confirm the reliability of the results, demonstrating consistent findings across identification strategies, monetary policy proxies, and economic conditions. Dividing the analysis into pre-ZLB, ZLB, and post-ZLB periods effectively isolates the impacts of conventional and unconventional monetary policies, while reversing the sign of shocks and implementing non-recursive SVAR approaches highlight the consistency of the responses. The inclusion of the SR as a proxy further supports these findings, affirming the significant influence of monetary policy on commodity prices. Additionally, controlling for fiscal policy, particularly through GCE during the COVID-19 pandemic, ensures that the observed effects are not confounded by fiscal interventions, reinforcing the distinct role of monetary policy in shaping commodity price dynamics. These comprehensive tests underline the robustness and reliability of the results.

3.10 Conclusion

This study examines the impact of U.S. monetary policies on commodity prices, contributing to the literature by highlighting the effects of unconventional monetary policy. It leverages an extended dataset that includes the COVID-19 pandemic period, characterized by unprecedented policy actions and sharp commodity price increases. Using VECM and SVAR analyses, I capture the dynamic interactions between monetary policy and commodity markets across three distinct periods: pre-ZLB, ZLB, and post-ZLB. In addition, this study is the first to incorporate sentiment-driven monetary policy shocks, derived from media narratives, to evaluate the effects of three types of forward guidance shocks on commodity prices.

The findings of this study reveal the significant and differentiated impact of U.S. monetary policy on commodity prices, emphasizing the contrasting effects of conventional and unconventional tools. Conventional monetary tightening, represented by a 1 pp increase in the EFFR, consistently leads to a long-term decline in commodity prices due to reduced borrowing, investment, and aggregate demand. In contrast, unconventional monetary measures, such as balance sheet expansions or reductions in the PFR, have pronounced expansionary effects, driving substantial increases in commodity prices. Notably, these tools were pivotal during the COVID-19 pandemic, amplifying credit availability and speculative demand, which significantly influenced commodity price trajectories.

In addition, the integration of sentiment-driven monetary policy shocks reveals significant dynamics through interest rate guidance and economic outlook assessment. Hawkish IRG suppresses commodity demand by raising borrowing costs, while dovish IRG stimulates it through liquidity expectations. Similarly, pessimistic EOA sentiment reduces demand by signaling economic weakness, whereas optimistic EOA sentiment boosts demand through growth expectations. These findings highlight the pivotal roles of IRG and EOA in shaping market reactions and commodity price dynamics.

From a policy perspective, the findings highlight the critical role of both conventional and unconventional monetary tools in stabilizing commodity markets during periods of economic uncertainty. Policymakers should recognize the differentiated transmission mechanisms of these tools. While interest rate adjustments remain effective in managing aggregate demand, unconventional measures, such as asset purchases, can significantly influence speculative behavior and market liquidity, particularly during crises. The study also emphasizes the vital role of forward guidance in shaping market expectations and commodity price movements. Policymakers should recognize the potency of IRG and EOA as a forward-looking tool, leveraging its ability to influence sentiment and steer market behavior. Clear and consistent communication of policy intentions can mitigate uncertainty, reduce speculative volatility, and enhance the overall transmission of monetary policy objectives to financial and commodity markets.

Appendix A: Unit Root and Cointegration Tests

A.1 Unit Root Test

Time series data is said to be (covariance) stationary if its mean and variance do not vary overtime, and, although it may display autocorrelation, the covariance between observations depend only on how far apart in time the observations are. In fact, most financial and macroeconomic variables are not stationary in the sense that they exhibit strong trends, high degree of persistence on shocks, higher volatility over time and meandering and sharing co-movements with other series. Therefore, in time series analysis, it is important to understand the behavior of variables and their interactions and integrations over time (Shrestha and Bhatta, 2018).

Granger and Newbold (1974) examined some of the possible empirical implications of nonsense or spurious regressions in econometrics. A focal point of their study is the specification of regression equations in terms of the levels of economic time series. Their study shows that when two independent random walks are used in linear regression, one tends to find a significant relationship between the variables. This phenomenon is termed "spurious regression". They argue that the levels of many economic time series are non-stationary and often they appear to be near random walks. It is also argued that regression equations that relate such time series frequently have high R^2 yet also typically display highly autocorrelated residuals, indicated by very low Durbin-Watson statistics. This, in turn, implies that the usual significance tests about the regression coefficients are very misleading. Therefore, it is important to check the stationarity of the variables and apply the relevant transformation, if required, and then employ the appropriate model.

To explain briefly the unit root test, consider the following AR(1) model with zero-mean, white noise innovations:

$$y_t = \alpha + \rho y_{t-1} + e_t, \qquad t = 1, 2, ..., \tag{3.19}$$

given the observed initial value y_0. If y_t follows (3.19), it has a unit root if, and only if, $\rho = 1$. If $\alpha = 0$ and $\rho = 1$, y_t follows a random walk without drift. If $\alpha \neq 0$ and $\rho = 1$, y_t is a random walk with drift. Although a unit root process with drift behaves very differently from one without drift, it is common to leave α unspecified under the null hypothesis (Wooldridge, 2015). Therefore, the null hypothesis is that y_t has a unit root:

$$H_0 : |\rho| = 1 \tag{3.20}$$

and the one-sided alternative hypothesis is:

$$H_1 : |\rho| < 1 \tag{3.21}$$

where $|\rho| < 1$ indicates that y_t is a stationary AR(1) process.

Unit root test can be carried out by subtracting y_{t-1} from both sides of (3.19). Letting $\theta = \rho - 1$, we have:

$$\Delta y_t = \alpha + \theta y_{t-1} + e_t \tag{3.22}$$

Therefore, we are testing $H_0 : \theta = 0$ against $H_1 : \theta < 0$. Since y_{t-1} is $I(1)$ under the null hypothesis, we cannot apply the usual central limit theorem that underlies the asymptotic standard normal distribution. The asymptotic distribution of the t statistic under H_0 is known as the **Dickey-Fuller distribution** after Dickey and Fuller (1979) (Wooldridge, 2015). Although we cannot use the usual critical values, we can use the usual t statistic for $\hat{\theta}$ in (3.22). The resulting test is known as the Dickey-Fuller (DF) test for a unit root.

The DF test is used to test the unit root for random walk processes only and does not apply for $AR(\rho)$ for $\rho > 1$. Equation (3.22) implies that Δy_t is serially uncorrelated, which in turn implies that e_t is serially uncorrelated.

The extended version of the DF test is called the augmented Dickey-Fuller (ADF) test because the regression has been augmented with the lagged changes, Δy_{t-h}:

$$\Delta y_t = \alpha + \theta y_{t-1} + \gamma_1 \Delta y_{t-1} + e_t \tag{3.23}$$

where the critical values and rejection rule are the same as before.

Another widely used test for unit root is the Phillips-Perron (PP) test for unit root which is performed to provide additional robustness to the unit root test. Philips-Perron (1988) developed a generalization of the Dickey-Fuller with less restrictive assumptions regarding the distribution of the error terms. The possibility of heteroskedastic errors is accommodated in the Philips-Perron test.

A.2 Cointegration Test

As a general rule, non-stationary time series variables should not be used in regression models to avoid the problem of spurious regression. However, there is an exception to this rule. If y_t and x_t are integrated of order one, $I(1)$, then we expect their difference, or any linear combination of them, such as:

$$e_t = y_t - \beta_1 - \beta_2 x_1 \tag{3.24}$$

to be $I(1)$ as well. However, there is an important case where (3.24) is a stationary $I(0)$. In this case, y_t and x_t are said to be **cointegrated**, thus we can apply the VEC model, which requires all variables to be I(1) and there exist at least one cointegration relationship.

Cointegration implies that y_t and x_t have similar stochastic trends, and, since the difference e_t is stationary, they never diverge too far from each other. The test for cointegration is effectively a test of the stationarity of the residuals. If the residuals are stationary, then y_t and x_t are said to be cointegrated. Otherwise they are not cointegrated and hence any regression relationship between them results in a spurious regression (Hill et al., 2018).

The usual approach is to use Johansen's method for testing whether or not cointegration exists. This method uses two tests to determine the number of cointegration relationships between the $I(1)$ variables: the Maximum Eigenvalue statistic test and the Trace test. The null hypotheses for the Maximum Eigenvalue statistic test is r cointegration relations against the alternative of r+1 cointegration relations for r=0, 1, 2, ..., k-1, where k is the number of variables in the system. The test statistic for the Maximum Eigenvalue statistic test is:

$$LR_{max}(r/k+1) = -T * log(1 - \hat{\lambda}) \tag{3.25}$$

where $\hat{\lambda}$ represents the eigenvalue.

The null hypotheses for the Trace test is r cointegration relations against the alternative of k cointegration relationships for r=0, 1, 2, ..., k-1. The test statistic for the Trace test is:

$$LR_{tr}(r/k) = -T * \sum_{i=r+1}^{k} log(1 - \hat{\lambda}) \tag{3.26}$$

Appendix B: Figures

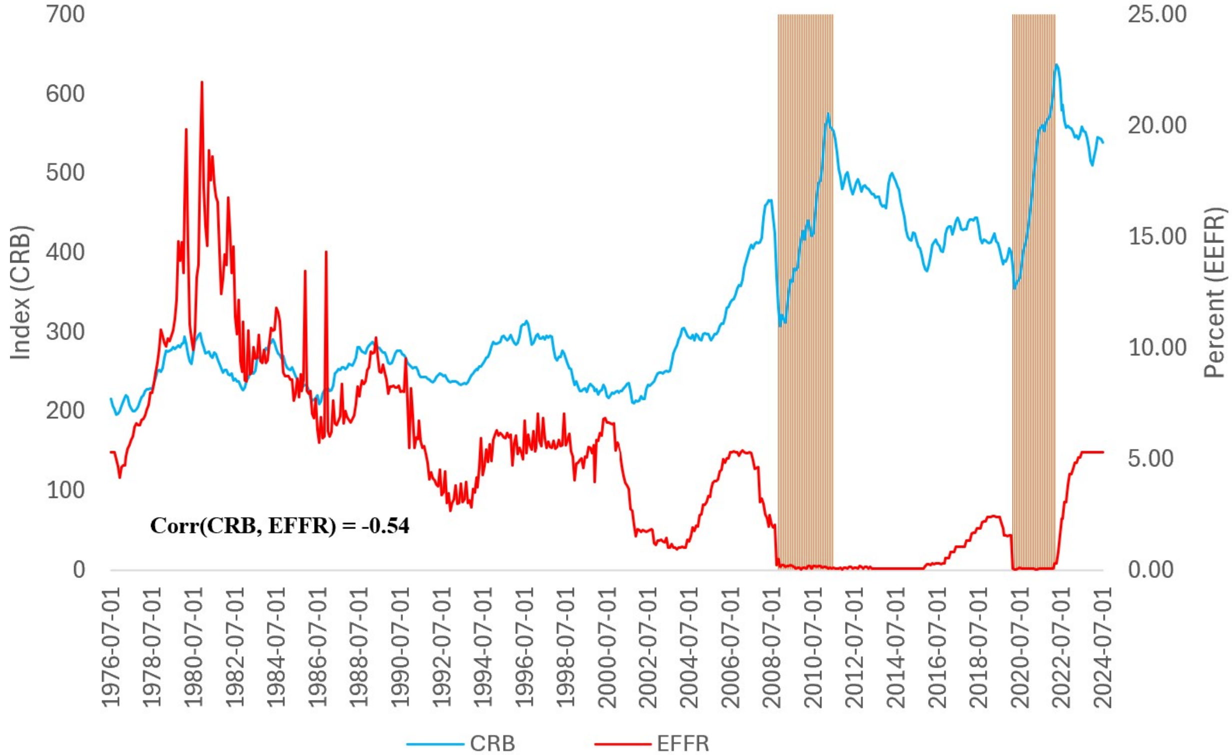

Figure 3.8: The trends in commodity prices (CRB, blue line) and the effective federal funds rate (EFFR, red line) spanning from July 1976 to July 2024. The brown bars indicate periods marked by the implementation of unconventional measures during the financial crisis and the COVID-19 pandemic.

B.1 Pre-ZLB Period

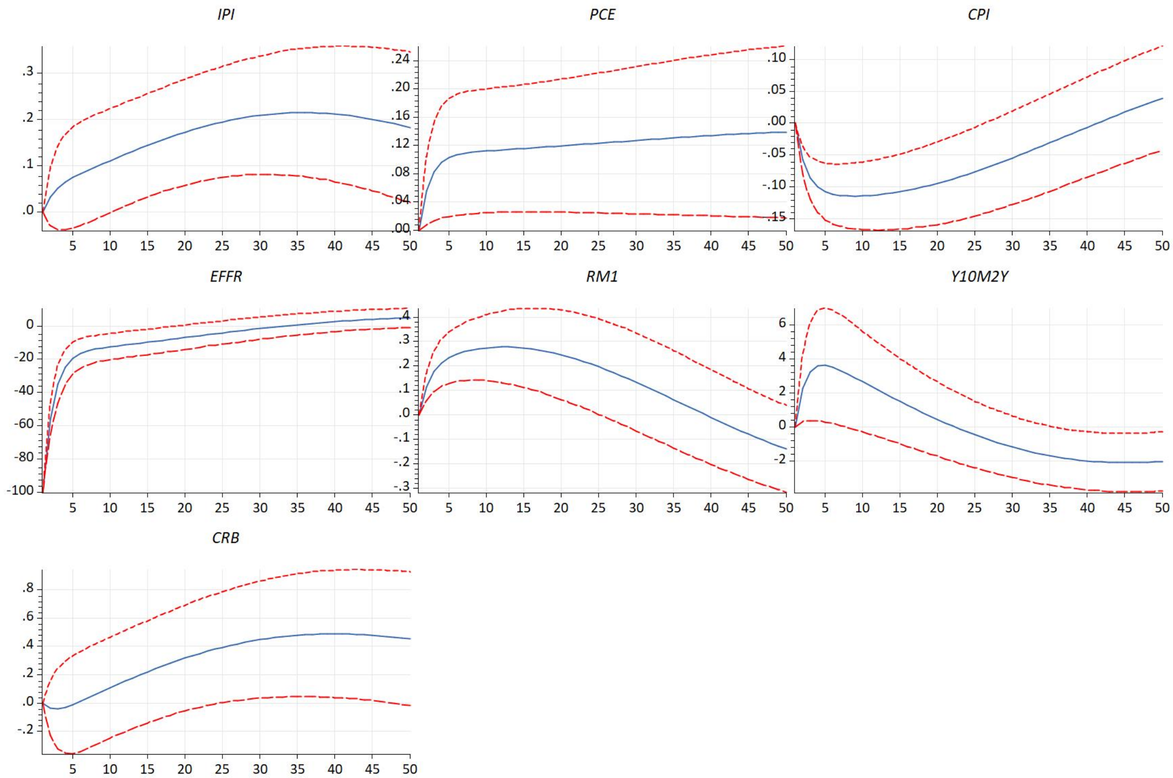

Figure 3.9: IRFs to a 100-basis-point decrease in the EFFR by applying the recursive approach during pre-ZLB period. The solid line shows the impulse response, while the dashed lines represent the 95 percent confidence interval computed using the analytic (asymptotic) method.

