Forward Guidance and the Dynamics of Bank Credit

The Bank Balance-Sheet Channel of Monetary News

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Abstract

This paper studies how forward guidance affects bank credit supply. Using high-frequency identification around FOMC announcements and local projections on U.S. bank-level data, I find a pronounced asymmetry: contractionary forward guidance triggers an immediate and persistent decline in lending, while expansionary guidance produces weak and delayed loan growth. The mechanism operates through bank balance sheets: tightening shocks reduce equity and raise leverage, pushing banks toward binding capital constraints and forcing credit contraction. A quantitative model with bank constraints matches these dynamics and implies limited stimulus from easing guidance.

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1 Introduction

According to the Federal Reserve Board's website, forward guidance "is a tool that central banks use to tell the public about the likely future course of monetary policy." [1] The Federal Reserve uses forward guidance to shape the expectations of the public at large, individuals and firms alike, so that they have reliable information on which to base their investment decisions. As of 2013, other central banks, such as the Bank of Japan, Bank of England, and European Central Bank, have added forward guidance into their set of monetary policy instruments, with mixed results.[2]

Since the latter half of the 1990s, forward guidance has been incorporated into FOMC announcements, which explains the relative scarcity of research in this area: it's only recently that we have been able to accumulate sufficient data to begin to study the effects of forward guidance on the economy. As central banks continue to make use of this policy mechanism, it's important to continue filling in the gaps in the literature surrounding the effects of this policy tool, which is the intention of this project.

The focus of this paper is on analyzing the effects of forward guidance on bank credit, specifically looking at how banks adjust credit issuance in response to both contractionary and expansionary forward guidance shocks. A very large amount of work already exists on the effects of innovations to the federal funds rate on bank balance sheets and risk-appetite, such as those by Bernanke and Gertler (1995), Adrian and Shin (2010), and Bruno and Shin (2015).

However, there has yet to be any work completed that specifically looks at the effects of the Federal Reserve's forward guidance policy on these variables, operating through an expectations channel, as opposed to an immediate rate change. Therefore, my findings contribute to the literature on the bank balance-sheet channel of monetary policy by illustrating how forward guidance uniquely shapes the timing and composition of bank credit adjustments.

In order to identify forward guidance shocks, I employ an established methodology in

[1] https://www.federalreserve.gov/faqs/what-is-forward-guidance-how-is-it-used-in-the-federal-reserve-monetary-policy.htm

[2] Gertler (2017) discusses the initial limited effects of forward guidance in Japan, identifying the BOJ's lack of credibility as a contributing factor to the relative ineffectiveness of its forward guidance efforts.

the forward guidance literature that originated in Gurkaynak et al. (2005) [3], where I gather high-frequency price data for federal funds rate futures from a thirty-minute window surrounding FOMC meetings, spanning the years 1995 to 2020. The purpose of tracking the data within such a narrow daily window is to isolate the effects that purely extend from FOMC announcements on these asset prices, as opposed to other macroeconomic news that might also influence the prices. At this point, the next step of the procedure is to use the tools of PCA to extract two factors from the effects of FOMC announcements on asset prices: a so-called "target" and a "path factor." They are then rotated so that the latter has zero correlation with the former. We take the path factor to be our forward guidance shock, while the target factor is the shock to the current federal funds rate.

Bauer and Swanson (2023) demonstrate that, despite the high-frequency nature of the federal funds futures data, it is still correlated with macreconomic news. In order to resolve this issue, I follow their procedure of regressing each realization of the path factor on contemporaneous realizations of macroeconomic news. I then collect the residuals of this regression and sum the derived bi-quarterly forward guidance shocks and divide them by two for an average measure each quarter.

I begin by replicating standard results in the literature such as those found in Campbell et al. (2012) and Bundick and Smith (2020); generating impulse response functions (IRFs) of real GDP, the GDP Deflator, and real investment in order to demonstrate that my shocks produce similar impulse responses for those variables. Building on these benchmarks and filling in current gaps in the literature, I extend the analysis to explore the impact of forward guidance shocks on banks' portfolio reallocation and leverage dynamics.

I find that, on impact, bank leverage rises in wake of a contractionary forward guidance shock, which is owing to the fact that banks' equity falls faster than their asset holdings. I also that lending falls immediately and, in line with Van den Heuvel et al. (2002), the adjustment of C&I loans is sluggish, relative to other loans categories, and consumer loans is a major driver of the change in total lending, which displays a large and immediate adjustment. Additionally, in line with the results of Bernanke and Gertler (1995), Kashyap et al. (1996) and Kashyap and Stein (2000) studies of the federal funds rate, I find that following a

[3] From here on referred to as GSS (2005)

contractionary forward guidance shock, the total loan volume issued by commercial banks steadily decreases over time.[4]

Interestingly, my results show an asymmetry in the responses of both bank leverage and lending in response to forward guidance shocks, depending on whether the shock is expansionary or contractionary. The responses of these variables to a contractionary signal from the central bank are larger than their responses to an expansionary shock. Not only this, but the dynamics are different. At early horizons, the response of bank balance sheets to a signal of monetary tightening is immediate. Under an expansion, by contrast, bank leverage and credit adjust gradually, peaking at much later horizons than what is observed in a contractionary environment. I argue that this is owing to capital requirements that force banks to change their lending behaviors in a manner unique to contractionary environments, providing a bank balance-sheet channel for monetary policy.