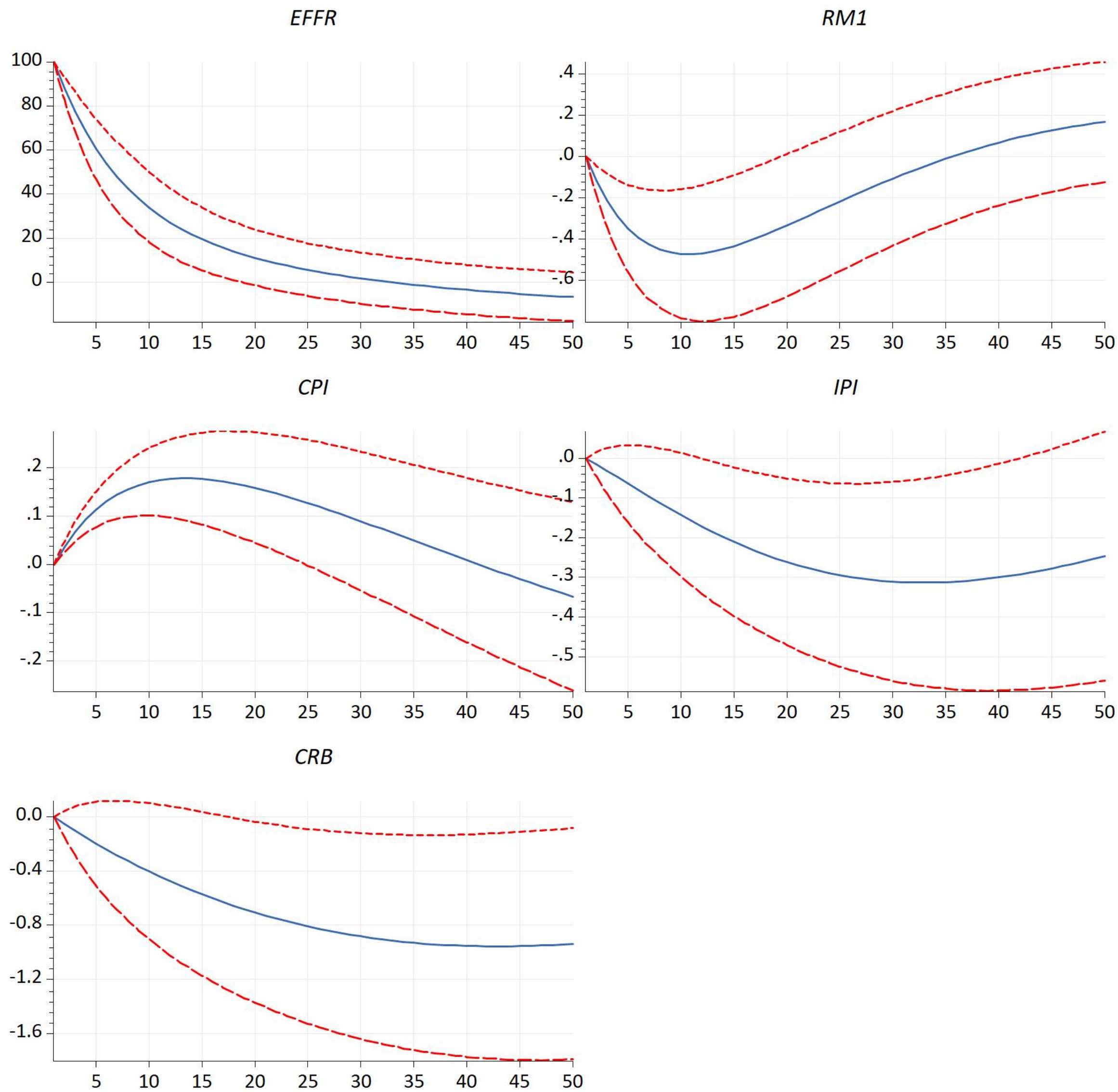

Figure 3.10: IRFs to a 100-basis-point increase in the EFFR by applying the non-recursive approach during pre-ZLB period. The solid line shows the impulse response, while the dashed lines represent the 95 percent confidence interval computed using the analytic (asymptotic) method.

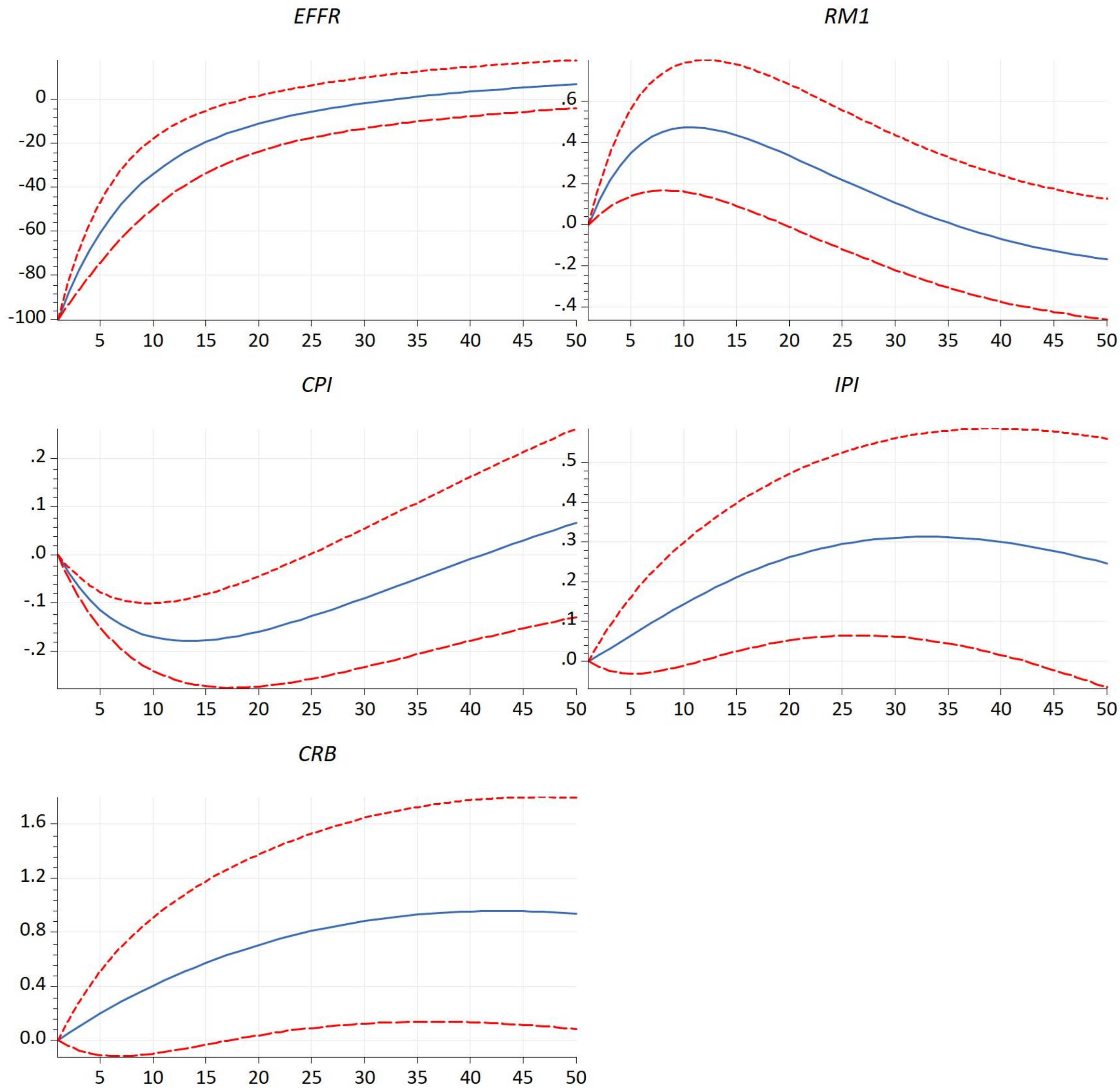

Figure 3.11: IRFs to a 100-basis-point decrease in the EFFR by applying the non-recursive approach during pre-ZLB period. The solid line shows the impulse response, while the dashed lines represent the 95 percent confidence interval computed using the analytic (asymptotic) method.

B.2 ZLB Period

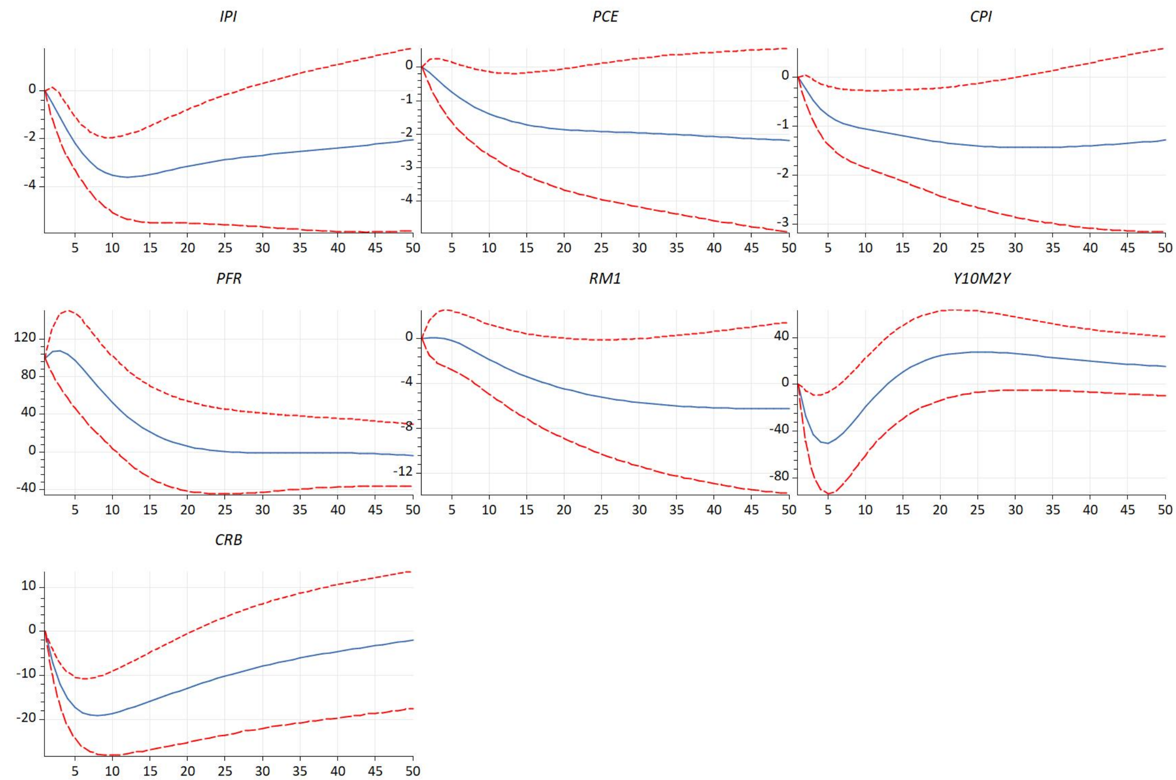

Figure 3.12: IRFs to a 100-basis-point increase in the PFR by applying the recursive approach during ZLB period. The solid line shows the impulse response, while the dashed lines represent the 95 percent confidence interval computed using the analytic (asymptotic) method.

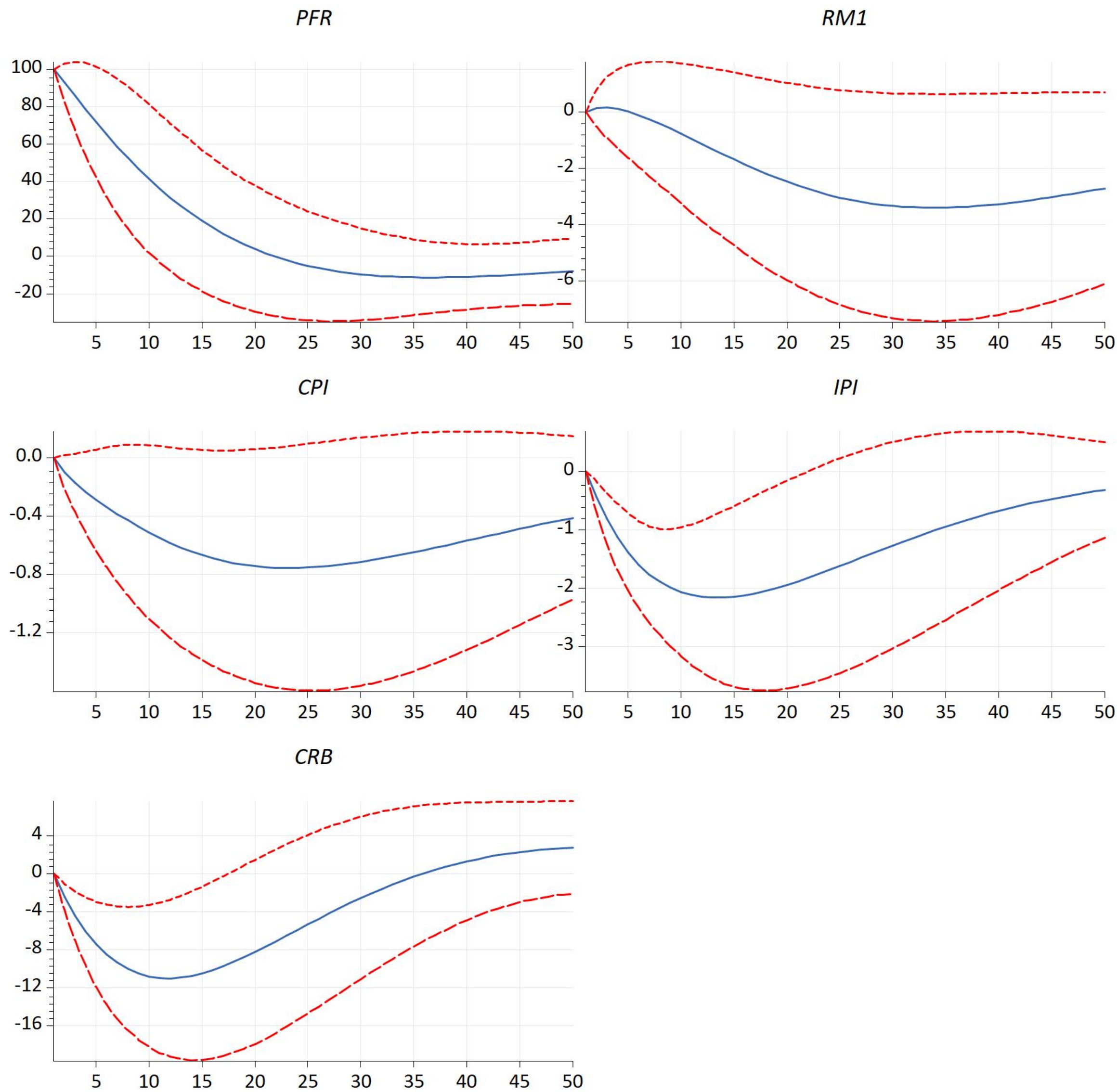

Figure 3.13: IRFs to a 100-basis-point increase in the PFR by applying the non-recursive approach during ZLB period. The solid line shows the impulse response, while the dashed lines represent the 95 percent confidence interval computed using the analytic (asymptotic) method.

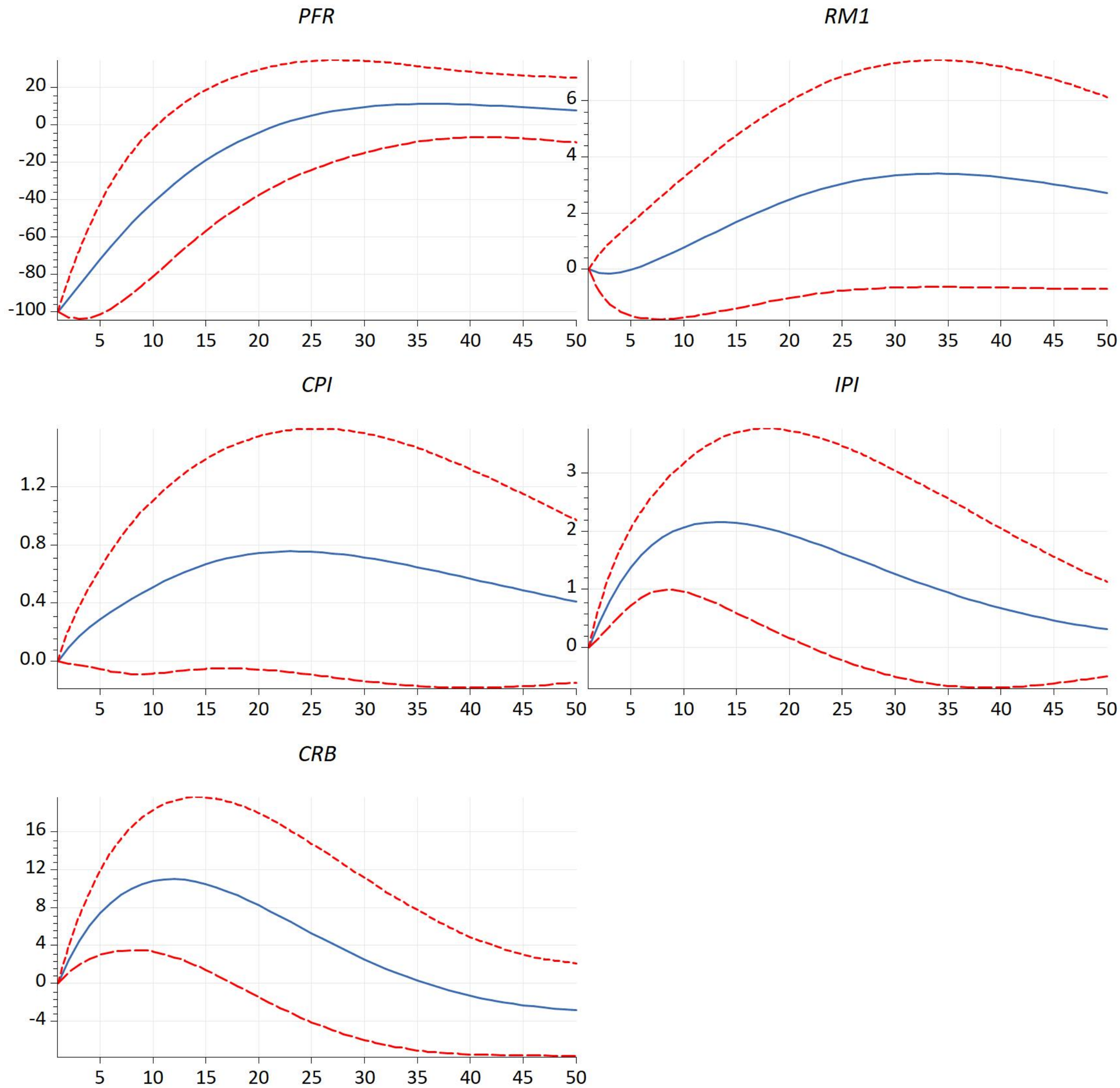

Figure 3.14: IRFs to a 100-basis-point decrease in the PFR by applying the non-recursive approach during ZLB period. The solid line shows the impulse response, while the dashed lines represent the 95 percent confidence interval computed using the analytic (asymptotic) method.

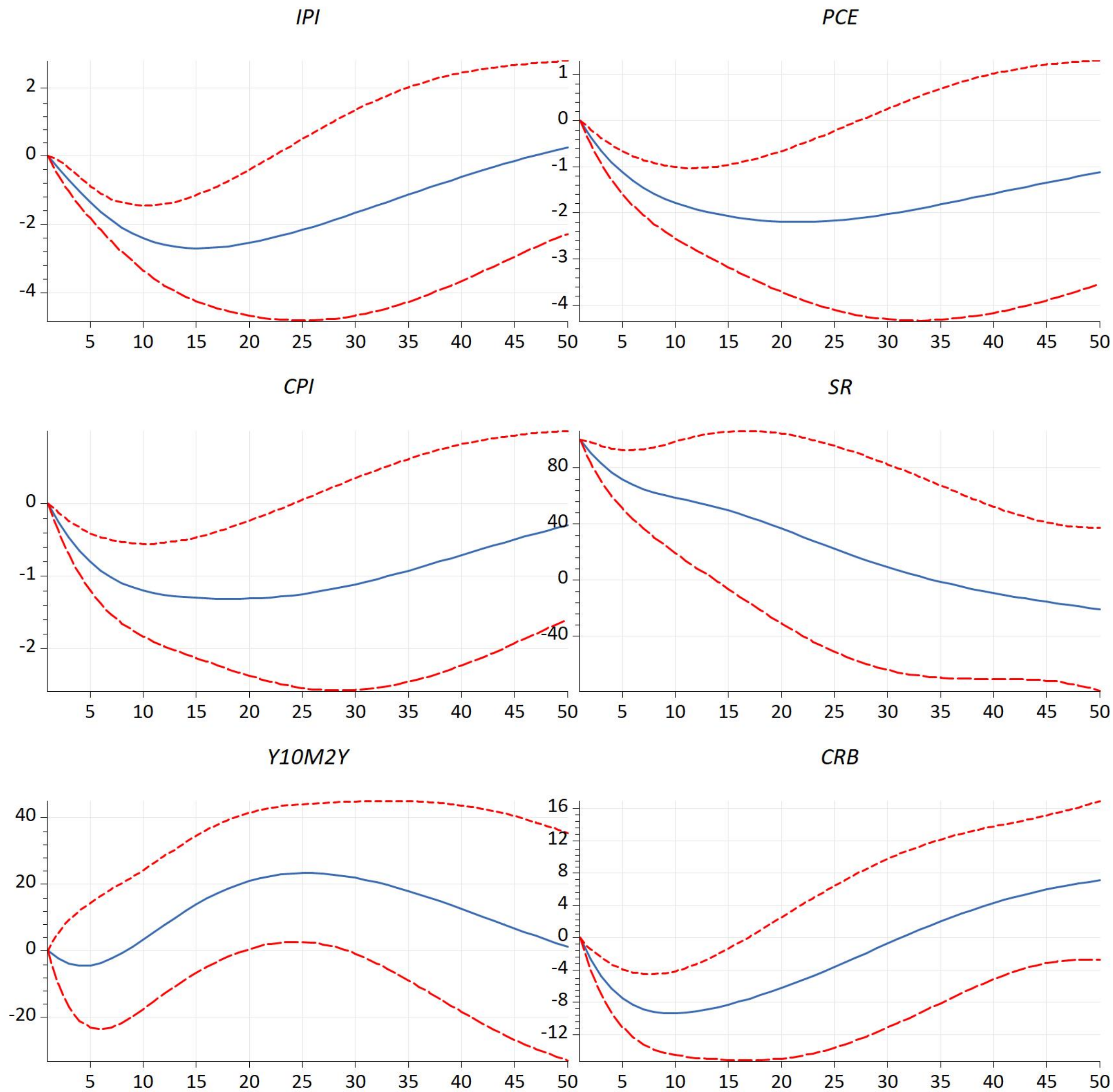

Figure 3.15: IRFs to a 100-basis-point increase in the SR by applying the recursive approach during ZLB period. The solid line shows the impulse response, while the dashed lines represent the 95 percent confidence interval computed using the analytic (asymptotic) method.

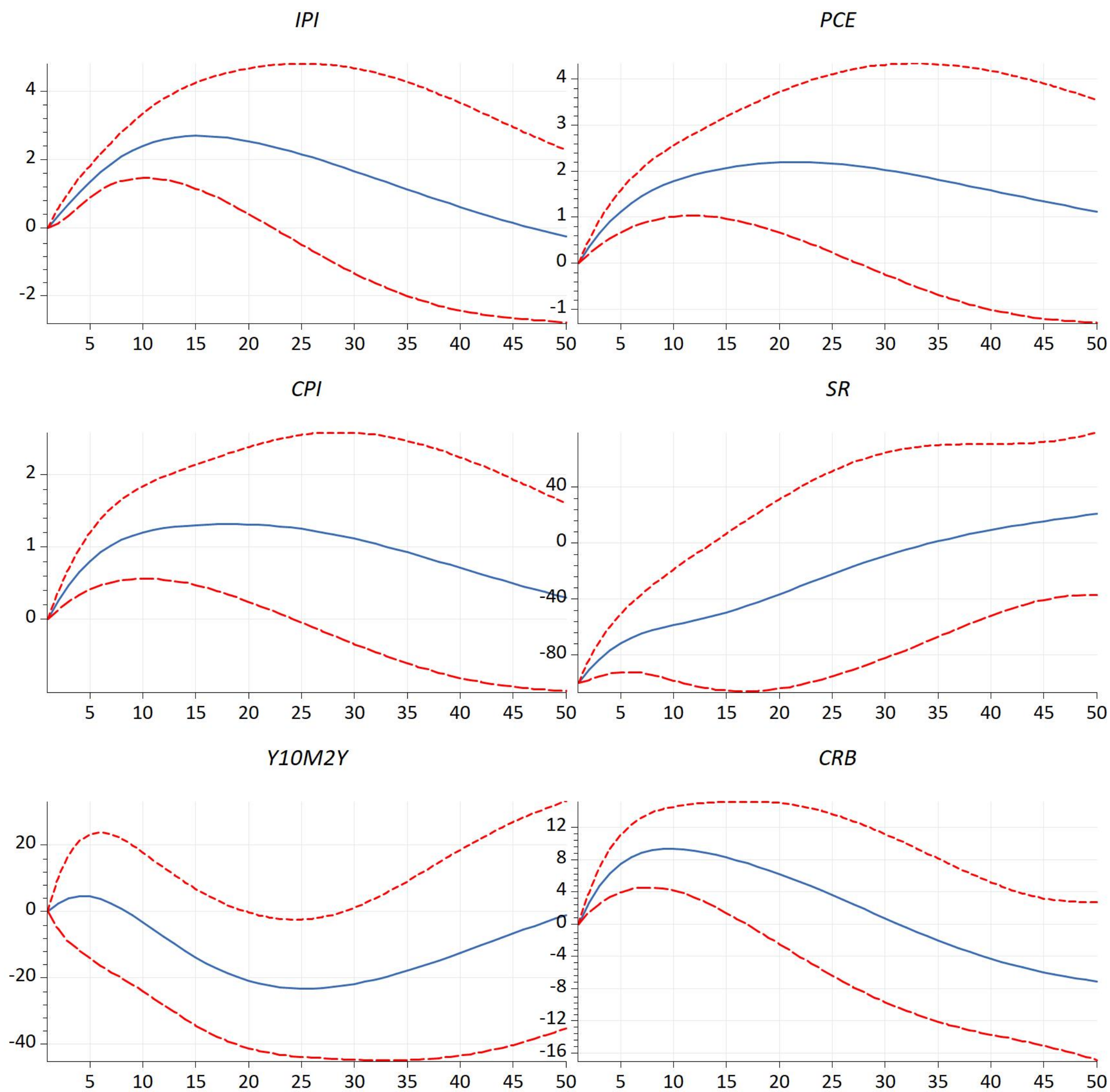

Figure 3.16: IRFs to a 100-basis-point decrease in the SR by applying the recursive approach during ZLB period. The solid line shows the impulse response, while the dashed lines represent the 95 percent confidence interval computed using the analytic (asymptotic) method.

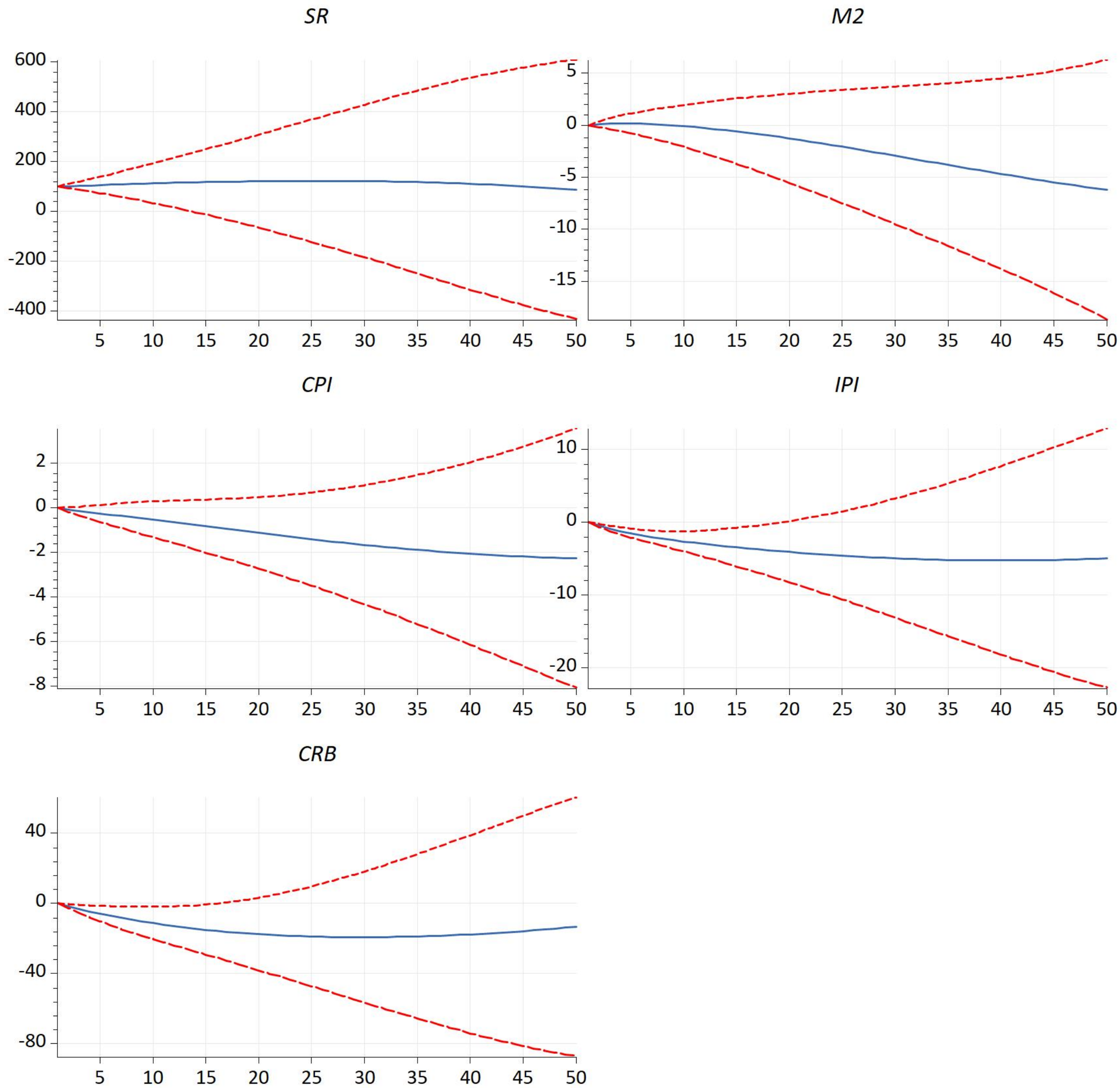

Figure 3.17: IRFs to a 100-basis-point increase in the SR by applying the non-recursive approach during ZLB period. The solid line shows the impulse response, while the dashed lines represent the 95 percent confidence interval computed using the analytic (asymptotic) method.