Taken together, the findings suggest that forward guidance can powerfully contract bank credit, but it has difficulty expanding or stimulating it. Given the fact that the primary interest in forward guidance is its potential to stimulate the economy at the zero bound, it's noteworthy that this paper finds forward guidance to be least effective in an expansionary environment.

Related Literature

This paper aims to fill a key gap in both the forward guidance literature as well as the "conventional"[5] monetary policy literature by assessing the effects of contractionary forward guidance shocks on bank balance sheets and holdings of risky assets. Presently, there exists a large body of literature analyzing the effects of shocks to the federal funds rate on bank balance sheet adjustments, like those of Bernanke and Bliner (1992), Van den Heuvel et al. (2002), and Kashyap and Stein (2000), who evaluate the effects of shocks to the federal funds rate on banks. Adrian and Shin (2010) explored the effects of financial markets on

[4] Bernanke and Blinder (1992) point out that the slow and gradual response of loans can be attributed to their contractual nature.

[5] The distinction between the Federal Reserve's adjustment of its current federal funds rate target and the Federal Reserve's forward guidance policy is often framed as a distinction between "conventional" and "unconventional" monetary policy. From here on, I follow Benigno (2025) in not referring to forward guidance as unconventional.

bank balance sheets and how banks adjust leverage in response to appreciations in their assets. Gambacorta and Shin (2018) show evidence of a differential impact of federal funds rate shocks on bank lending behavior that depends on bank capitalization. Although this literature investigates the effects of monetary policy on bank balance sheets, it lacks an analysis of the effects of forward guidance on these factors in particular.

In terms of the forward guidance literature, there is a diverse range of analysis that has been conducted, with some authors such as Campbell et al. (2012), Nakamura and Steinsson (2018), Bauer and Swanson (2020), and Bundick and Smith (2020) looking at macro aggregates like GDP, unemployment, inflation, consumption, and investment. Other papers break down the responses of these variables even further, like Kroner (2021), who looks at how differences in firm-level uncertainty result in heterogeneous effects of forward guidance on investment. Several papers have investigated the effects of forward guidance on key asset prices such as treasuries and corporate bonds, along with commodity prices and the S&P 500, as in Gurkaynak et al. (2005), and Bauer and Swanson (2023). Swanson (2021) also looks at the effects of forward guidance on dollar/euro and dollar/yen exchange rates. However, just as the monetary policy shock literature which looks at balance sheet effects lacks an investigation of the effects of forward guidance, the forward guidance literature lacks an investigation of the effects on bank balance sheets. My aim here is to bridge this gap.

The methodology employed in this paper to identify forward guidance shocks follows GSS 2005 and its subsequent applications in related papers (Gurkaynak (2005), Swanson (2020), Swanson and Jayawickrema (2023), and Bauer and Swanson (2023))). GSS 2005 builds upon a single-factor approach to measuring the impact of monetary policy surprises on asset prices developed by Kuttner (2001), and Cochrane and Piazzesi (2002), where GSS 2005 shows an improvement upon the single-factor approach via their two-factor approach.

Ultimately, this study contributes to the broader literature examining the intricate linkages between monetary policy shifts and the financial sector. By focusing on forward guidance shocks, this paper sheds light on how these shocks influence the balance sheet decisions of commercial banks, a critical channel through which monetary policy propagates to the real economy. Now that forward guidance appears to have become a permanent fixture of the Federal Reserve monetary policy apparatus, understanding these dynamics is becoming increasingly important. My findings provide new empirical evidence on banks' portfolio reallocation behavior and highlight the nuanced ways in which banks balance trade-offs between liquidity, risk, and profitability across different horizons. These insights stress the importance of forward guidance as a tool for influencing financial intermediation and, ultimately, macroeconomic outcomes.

In the next section, section 2, I will provide a more detailed explanation of how the forward guidance shocks are constructed and identified. Then, in section 3, I will describe the variables involved in my analysis of bank behavior in response to these shocks. Section 4 contains the empirical results of this paper. Section 5 will setup the quantitative model for our analysis. Section 6 will discuss the results of the quantitative model and the final section, section 7, will conclude.