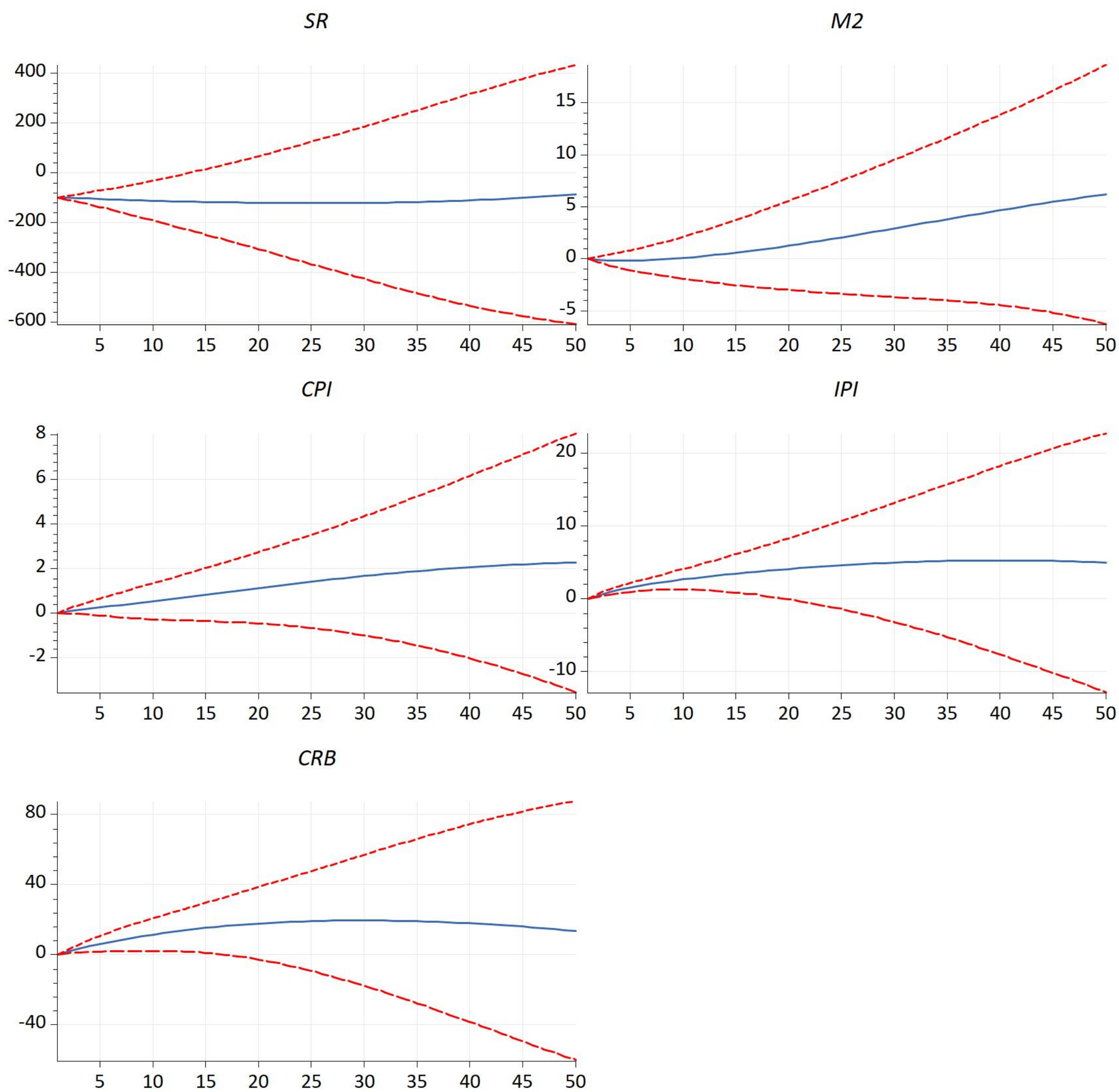

Figure 3.18: IRFs to a 100-basis-point decrease in the SR by applying the non-recursive approach during ZLB period. The solid line shows the impulse response, while the dashed lines represent the 95 percent confidence interval computed using the analytic (asymptotic) method.

B.3 Post-ZLB Period

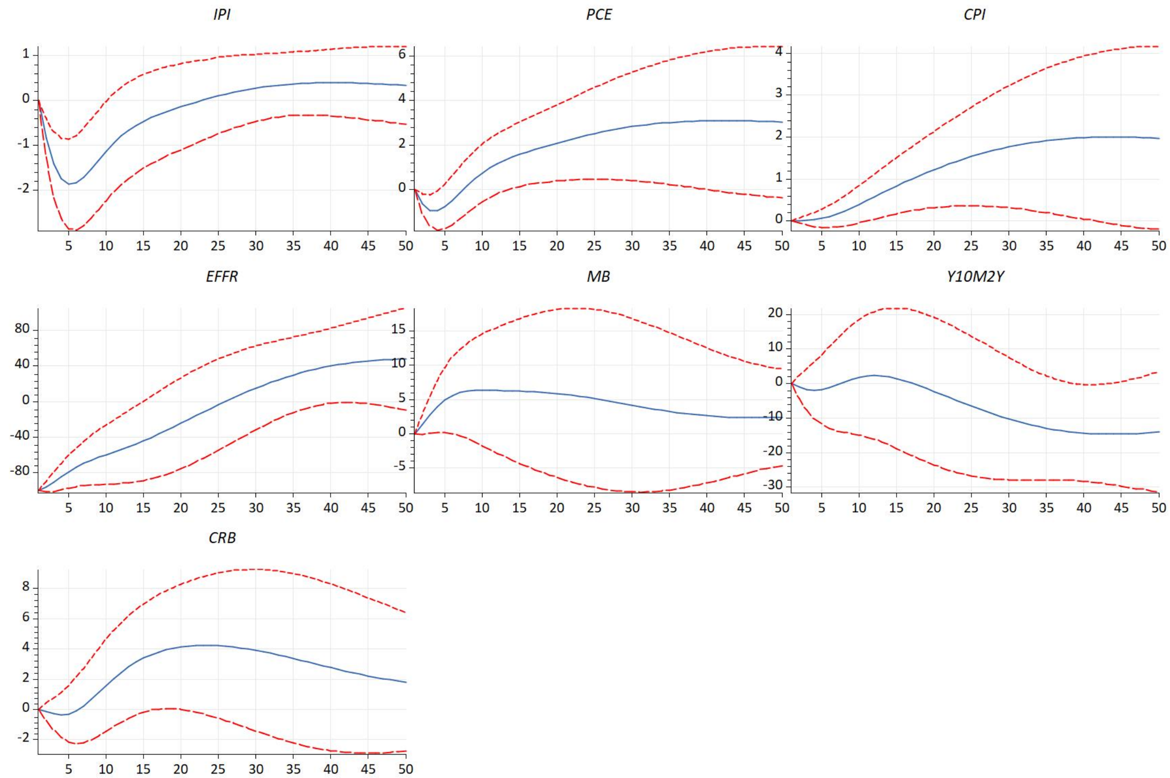

Figure 3.19: IRFs to a 100-basis-point decrease in the EFFR by applying the recursive approach during post-ZLB period. The solid line shows the impulse response, while the dashed lines represent the 95 percent confidence interval computed using the analytic (asymptotic) method.

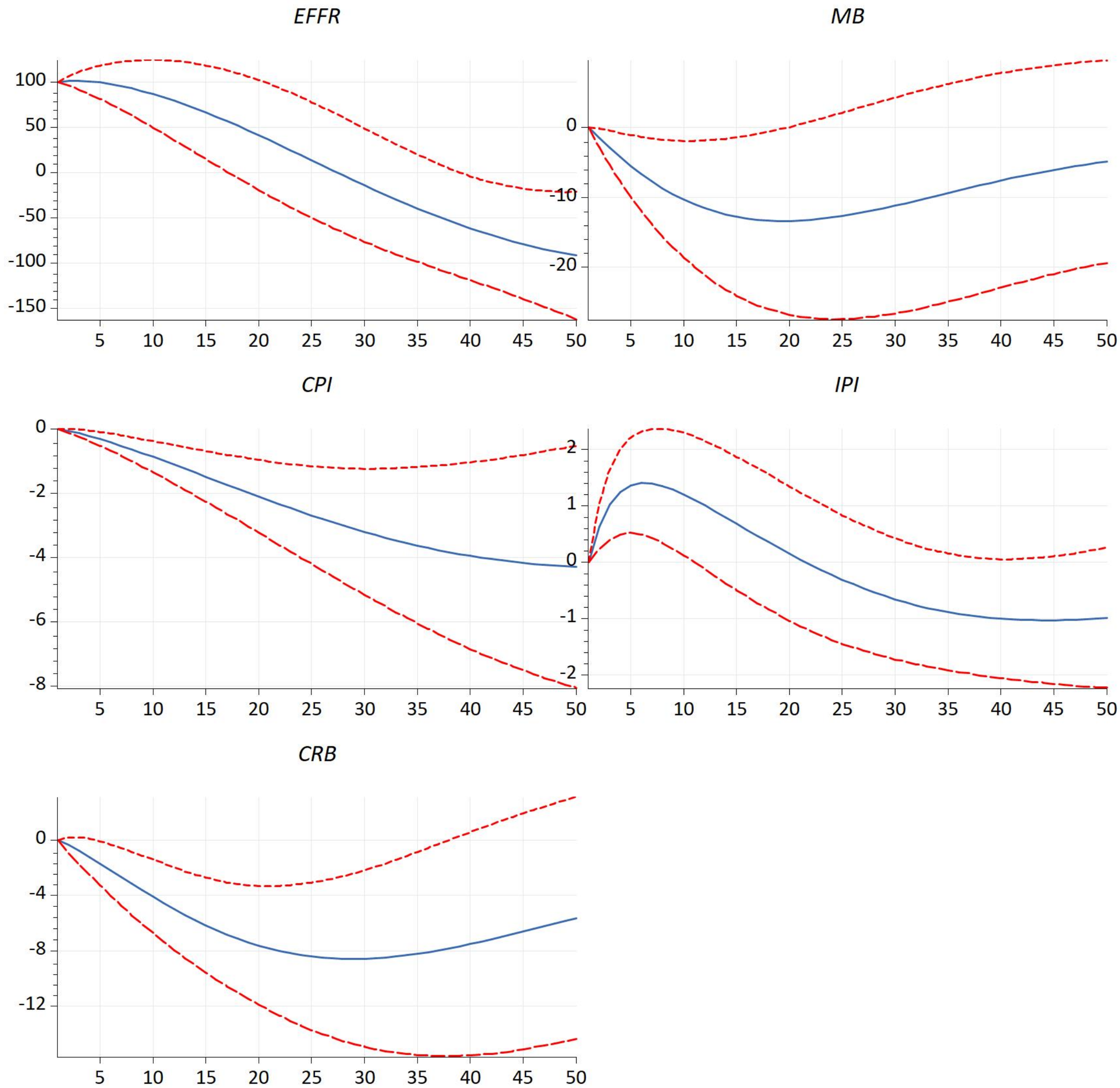

Figure 3.20: IRFs to a 100-basis-point increase in the EFFR by applying the recursive approach during post-ZLB period. The solid line shows the impulse response, while the dashed lines represent the 95 percent confidence interval computed using the analytic (asymptotic) method.

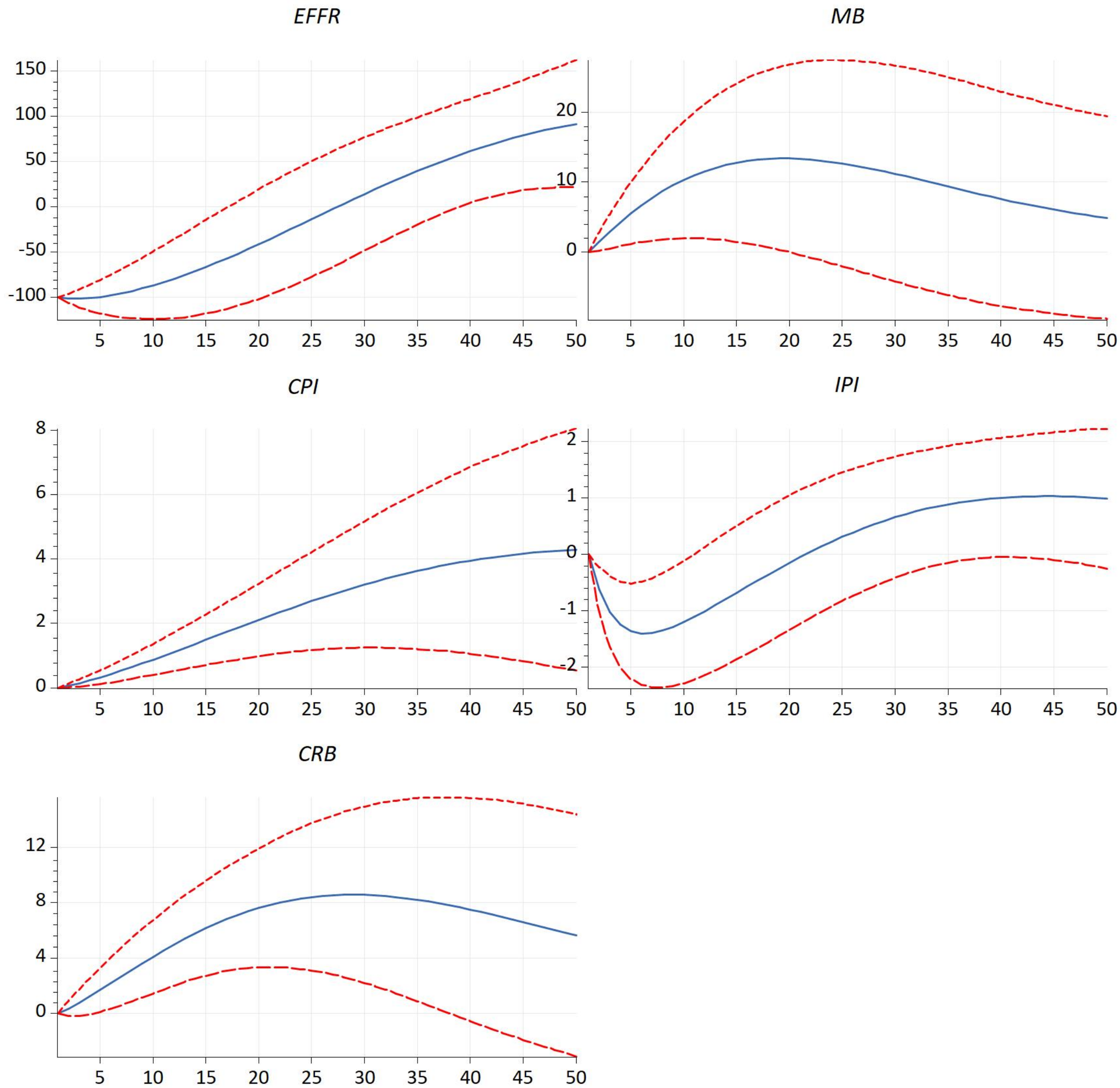

Figure 3.21: IRFs to a 100-basis-point decrease in the EFFR by applying the recursive approach during post-ZLB period. The solid line shows the impulse response, while the dashed lines represent the 95 percent confidence interval computed using the analytic (asymptotic) method.