2 Forward Guidance Shocks

The construction of the forward guidance shocks follows the methodology employed in GSS 2005. To begin, I obtain high-frequency data from Acosta et al. (2024) that spans July 1995 to July 2020. The data is collected from a 30-minute window surrounding every FOMC announcement in that time-span where the window starts 10 minutes before and ends 20 minutes after the announcement time. I end up with a total of 204 observations. Within those 30-minute windows, changes in five key futures contracts are tracked: the current-month and three-month-ahead federal funds futures contracts, and the second, third, and fourth eurodollar futures contracts, which have an average of 1.5, 2.5, and 3.5 quarters to expiration, respectively. Please see the appendix for additional detail on how these changes are constructed, which simply follows the methodology employed by Kuttner (2001) and GSS 2005.[6]

Using principal components analysis, Acosta et al. (2024) investigate how many unobserved factors can be accounted for in the observed changes in asset prices immediately following FOMC announcements. Let X be our (204×5) matrix, where the rows correspond

[6]Some outlier observations, such as the emergency meeting after 9/11, were omitted. Please see the appendix for more details.

to FOMC announcement dates, and the columns represent our five futures variables. Let F be a (204×2) Factor matrix, where the two rows correspond to the two factors. Let Λ correspond to the (2×5) factor loadings matrix, and let e represent the (204×5) white-noise disturbance matrix. We want to estimate:

$$X = F\Lambda + e$$

After estimation, one finds that two factors explain a large fraction of the variance in X, as in GSS 2005. It turns out that two factors are sufficient to explain the bulk of the variation in X, which entails that markets extract two major pieces of information from FOMC announcements. The first factor is highly correlated with changes to the federal funds rate. The second factor is also correlated with changes to the current federal funds rate. In order to identify the first factor as the contemporaneous federal funds rate surprise, we need to orthogonalize the two factors via a rotation that yields two new factors. The rotation ensures that the first factor remains highly correlated with the federal funds rate, while the second factor has zero loading on the federal funds rate. Hence, the second factor includes all information that affects futures in the coming year, with the exception of the innovation to the current federal funds rate. This logic follows GSS 2005 and explains why they call the former the "target factor", and the latter a "path factor." The path factor represents the forward guidance shock. The details of how this rotation is performed can be found in the appendix.

Figure 1 is a plot of the forward guidance shocks that spans the years 2012 to 2024. The red bars represent monetary easing surprises and the blue bars monetary tightening surprises. The height of the bars represent the magnitude of the surprise. In accordance with what one might expect, the magnitude of the surprise upon the advent of COVID-19 in the beginning of 2020 is huge, with much more easing than previously anticipated. This illustrates why I ultimately decide to limit the observations to data collected before 2020.

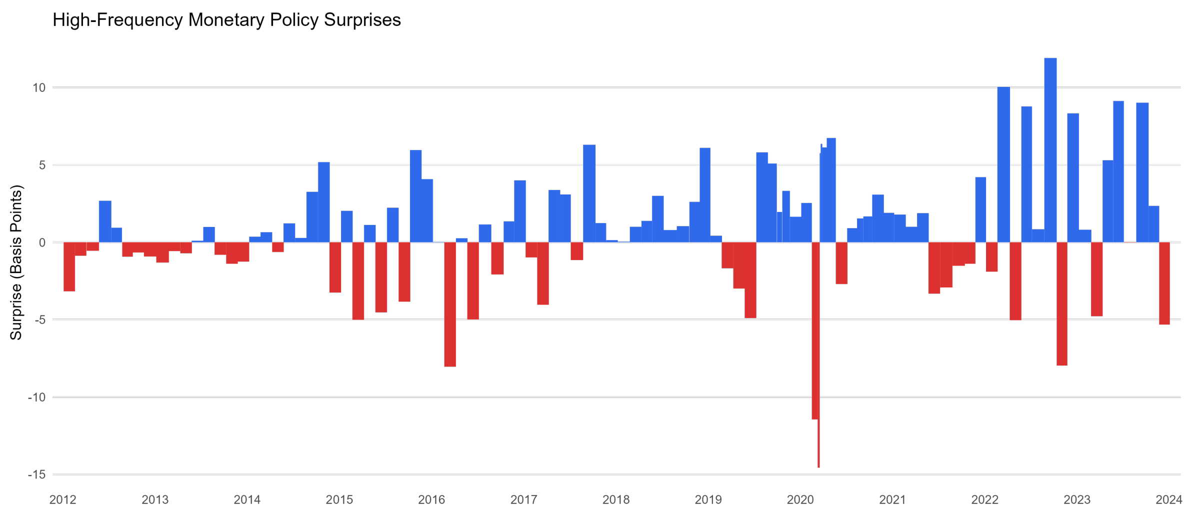


Figure 1: Forward Guidance Shocks Over Time

This plot was retrieved from the San Francisco Fed's website. The data is part of the Center for Monetary Research.

Much of my bank data is only available at quarterly-level frequencies, whereas the forward guidance shocks extracted from PCA are bi-quarterly. To reconcile this frequency mismatch, I sum up the forward guidance shocks that I previously obtained and divide that quantity by two for an average quarterly measure. Before summing the shocks, and in step with Cieslak (2018), Kroner (2021), and Bauer and Swanson (2023), I take each forward guidance shock and regress it on a vector of macroeconomic and financial variables data which were made available before the FOMC announcement. This is to control for the effects that macro and financial news might have on the estimation of both the forward guidance shock and the banks' adjustments to their balance sheets.

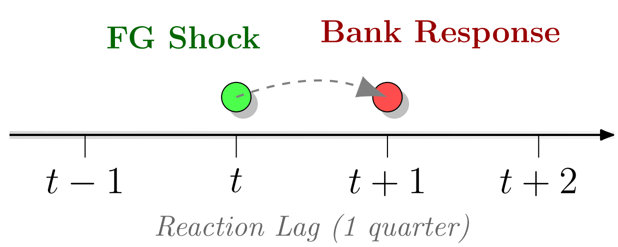
Following Bauer and Swanson (2023), I use six variables that are related to the Federal Reserve's monetary policy decisions: nonfarm payrolls surprise, employment growth, S&P 500, yield curve slope, commodity prices, and treasury skewness. The nonfarm payrolls surprise is calculated as the difference between the value of the most recent nonfarm payrolls release and the expectation for that release based upon surveys of financial market participants. Employment growth is calculated in terms of the log difference between the current and previous years' nonfarm payroll employment releases, which follows Cieslak (2018). The S&P 500 variable represents a log difference between in the stock market index the day prior to the announcement and 65 trading days prior to the announcement. The yield curve slope is the difference between the slope of the yield curve the day before the announcement and three months prior to the announcement. For commodity prices, I look at the log difference in the Bloomberg Commodity Spot Price index between three months prior to the announcement and the day prior to the announcement. Last, the treasury skewness measure is the implied skewness of the 10-year Treasury yield, following Bauer and Chernov (2024). I add the residuals of each bi-quarterly regression to a single quarterly shock that represents the final forward guidance shock. The news-effects are projected out in the following manner:

$$Path_\tau = \alpha + \beta V_\tau + u_\tau$$

Where $Path_\tau$ is one of the bi-quarterly forward guidance shocks (path factor) at time τ, and V_τ is our vector of controls for macroeconomic news that is released prior to the FOMC announcement, as described above. Then, summing our bi-quarterly shock to a single measure we obtain:

$$\psi_t = \frac{\sum_{\tau \in t} u_\tau}{2}$$

Due to the delay in banks' ability to respond to these shocks, I offset the shocks by a single quarter so that I estimate banks' reactions to the forward guidance shock one quarter after the initial forward guidance shock is observed. This procedure also follows Kroner (2021) and Bauer and Swanson (2023), as illustrated below:



The appendix provides details on the macroeconomic and financial variables used to control for the effects of news releases on surprises to the futures data.

3 Contractionary versus Expansionary Forward Guidance Shocks

To begin, I'd like to contrast the effects of contractionary versus expansionary forward guidance surprises. To this end, I present the IRFs of real GDP, real investment, and the GDP deflator in response to each shock. Contractionary forward guidance is a signal from the FOMC that a monetary tightening is on the horizon, whereas an expansionary shocks signals a future federal funds rate decrease.

Each of these variables are recorded in billions of dollars. Due to scale mismatch with my forward guidance shocks, I apply a log-difference transformation to convert levels into growth rates, following Galí and Gertler (1999). This transformation helps mitigate the scale mismatch, allowing us to interpret the coefficients as the percentage change in the variable in response to a shock.

To estimate the dynamic responses of bank-level variables to a contractionary forward guidance shock, I use the Local Projections (LP) method from Jordà (2005). Unlike vector autoregressions (VARs), LPs estimate the response at each horizon separately, which has an enhanced capacity for handling nonlinearities and is less sensitive to lag-length misspecification as a linear estimator than VARs.

In anticipation of questions regarding why I have chosen to use LPs instead of a VAR, the simple answer is that, when we have large samples and the VAR has the correct lag order, these two methods are equivalent (Plagborg-Møller and Wolf (2021)). However, my sample size is relatively small, which, given the amount of endogenous variables I have in my regression, would quickly exhaust the degrees of freedom. Although these two approaches are on opposite ends of the bias-variance spectrum, (LPs having low bias and high variance in smaller samples), this is dealt with by estimating each regression with Newey-West standard errors. Following Barnichon and Brownlees (2019) I apply cubic smoothing splines with a smoothing parameter to the estimated impulse responses and their confidence intervals. This smoothing preserves the fundamental dynamic movements while also reducing excessive noise.