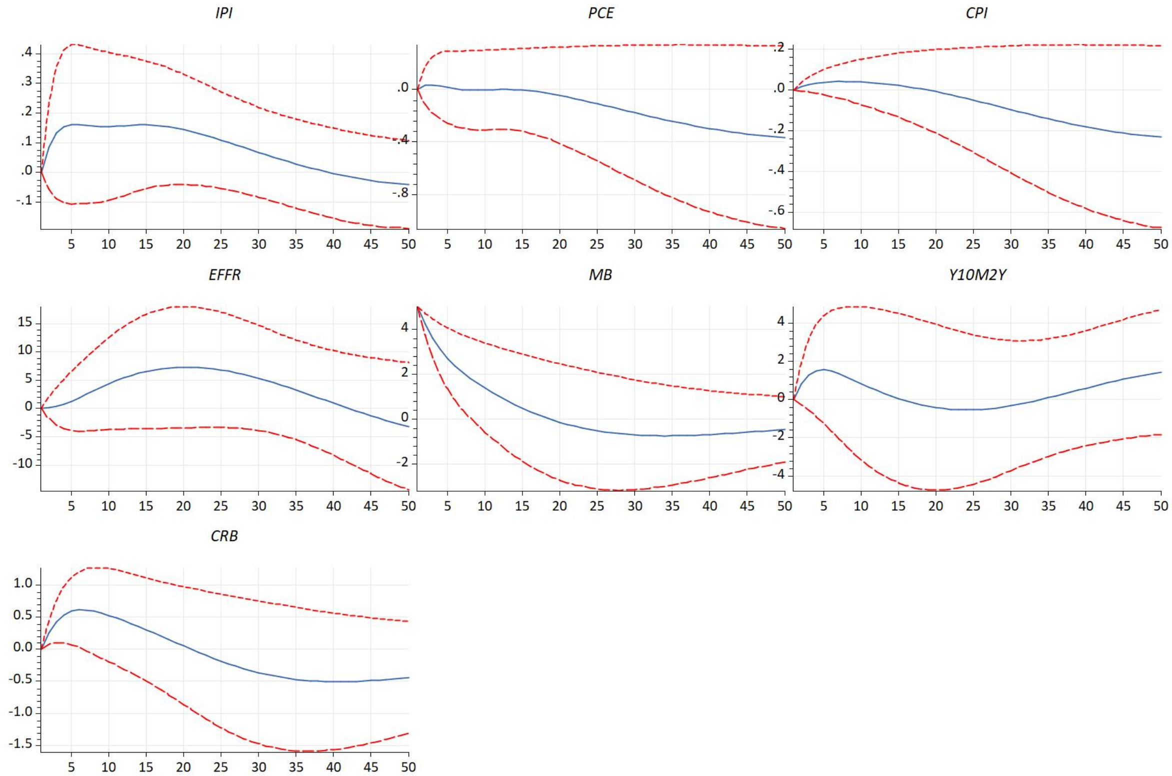

Figure 3.22: IRFs to a 5 percent increase in the MB by applying the recursive approach during post-ZLB period. The solid line shows the impulse response, while the dashed lines represent the 95 percent confidence interval computed using the analytic (asymptotic) method.

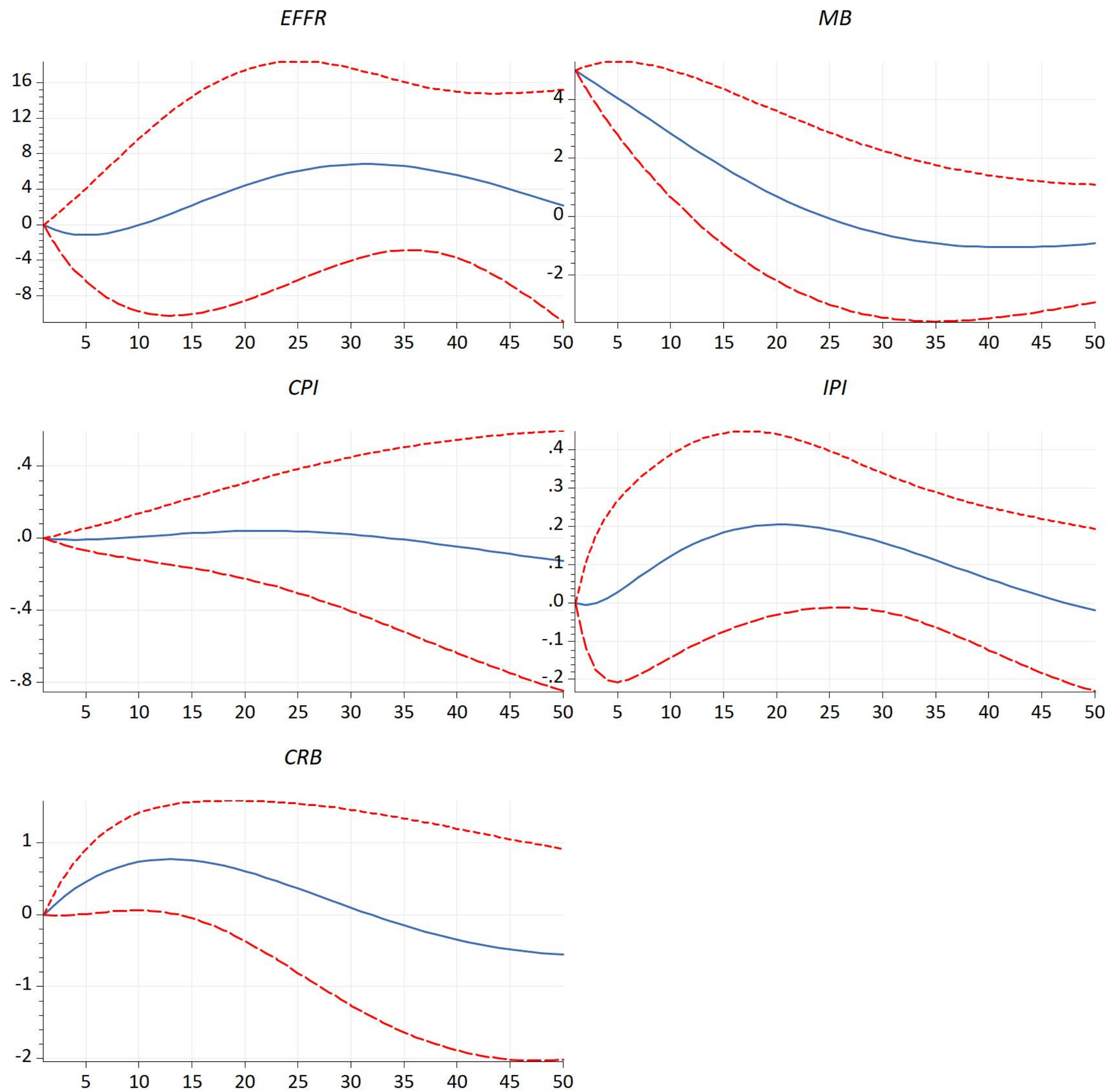

Figure 3.23: IRFs to a 5 percent increase in the MB by applying the non-recursive approach during post-ZLB period. The solid line shows the impulse response, while the dashed lines represent the 95 percent confidence interval computed using the analytic (asymptotic) method.

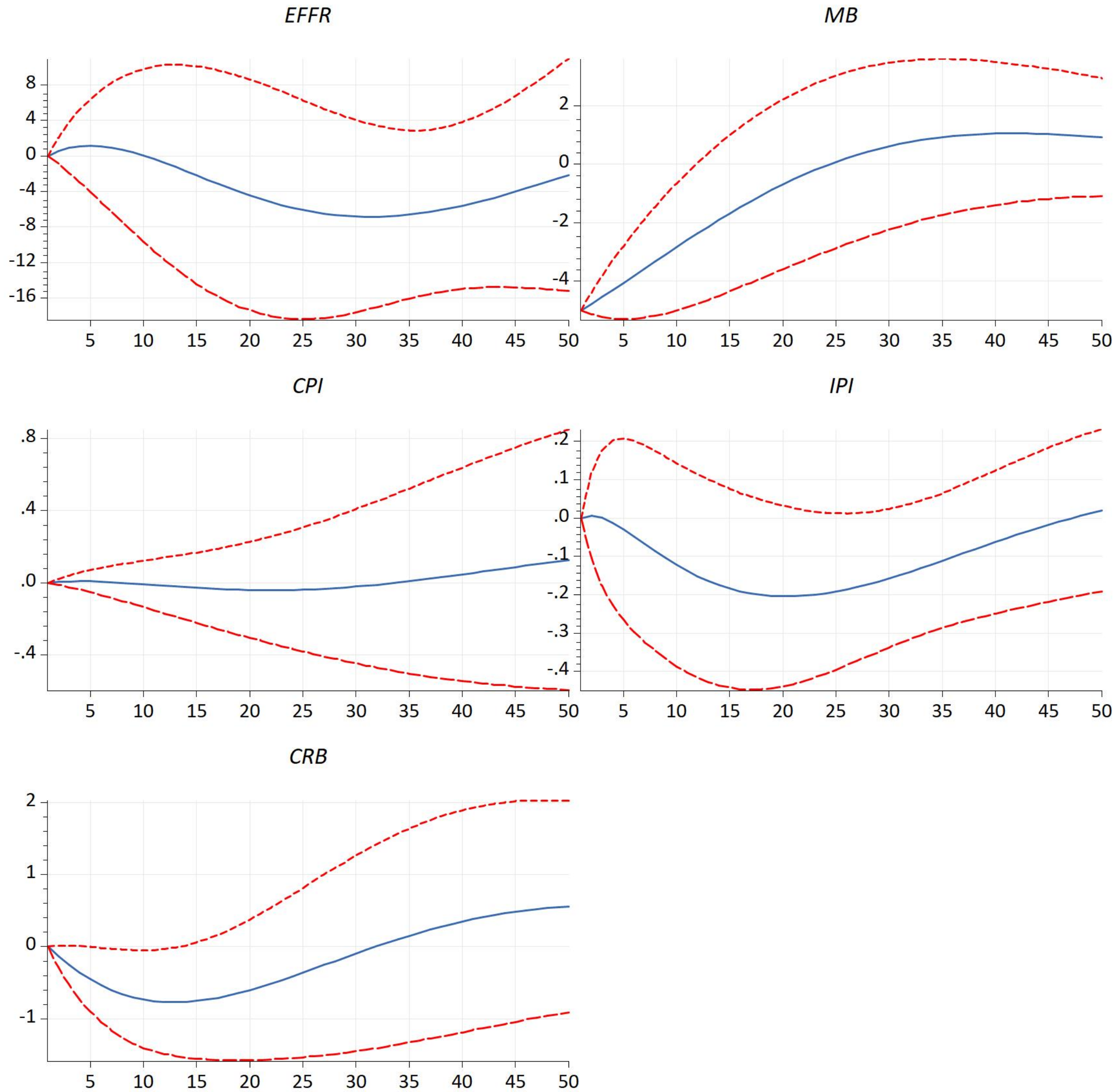

Figure 3.24: IRFs to a 5 percent decrease in the MB by applying the non-recursive approach during post-ZLB period. The solid line shows the impulse response, while the dashed lines represent the 95 percent confidence interval computed using the analytic (asymptotic) method.

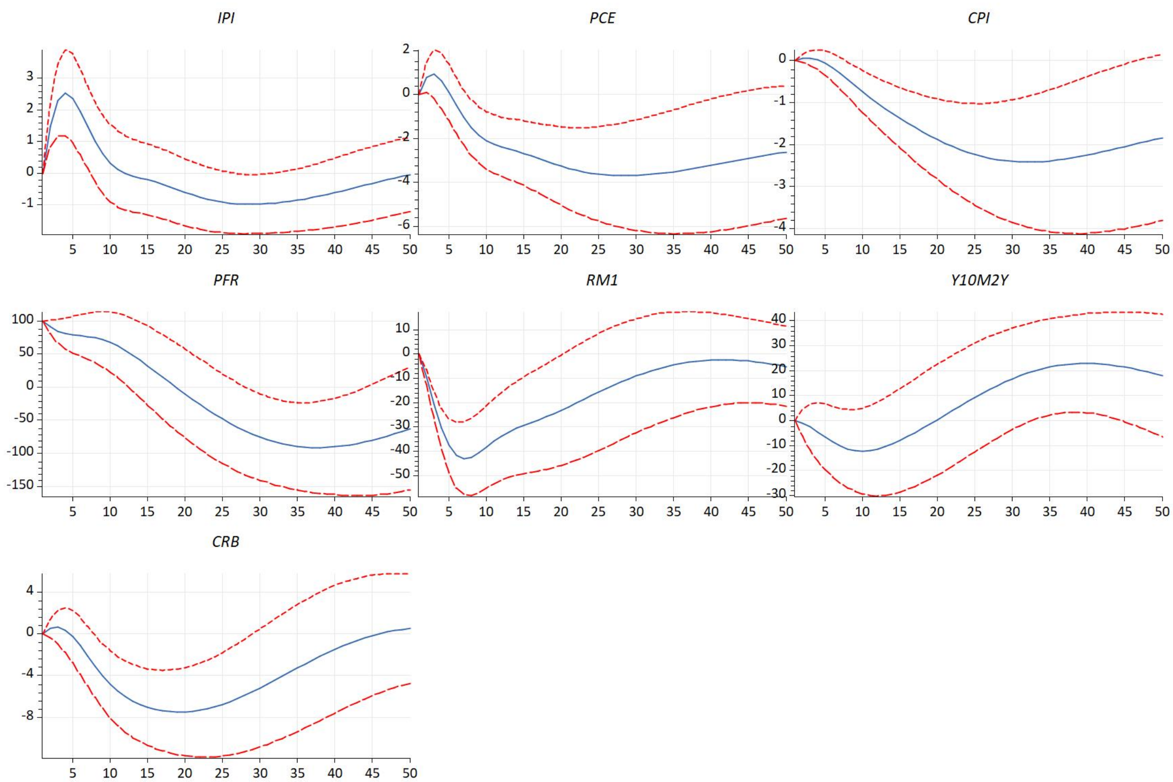

Figure 3.25: IRFs to a 100-basis-point increase in the PFR by applying the recursive approach during post-ZLB period. The solid line shows the impulse response, while the dashed lines represent the 95 percent confidence interval computed using the analytic (asymptotic) method.

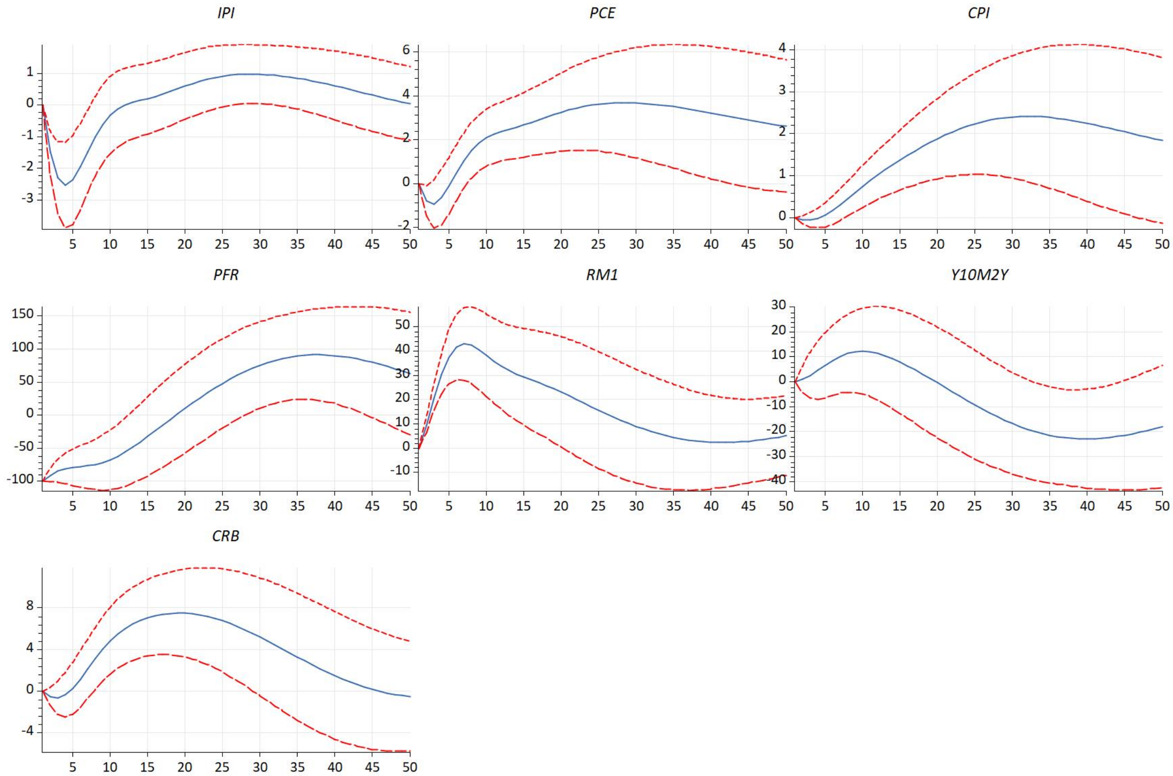

Figure 3.26: IRFs to a 100-basis-point decrease in the PFR by applying the recursive approach during post-ZLB period. The solid line shows the impulse response, while the dashed lines represent the 95 percent confidence interval computed using the analytic (asymptotic) method.