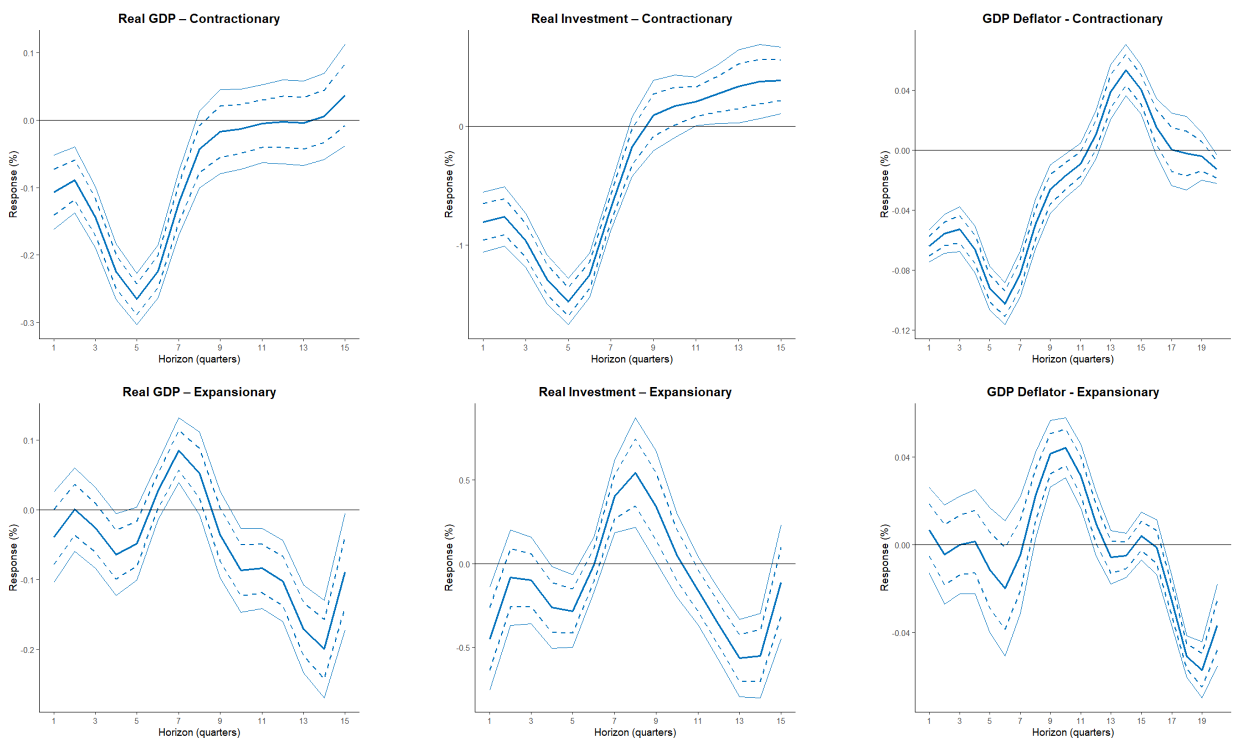


Figure 2: IRFs of Aggregates

The figures are the impulse responses of various aggregate variables to the one standard deviation contractionary forward guidance shock. The inner dashed band corresponds to the 68% confidence band, while the. outer solid band corresponds to the 90% confidence band.

As a result, my impulse response function is specified as:

$$\Delta_\tau \log(y_{t+\tau}) = \alpha + \beta_\tau \, \psi_t + \sum_{i=1}^{4} \gamma'_{\tau,i} Z_{t-i} + \varepsilon_{t+\tau}, \quad \tau = 0, 1, \ldots, 20,$$

where $\Delta_\tau \log(y_{t+\tau}) \equiv \log(y_{t+h}) - \log(y_{t-1})$ is the percentage change in the variable at horizon τ, ψ_t represents the forward guidance shock, and Z_t is a vector of control variables, which includes log transformations of real GDP, the GDP deflator, real investment, and the federal funds rate, the 10-year Treasury rate, Moody's corporate bond yield, and VIX. The coefficient β_τ then measures the impact of a one standard deviation contractionary forward guidance shock on the growth rate of y_τ (in percentage points).

The key macro-aggregates and their IRFs are displayed in Figure 2. I present the IRFs in response to both contractionary and expansionary shocks. In a contractionary environment, there are immediate declines in real GDP, real investment, and the GDP deflator. The expansionary shocks lead to more delayed reactions in the economy. We only begin to start seeing movements in the expected direction five to six quarters out from the initial shock. This appears consistent with the narrative of pessimism driving the asymmetric reactions to contractionary versus expansionary forward guidance shocks Kroner (2021).

4 Bank Data

When examining the effects of forward guidance shocks on bank balance sheets, I'm primarily interested in looking at broad trends in the banking sector. My dataset covers a sample spanning from 1995Q3 to 2024Q3. Many of the bank balance sheet items of interest can be obtained via public data provided by the Board of Governors of the Federal Reserve System and the Federal Deposit Insurance Corporation (FDIC). However, a few of the key variables of interest in my study are not available from these sources over the desired date range. Those variables are bank loans and bank leverage. Loan data is obtained from FFIEC Call Reports via Wharton Reasearch Data Services (WRDS).