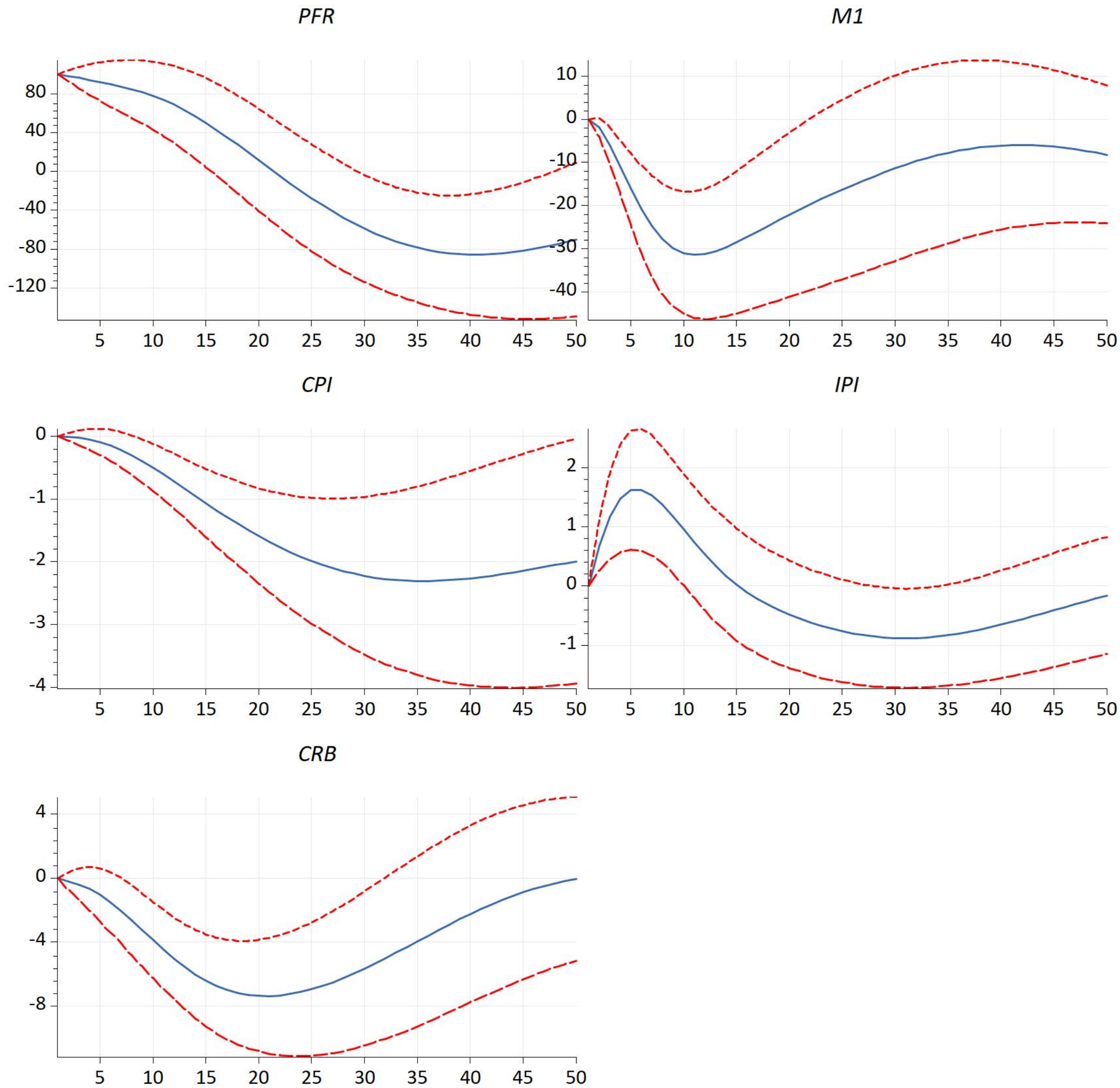

Figure 3.27: IRFs to a 100-basis-point increase in the PFR by applying the non-recursive approach during post-ZLB period. The solid line shows the impulse response, while the dashed lines represent the 95 percent confidence interval computed using the analytic (asymptotic) method.

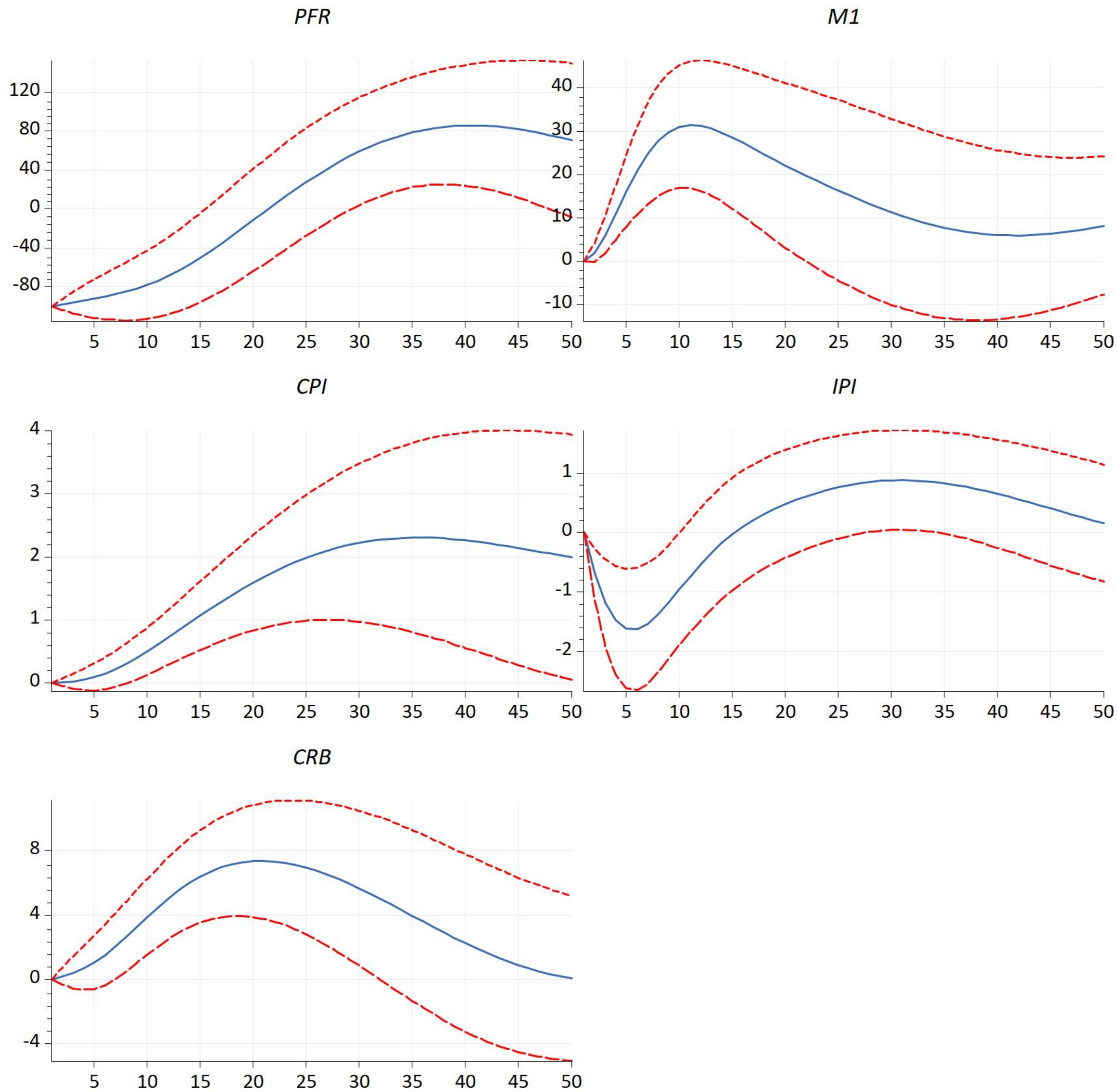

Figure 3.28: IRFs to a 100-basis-point decrease in the PFR by applying the recursive approach during post-ZLB period. The solid line shows the impulse response, while the dashed lines represent the 95 percent confidence interval computed using the analytic (asymptotic) method.

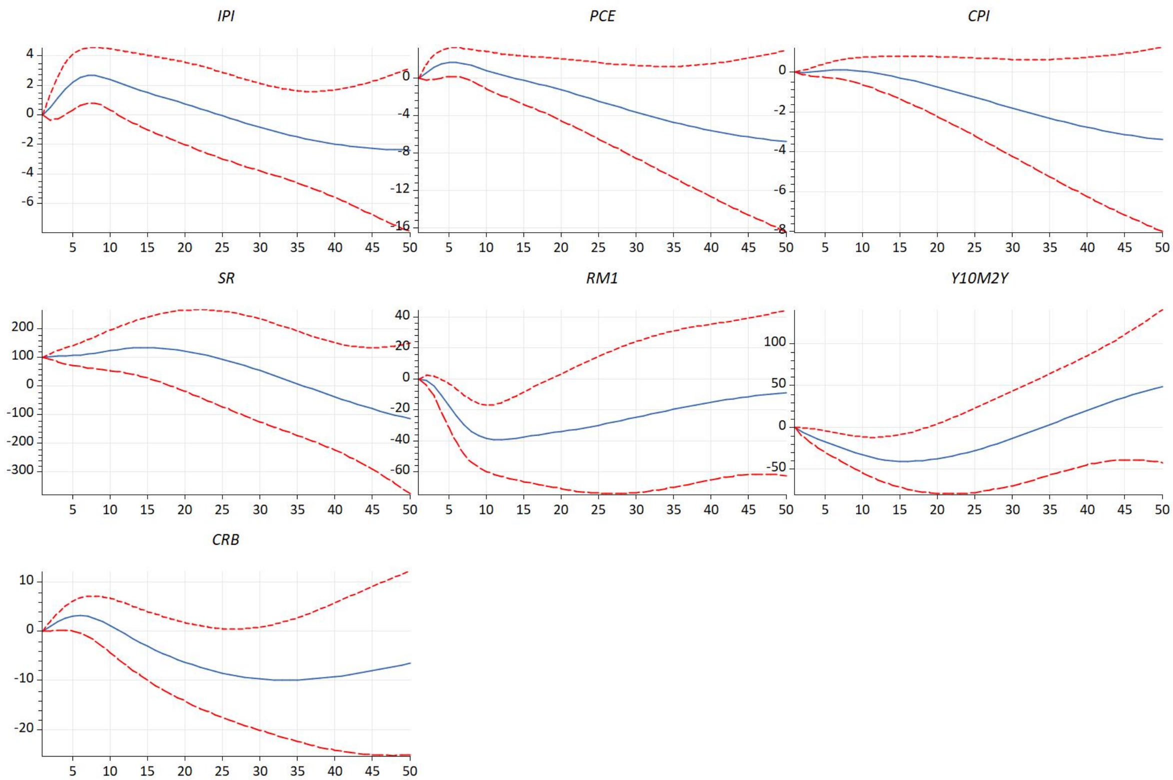

Figure 3.29: IRFs to a 100-basis-point increase in the SR by applying the recursive approach during post-ZLB period. The solid line shows the impulse response, while the dashed lines represent the 95 percent confidence interval computed using the analytic (asymptotic) method.

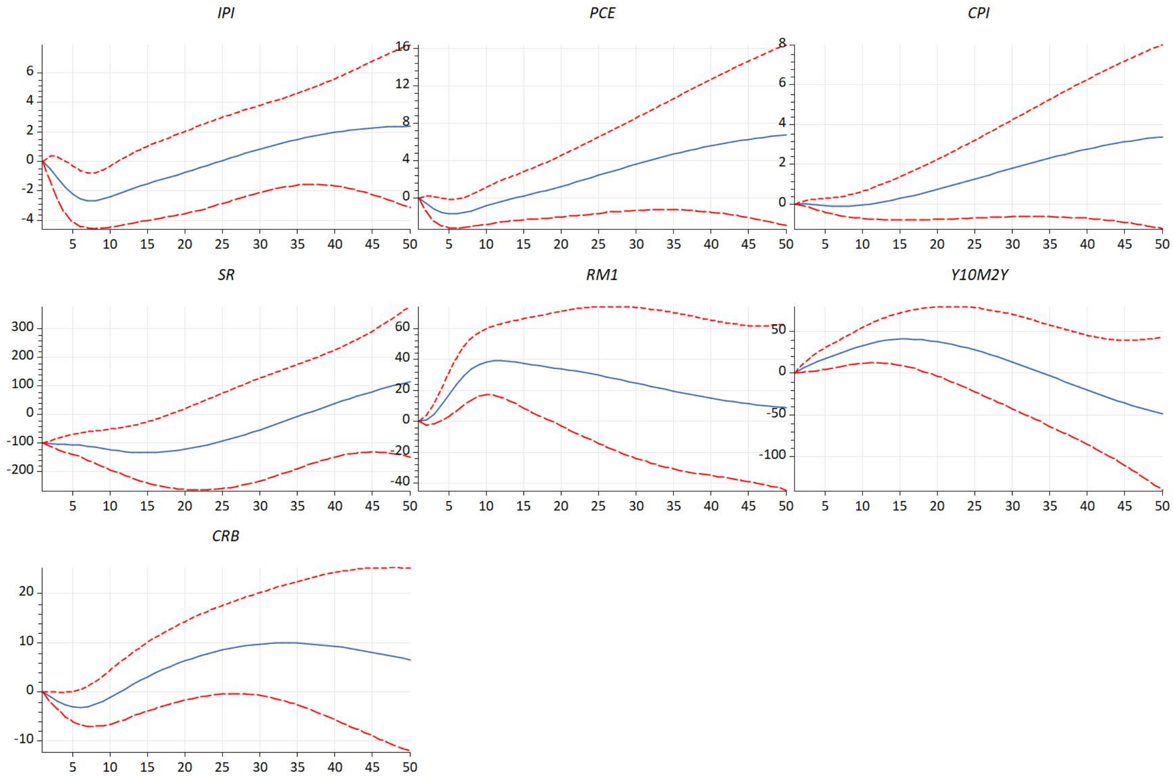

Figure 3.30: IRFs to a 100-basis-point decrease in the SR by applying the recursive approach during post-ZLB period. The solid line shows the impulse response, while the dashed lines represent the 95 percent confidence interval computed using the analytic (asymptotic) method.