In order to obtain a broad measure of bank leverage, I pull data on its individual components and combine them to make a single measure. The data for the leverage components only extend to the year 2020 in the Board of Governors' public database. To get a measure that extends through 2024, I construct a broad measure of leverage, I obtain data from WRDS; specifically, I obtain the necessary data from Compustat's Capital IQ bank fundamentals. The Compustat data contains information on about 10,800 large and mid-sized U.S. commercial banks that serve as the representative sample of "commercial banks." For the remaining bank-level variables in my dataset, the Board of Governors and FDIC provide public data over the appropriate date range.

To ameliorate any concerns regarding this approach, I acquired data from the Board of Governors' public database and constructed a measure of leverage from 1995 to 2020 which is similar to my leverage measure constructed via the Compustat data. I then compared the magnitudes and directions of the impulse responses of the leverage measures from both data sources over this mutually shared horizon (1995-2020). The magnitudes and directions of the IRFs for leverage, assets, debt, and equity were virtually identical across both datasets.

Hence, my 1995 to 2024 Compustat sample is a consistent representation of broader banking industry leverage trends. A comprehensive list of the representative banks can be found in the appendix.

In constructing a measure of leverage for the banking system at large, I follow Adrian et al. (2014) in employing the following specification:

$$\text{Leverage}_t = \frac{\text{Assets}_t}{\text{Equity}_t}$$

which is the inverse of the He et al. (2017) capital ratio. For each quarter t, I put together an aggregated leverage measure as:

$$\text{Leverage}_t = \frac{\sum_i (\text{Market Equity}_{i,t} + \text{Book Debt}_{i,t})}{\sum_i \text{Market Equity}_{i,t}}$$

where firm i is one of the commercial banks during quarter t. As stated above, the individual components of this measure come from the Compustat database for U.S. banks. The market value of equity is simply the firm's individual share price multiplied by its number of outstanding shares. The book value of debt is the bank's total assets minus its common equity.

Data on these banks' holdings of U.S. Treasury securities was taken from Call Reports in Compustat. All of the remaining data in my study is publicly available from either the FDIC or the Board of Governors' websites.

5 Forward Guidance Shocks and Bank Balance Sheets

5.1 Local Projections

For several bank-level variables, such as: total loans, assets, equity, etc., the data are recorded in billions of dollars. Due to scale mismatch with my forward guidance shocks, I apply a log-difference transformation to convert levels into growth rates, following Galí and Gertler (1999).

This transformation helps mitigate the scale mismatch, allowing us to interpret the coefficients as the percentage change in the variable in response to a shock. To estimate the dynamic responses of bank-level variables to a contractionary forward guidance shock, I use the Local Projections (LP) method from Jordà (2005). Unlike vector autoregressions (VARs), LPs estimate the response at each horizon separately, which has an enhanced capacity for handling nonlinearities and time variation. As a result, my impulse response function is specified as:

$$\Delta_\tau \log(y_{t+\tau}) = \mu_i + \alpha_h FG^{\text{con}}_{i,t} + \gamma_h FG^{\text{exp}}_{i,t} + \sum_{i=1}^{4} \gamma'_{\tau,i} Z_{t-i} + \varepsilon_{t+\tau}, \quad \tau = 0, 1, \ldots, 20,$$

where $\Delta_\tau \log(y_{t+\tau}) \equiv \log(y_{t+h}) - \log(y_{t-1})$ is the percentage change in the variable at horizon τ, $FG^{\text{con}}_{i,t}$ represents the expansionary forward guidance shock, and $FG^{\text{exp}}_{i,t}$ is its expansionary counterpart. They are constructed as follows:

$$FG^{\text{con}}_{i,t} = \max(\text{shock}_t, 0)$$
$$FG^{\text{exp}}_{i,t} = \max(-\text{shock}_t, 0)$$

With "shock_t" being the residual of the regression that projects out the effects of macro news. Z_t is a vector of control variables, which includes log transformations of real GDP, the GDP deflator, real investment, and the federal funds rate. μ_i represents bank-level fixed effects. The coefficients α_h and γ_h measure the impact of a one standard deviation contractionary and expansionary forward guidance shock, respectively, on the growth rate of y_τ (in percentage points).

Figure 3 shows the impulse responses of two loan categories to a contractionary forward guidance shock over 20 quarters, in addition to the impulse response of the total amount of loans issued by commercial banks.