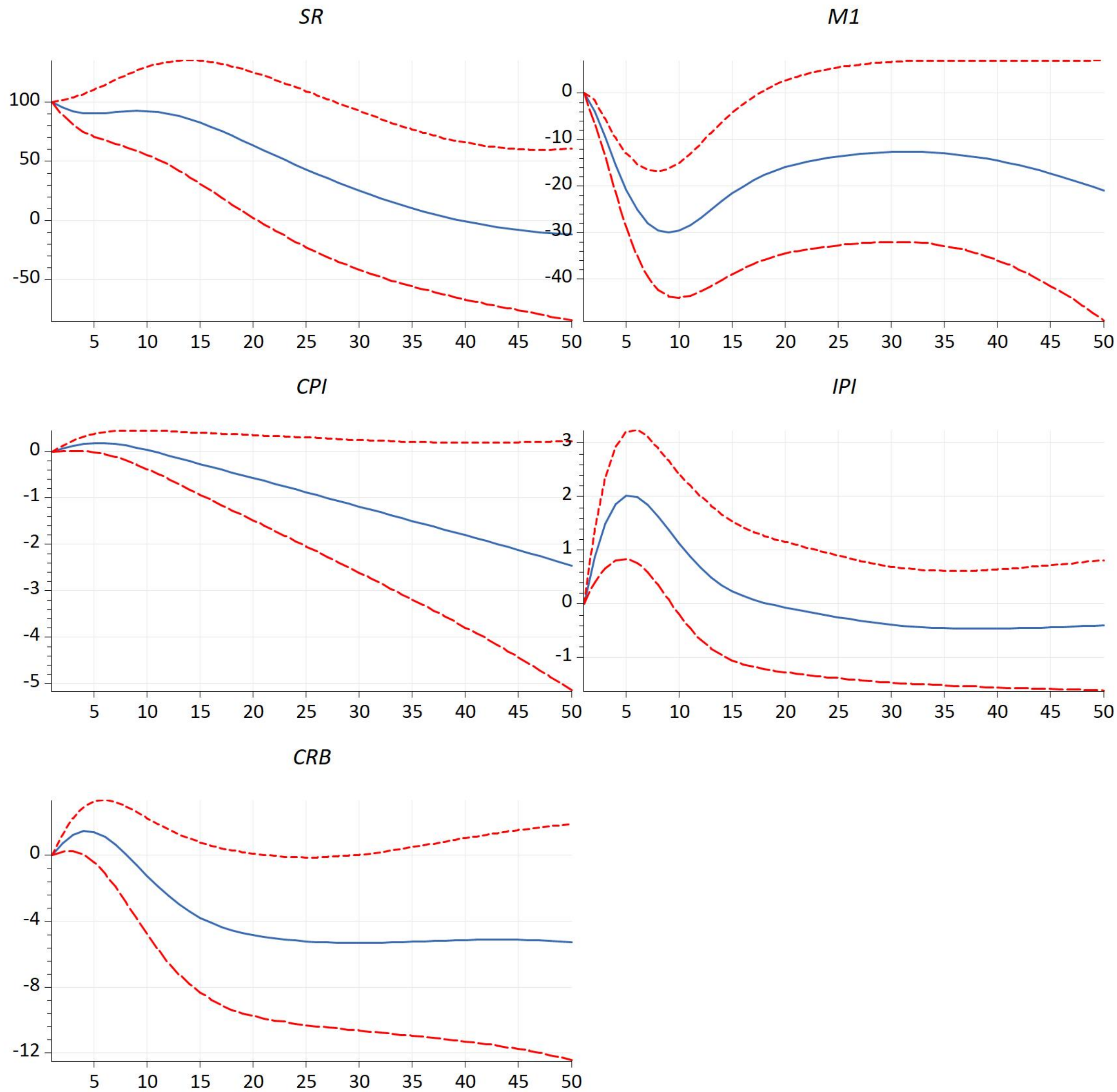

Figure 3.31: IRFs to a 100-basis-point increase in the SR by applying the non-recursive approach during post-ZLB period. The solid line shows the impulse response, while the dashed lines represent the 95 percent confidence interval computed using the analytic (asymptotic) method.

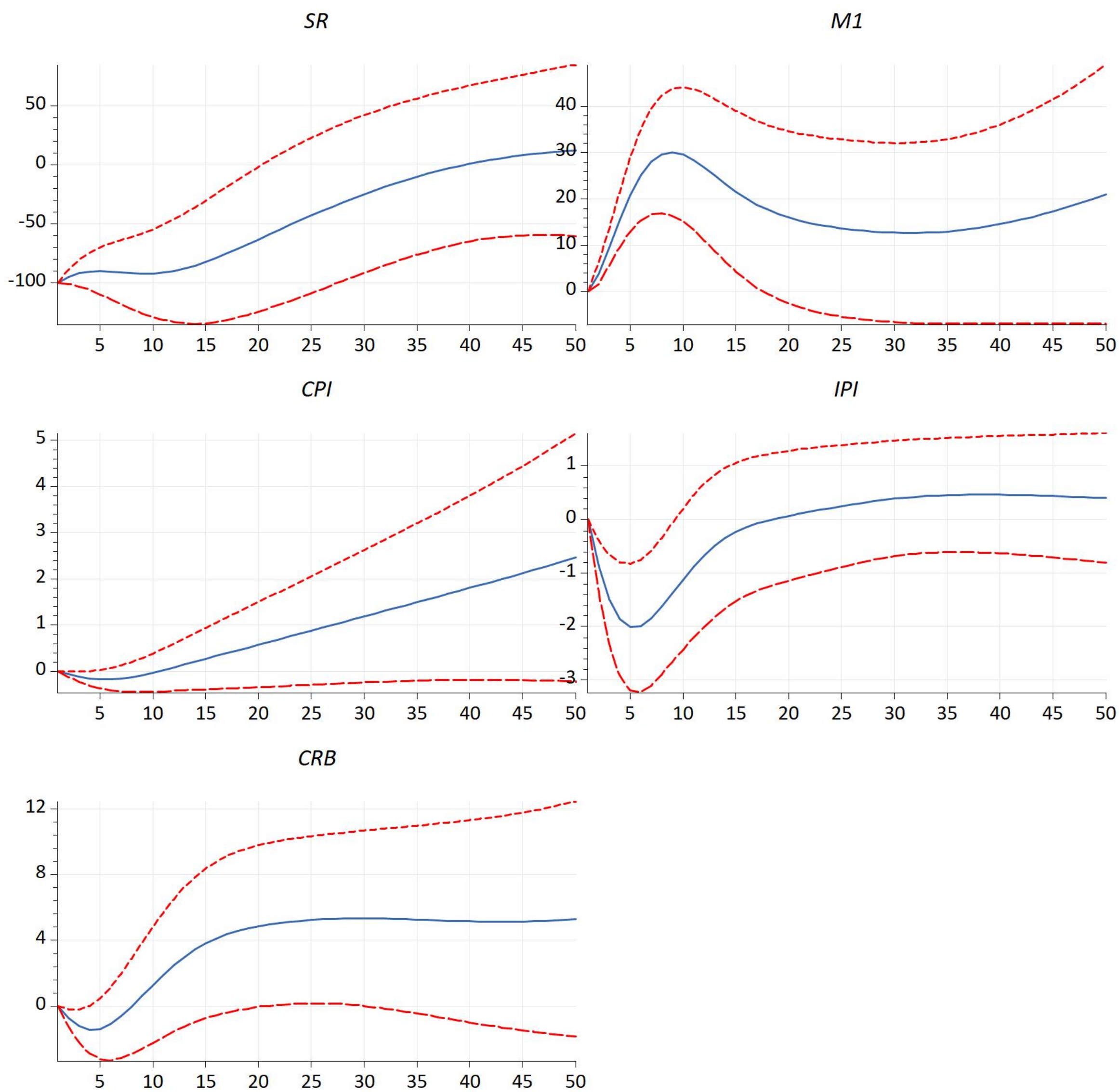

Figure 3.32: IRFs to a 100-basis-point decrease in the SR by applying the non-recursive approach during post-ZLB period. The solid line shows the impulse response, while the dashed lines represent the 95 percent confidence interval computed using the analytic (asymptotic) method.

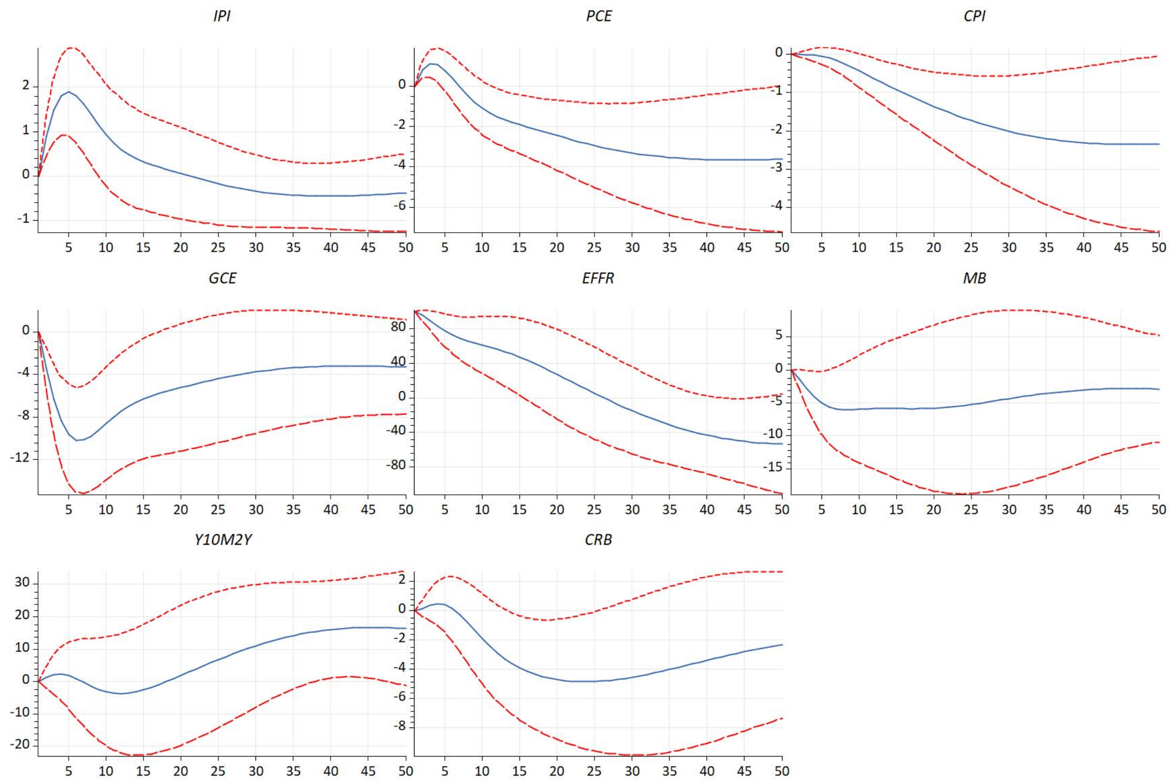

Figure 3.33: IRFs to a 100-basis-point increase in the EFFR and controlling for the fiscal policy (GCE) by applying the recursive approach during post-ZLB period. The solid line shows the impulse response, while the dashed lines represent the 95 percent confidence interval computed using the analytic (asymptotic) method.

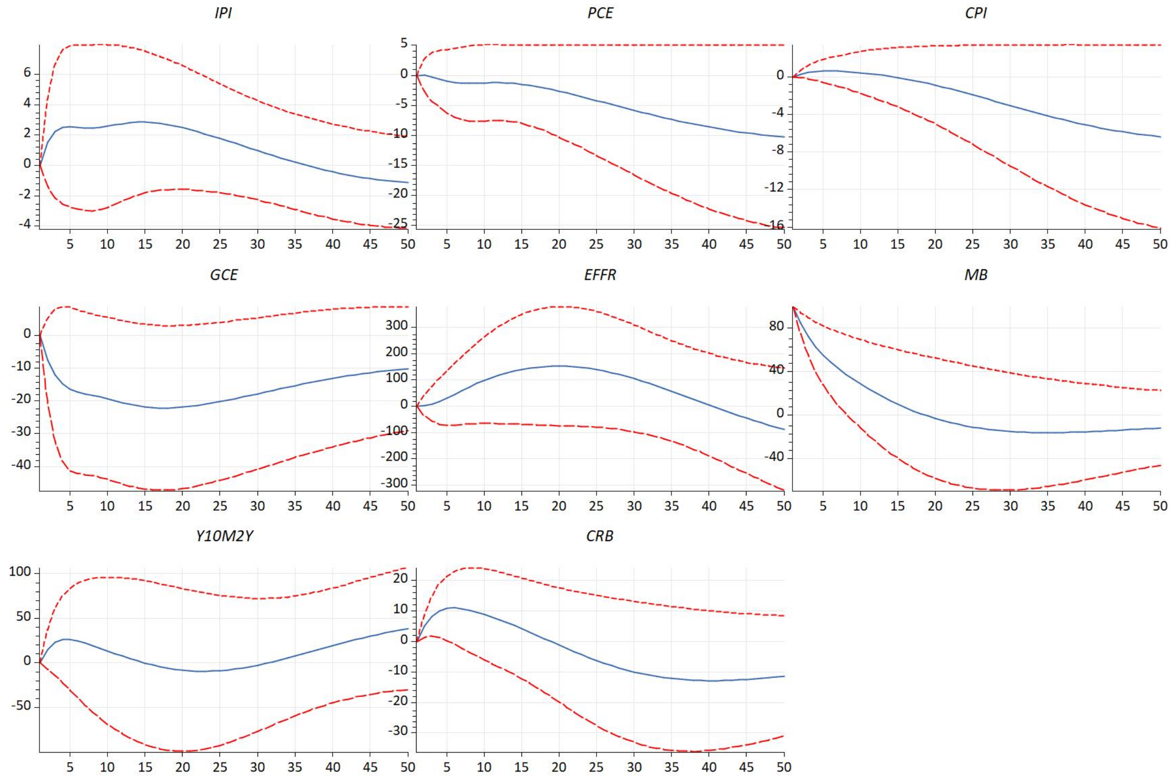

Figure 3.34: IRFs to a 5 percent increase in the MB and controlling for the fiscal policy (GCE) by applying the recursive approach during post-ZLB period. The solid line shows the impulse response, while the dashed lines represent the 95 percent confidence interval computed using the analytic (asymptotic) method.

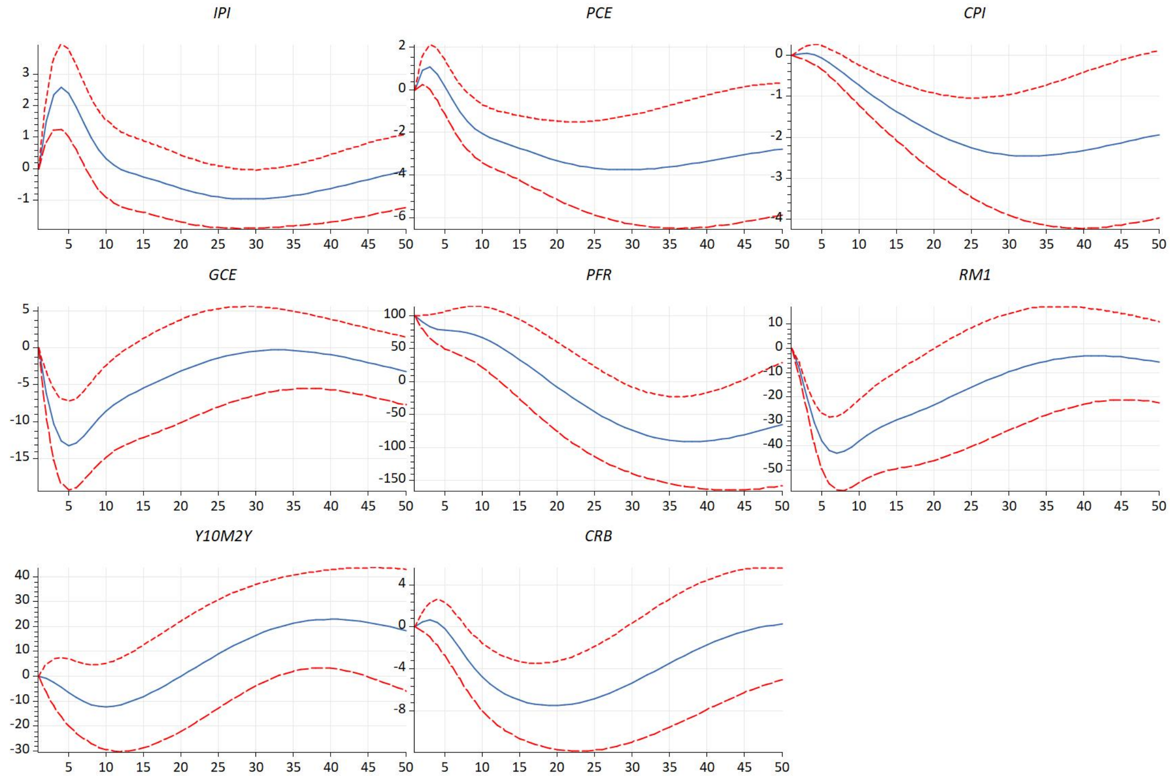

Figure 3.35: IRFs to a 100-basis-point increase in the PFR and controlling for the fiscal policy (GCE) by applying the recursive approach during post-ZLB period. The solid line shows the impulse response, while the dashed lines represent the 95 percent confidence interval computed using the analytic (asymptotic) method.