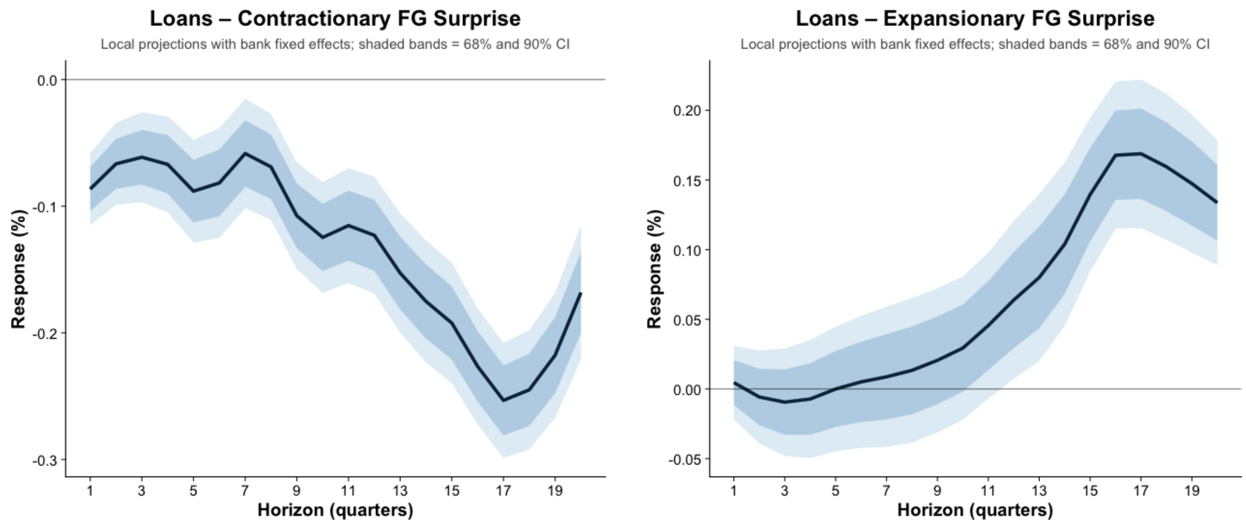


Figure 3: Loan Responses to Forward Guidance Shocks

The figures are the impulse responses of total loans for banks to a one standard deviation contractionary (left) and expansionary (right) forward guidance shock. The inner dark band corresponds to the 68% confidence band, while the outer light band corresponds to the 90% confidence band.

For each of the IRFs, I conduct a Wald test in order to test the null hypothesis that the IRF responses across the 20 horizons are jointly zero. For the IRFs presented in Figure 3, the null hypothesis is strongly rejected, indicating statistically significant responses over time. I also looked at the signifiance at each horizon. The pointwise estimates are significant at the 5% level across every horizon for loans following a contractionary surprise, with the exception of horizons three and seven. For loans following an expansionary surprise, the pointwise estimates become significant at the 13th horizon and remain significant over the remainder of the horizons thereafter.

The left panel of figure 3 shows an immediate and significant decline in lending following a contractionary signal from the Fed. The credit contraction sustains itself and even intensifies until 17 quarters out from the initial shock, at which point lending begins its rebound. From this we can conclude that, in an environment of monetary tightening, banks react quickly and forcefully to forward guidance surprises. The reaction is not only immediate, but it is also sustained over a long period of time.

For the right panel, by contrast, the first 12 point estimates are insignificant at the 5% level. This means that the change in lending is indistinguishable from zero until 13 quarters after the initial shock. Once, we reach quarter 13 and beyond, we see a statisically significant increase in lending. It is also noteworthy that the absolute value of the lending response is smaller in an expansionary environment than it is in a contractionary environment. With a trough of about 29 basis points by quarter 17 in the case of tightening, and a peak of about 19 basis points in the case of an expansion.

We see a clear asymmetry here: forward guidance shocks have more of an impact on bank lending in a contractionary environment than they do in an expansionary environment. The tightening results in a fast, large, and significant contraction in lending, which is sustained over several years. The expansion on the other hand, doesn't have a tangible effect on lending until several quarters after the initial surprise. The reaction in this latter case is both delayed and smaller.

Another noteworthy feature is that the change in lending accelerates over time in both cases. Along the initial horizons of the left panel, we see an immediate drop in lending, then the dropoff gradually accelerates, indicating a bit of a lag in the response of bank lending in a contractionary environment. Bernanke and Blinder (1992) and Kashyap, Stein, and Wilcox (1993) point out that banks have contractual obligations with other firms that they cannot immediately terminate. Additionally, even when the contractionary shock hits, previously approved loans will still fund at the previously agreed upon rate. During the approval process, a rate may get locked-in before the shock, and finalize well after the shock. Hence, subsequent to the FOMC announcement, many loans are still being finalized at older rates.

A second factor involved with the acceleration in the decline in lending has to do with "relationship lending." After a contractionary credit shock, some banks are better able to smooth loans rates than others, especially banks funded through deposits with inelastic rates, as shown in Berlin and Mester (1999). A third factor relates to demand-side preexisting commitments where, as a result of investments and expenditures by firms having been planned for several months leading up to the FOMC announcement, firms continue with short-term borrowing for things like inventory finance; a trend observed by Gertler and Gilchrist (1994).