Appendix C: Tables

Table 3.6: Data source and description

Identifier	Abbr.	Description	Frequency	Unit	SA	Source
INDPRO	IPI	Industrial Production: Total Index	Monthly	Index (2017=100)	SA	Board of Governors of the Federal Reserve System (retrieved from FRED)
PCE	PCE	Personal Consumption Expenditures	Monthly	Billions of Dollars	SA	U.S. Bureau of Economic Analysis (retrieved from FRED)
CPIAUCSL	CPI	Consumer Price Index for All Urban Consumers: All Items	Monthly	Index (1982-84=100)	SA	U.S. Bureau of Labor Statistics (retrieved from FRED)
M1REAL	RM1	Real M1 Money Stock	Monthly	Billions of 1982-84 Dollars	SA	Federal Reserve Bank of St. Louis (retrieved from FRED)
T10Y2Y	Y10M2Y	10-Year Treasury Constant Maturity Minus 2-Year Treasury Constant Maturity	Monthly	Percent	NSA	Federal Reserve Bank of St. Louis (retrieved from FRED)
CRB	CRB	CRB Spot Commodity Price Index: All Commodities	Monthly	Index (1967=100)	SA	Commodity Research Bureau (retrieved from Haver Analytics)
DFF	EFFR	Federal Funds Effective Rate	Monthly	Percent	NSA	Board of Governors of the Federal Reserve System (retrieved from FRED)
PFR	PFR	Proxy Funds Rate	Monthly	Percent	NSA	Choi et al. (2022), FRBSF Economic Letter 2022-30
SR	SR	Wu-Xia Shadow Federal Funds Rate	Monthly	Percent	NSA	Board of Governors of the Federal Reserve System, Wu and Xia (2015)
BOGMBBM	MB	Monetary Base; Reserve Balances	Monthly	Millions of Dollars	NSA	Board of Governors of the Federal Reserve System (retrieved from FRED)
IRG Shock	IRG Shock	Interest Rate Guidance Shock	FOMC Meetings	Sentiment Index	NSA	Qaddoura (2024), unpublished paper
BSP Shock	BSP Shock	Balance Sheet Policy Shock	FOMC Meetings	Sentiment Index	NSA	Qaddoura (2024), unpublished paper
EOA Shock	EOA Shock	Economic Outlook Assessment Shock	FOMC Meetings	Sentiment Index	NSA	Qaddoura (2024), unpublished paper
DEXJPUS	DEXJPUS	Japanese Yen to U.S. Dollar Spot Exchange Rate	Monthly	Yen per Dollar	NSA	Board of Governors of the Federal Reserve System (retrieved from FRED)
HYIELD	HYIELD	ICE BofA US High Yield Index Option-Adjusted Spread	Monthly	Percent	NSA	ICE Data Indices, LLC (retrieved from FRED)
DGS5	DGS5	Market Yield on 5-Year U.S. Treasury Securities	Monthly	Percent	NSA	Board of Governors of the Federal Reserve System (retrieved from FRED)
DAAA	DAAA	Moody's Seasoned Aaa Corporate Bond Yield	Monthly	Percent	NSA	Moody's (retrieved from FRED)
FGEXPND	GCE	Federal Government: Current Expenditures	Quarterly	Percent	SA	U.S. Bureau of Economic Analysis (retrieved from FRED)
RBUSBIS	REER	Real Broad Effective Exchange Rate for United States	Monthly	Index 2020=100	NSA	Bank for International Settlements (retrieved from FRED)
INDU:IND	DJIA	Dow Jones Industrial Average (Bloomberg)	Monthly	Index	NSA	Bloomberg

Table 3.7: Unit root test

Variables	ADF		PP		Conclusion
	Level	**1st Diff.**	**Level**	**1st Diff.**	
IPI	-1.9727	-21.002^{***}	-1.7926	-20.594^{***}	I(1)
PCE	0.2806	-22.769^{***}	0.2409	-26.631^{***}	I(1)
CPI	-1.2566	-5.406^{***}	-0.6127	-20.057^{***}	I(1)
EFFR	-2.7715	-8.161^{***}	-3.3214	-40.770^{***}	I(1)
RM1	-0.5040	-24.866^{***}	-0.5637	-24.957^{***}	I(1)
Y10M2Y	-2.9040	-10.442^{***}	-2.7512	-17.127^{***}	I(1)
CRB	-3.1191	-18.310^{***}	-2.9839	-18.190^{***}	I(1)
PFR	-2.0812	-17.429^{***}	-2.0701	-14.709^{***}	I(1)
SR	-2.3214	-8.698^{***}	-2.4736	-14.451^{***}	I(1)
M2	-2.2853	-4.680^{***}	-1.7697	-20.025^{***}	I(1)
MB	-1.5109	-18.101^{***}	-1.4489	-18.050^{***}	I(1)

Note: The table presents the test statistics for the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. *, **, and *** indicate significance at the 10 percent, 5 percent, and 1 percent levels, respectively. The null hypothesis states that the variable has a unit root. The tests are conducted under the assumption of an intercept and a trend.

Table 3.8: Cointegration test results for pre-ZLB, ZLB, and post-ZLB periods

Period	Test	Hyp. CE(s)	Statistic	Critical Value	No. of CE(s)
Pre-ZLB	Trace	None	178.03	125.61	4
		At most 1	124.65	95.75	
	Max-Eigen	None	53.38	46.23	2
		At most 1	44.94	40.08	
ZLB	Trace	None	187.83	125.61	3
		At most 1	123.84	95.75	
	Max-Eigen	None	63.99	46.23	3
		At most 1	48.70	40.08	
Post-ZLB	Trace	None	232.49	159.53	3
		At most 1	157.05	125.62	
	Max-Eigen	None	75.44	52.36	3
		At most 1	56.33	46.23	

Note: Hyp. CE(s): Hypothesized number of cointegrating equations. **No. of CE(s):** Number of cointegrating equations identified at the 5 percent significance level. **Statistic:** Test statistic for the cointegration test. **Critical Value:** Critical value at the 5 percent significance level.

Table 3.9: VECM lag order selection criteria

Model	AIC	SC	HQ
Pre-ZLB Model	7	1	1
ZLB Model	5	2	2
Post-ZLB Model	2	1	1

Note: The figures in the table represent the number of lags selected by each lag selection test: AIC (Akaike Information Criterion), SC (Schwarz Information Criterion), and HQ (Hannan-Quinn Information Criterion).

Table 3.10: Summary of diagnostic checks

Test	Pre-ZLB	ZLB	Post-ZLB
Normality (p-value)	0.8350	0.5938	0.3153
Serial Correlation (p-value)	0.1165	0.2871	0.3207
Heteroskedasticity (p-value)	0.1278	0.1467	0.2724

Note: Normality is tested using the Jarque-Bera test, serial correlation using the Breusch-Godfrey test, and heteroskedasticity using the Breusch-Pagan-Godfrey test.

Table 3.11: VAR lag order selection criteria

		AIC	SC	HQ
Pre-ZLB model	Recursive	3	1	1
	Non-recursive	2	1	1
ZLB model	Recursive	4	1	2
	Non-recursive	3	1	2
Post-ZLB model	Recursive	2	1	1
	Non-recursive	3	1	2

Note: The figures in the table represent the number of lags selected by each lag selection test: AIC (Akaike Information Criterion), SC (Schwarz Information Criterion), and HQ (Hannan-Quinn Information Criterion).

Table 3.12: SVAR exercises

Period	Approach	MP	Endog. Variables (Ordered)	Shock	Time Period	Obs.
Pre-ZLB	Recursive	Contractionary	ipi pce cpi effr rm1 y10m2y crb	effr	1976M07-2008M10	388
	Recursive	Expansionary	ipi pce cpi effr rm1 y10m2y crb	effr	1976M07-2008M10	388
	Non-recursive	Contractionary	effr rm1 cpi ipi crb	effr	1975M02-2008M10	398
	Non-recursive	Expansionary	effr rm1 cpi ipi crb	effr	1975M02-2008M10	398
ZLB	Recursive	Contractionary	ipi pce cpi pfr rm1 y10m2y crb	pfr	2008M11-2015M11	85
	Recursive	Expansionary	ipi pce cpi pfr rm1 y10m2y crb	pfr	2008M11-2015M11	85
	Non-recursive	Contractionary	pfr rm1 cpi ipi crb	pfr	2008M11-2015M11	85
	Non-recursive	Expansionary	pfr rm1 cpi ipi crb	pfr	2008M11-2015M11	85
	Recursive	Contractionary	ipi pce cpi sr rm1 y10m2y crb	sr	2008M11-2015M11	85
	Recursive	Expansionary	ipi pce cpi sr rm1 y10m2y crb	sr	2008M11-2015M11	85
	Non-recursive	Contractionary	sr rm1 cpi ipi crb	sr	2008M11-2015M11	85
	Non-recursive	Expansionary	sr rm1 cpi ipi crb	sr	2008M11-2015M11	85
Post-ZLB	Recursive	Contractionary	ipi pce cpi effr mb y10m2y crb	effr	2015M01-2024M07	114
	Recursive	Expansionary	ipi pce cpi effr mb y10m2y crb	effr	2015M01-2024M07	114
	Non-recursive	Contractionary	effr mb cpi ipi crb	effr	2015M01-2024M07	114
	Non-recursive	Expansionary	effr mb cpi ipi crb	effr	2015M01-2024M07	114
	Recursive	Expansionary	ipi pce cpi effr mb y10m2y crb	mb	2015M01-2024M07	114
	Recursive	Contractionary	ipi pce cpi effr mb y10m2y crb	mb	2015M01-2024M07	114
	Non-recursive	Expansionary	effr mb cpi ipi crb	mb	2015M01-2024M07	114
	Non-recursive	Contractionary	effr mb cpi ipi crb	mb	2015M01-2024M07	114
	Recursive	Contractionary	ipi pce cpi pfr rm1 y10m2y crb	pfr	2015M01-2024M07	114
	Recursive	Expansionary	ipi pce cpi pfr rm1 y10m2y crb	pfr	2015M01-2024M07	114
	Non-recursive	Contractionary	pfr m1 cpi ipi crb	pfr	2015M01-2024M07	114
	Non-recursive	Expansionary	pfr m1 cpi ipi crb	pfr	2015M01-2024M07	114

Table 3.13: Vector error correction estimates (Pre-ZLB period)

Variable	Coefficient	Std. Error	t-statistic
Cointegrating Equation (CointEq1):			
IPI(-1)	4.127131	0.75339	5.47806
CPI(-1)	2.731815	0.43963	6.21393
EFFR(-1)	−0.036642	0.01803	−2.03175
REER(-1)	1.756370	0.37029	4.74326
Y10M2Y(-1)	0.093585	0.02338	4.00202
DJIA(-1)	0.629640	0.09602	6.55723
C	−41.32000	–	–
Error Correction Coefficients:			
CointEq1	−0.209566	0.04589	−4.56718
D(CRB(-1))	0.479395	0.11655	4.11333
D(IPI(-1))	0.913004	0.32243	2.83167
D(CPI(-1))	0.324385	0.66128	0.49054
D(EFFR(-1))	0.011362	0.00742	1.53206
D(REER(-1))	−0.007328	0.17078	−0.04291
D(Y10M2Y(-1))	−0.004978	0.01698	−0.29310
D(DJIA(-1))	0.128468	0.06438	1.99561
C	0.001235	0.00265	0.46595
Model Summary Statistics:			
R-squared	0.603297	–	–
Adj. R-squared	0.557302	–	–

Table 3.14: Vector error correction estimates (ZLB period)

Variable	**Coefficient**	**Std. Error**	**t-statistic**
Cointegrating Equation (CointEq1):			
IPI(-1)	1.444075	1.78257	0.81011
CPI(-1)	−9.225579	1.54559	−5.96897
PFR(-1)	−0.476465	0.05210	−9.14481
REER(-1)	1.499046	0.66538	2.25292
Y10MFFR(-1)	−0.330285	0.04967	−6.64925
DJ(-1)	0.491741	0.43162	1.13929
C	38.88845	–	–
Error Correction Coefficients:			
CointEq1	−0.096302	0.01523	−6.32354
D(CRB(-1))	0.285061	0.12898	2.21011
D(CRB(-2))	−0.207301	0.12399	−1.67190
D(IPI(-1))	−0.024997	0.35695	−0.07003
D(IPI(-2))	−0.422862	0.36872	−1.14683
D(CPI(-1))	0.461682	1.08990	0.42360
D(CPI(-2))	3.021916	1.15364	2.61947
D(PFR(-1))	0.025577	0.01279	1.99957
D(PFR(-2))	0.037116	0.01451	2.55759
D(REER(-1))	−0.646055	0.26878	−2.40369
D(REER(-2))	−0.102017	0.23816	−0.42836
D(Y10MFFR(-1))	0.004190	0.01302	0.32169
D(Y10MFFR(-2))	0.028622	0.01194	2.39679
D(DJ(-1))	−0.005669	0.08233	−0.06886
D(DJ(-2))	−0.105563	0.08046	−1.31196
C	−0.002652	0.00293	−0.90619
Model Summary Statistics:			
R-squared	0.638043	–	–
Adj. R-squared	0.570177	–	–

Table 3.15: Vector error correction estimates (Post-ZLB period)

Variable	Coefficient	Std. Error	t-statistic
Cointegrating Equation (CointEq1):			
IPI(-1)	3.104326	1.08656	2.85703
CPI(-1)	−6.728891	1.51144	−4.45196
EFFR(-1)	−0.026085	0.03386	−0.77046
MB(-1)	0.857413	0.15263	5.61773
REER(-1)	2.735014	0.95438	2.86574
Y10MFFR(-1)	−0.280392	0.05292	−5.29806
DJ(-1)	0.827972	0.22153	3.73745
C	−4.088347	–	–
Error Correction Coefficients:			
CointEq1	−0.044002	0.01231	−3.57386
D(CRB(-1))	0.486990	0.09369	5.19775
D(IPI(-1))	−0.283495	0.14600	−1.94177
D(CPI(-1))	0.978111	0.77152	1.26777
D(EFFR(-1))	0.031128	0.01044	2.98052
D(MB(-1))	−0.003079	0.04236	−0.07268
D(REER(-1))	0.005090	0.16327	0.03117
D(Y10MFFR(-1))	0.017646	0.00862	2.04787
D(DJ(-1))	0.053463	0.05953	0.89810
C	−0.002759	0.00257	−1.07379
Model Summary Statistics:			
R-squared	0.454654	–	–
Adj. R-squared	0.407461	–	–

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