A key balance sheet metric of interest in measuring the effects of contractionary forward guidance shocks is bank leverage. The details for how the leverage variable is constructed can be found in section three. There are conflicting findings in the literature regarding the response of bank leverage to macroeconomic shocks, that is, whether bank leverage is procyclical or countercyclical. Brunnermeier and Pedersen (2009), Adrian and Boyarchenko (2012), Adrian et al. (2013), and Adrian, Etula, and Muir (2014) document results consistent with procyclical broker-dealer leverage. On the other hand, He and Krishnamurthy (2013), Di Tella (2017), and He, Kelly, and Manella (2017) find that intermediary leverage is countercyclical.

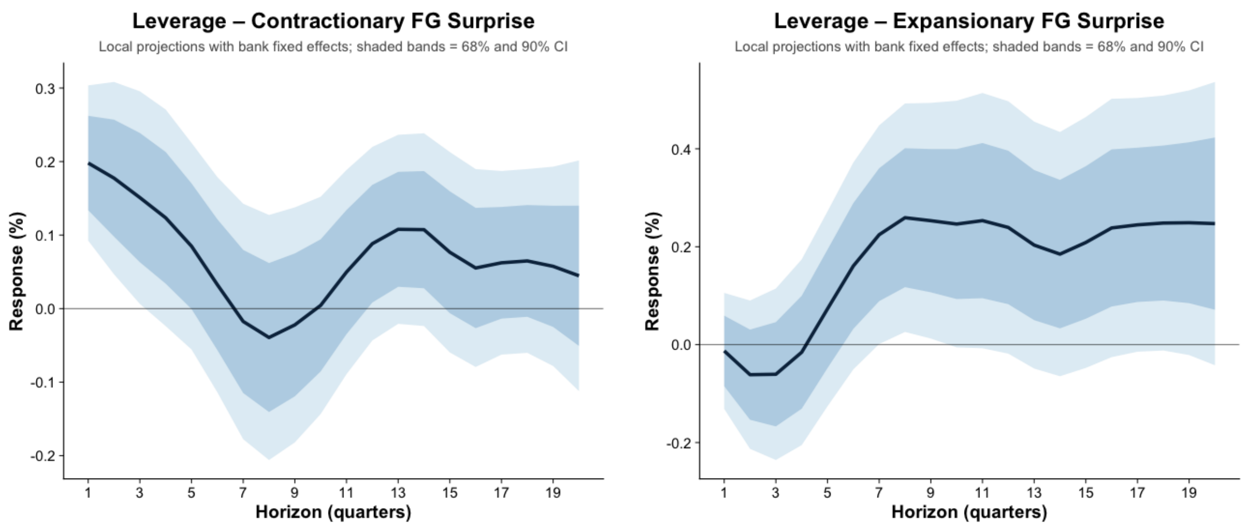


Figure 4: Leverage Responses to Forward Guidance Shocks

The figures are the impulse responses of leverage for banks to a one standard deviation contractionary (left) and expansionary (right) forward guidance shock. The inner dashed band corresponds to the 68% confidence. band, while the outer solid band corresponds to the 90% confidence band.

A similar asymetric pattern emerges when looking at the dynamics of leverage in Figure 4, depending upon whether we're examining its response to a contractionary or expansionary forward guidance shock. Both IRFs exhibit joint significance at the 1% level over the 20 quarter window. The pointwise estimates for the contractionary panel are highly significant at horizons 1, 3, and 13. For the expansionary panel, the pointwise estimates are significant at the 5% level at horizons 8 and 11.

The top left panel in Figure 2 shows the response of real GDP to a contractionary forward guidance shock. One notable feature that becomes apparent when you compare the movements of the IRF of real GDP to that of bank leverage with minimal smoothing is that the slopes of the IRFs (i.e., whether a variable is trending up or down) often move in opposite directions, even when real GDP and leverage are both above or below their baselines. For example, on impact, leverage and real GDP move in opposite directions. Then, between quarters five and eight, GDP begins to trend upward, indicating a phase of partial recovery. During roughly the same period, leverage decreases, suggesting that banks are reducing their leverage while the economy is attempting to rebound. This pattern suggests countercylical leverage as leverage and real GDP are moving in opposite directions in terms of growth: when real activity weakens, bank leverage expands.

On the other hand, when the economy experiences monetary easing, there is no significant effect on leverage over the first eight quarters, where it begins to increase, this indicates that a forward guidance signal of monetary easing takes time to translate into any discernible effect on bank leverage. This mirrors the asymmetric pattern that emerges in bank lending: we have an immediate and significant reaction in a contractionary environment that creates a jump in bank leverage on impact, and a delayed, back-loaded reaction of bank leverage to expansionary forward guidance surprises.

The countercyclical pattern observed in bank leverage can be understood through the framework outlined by He, Kelly, and Manela (2017). The dynamics of leverage fluctuations depend on whether financial intermediaries operate under "equity constraints" or "debt constraints." Different types of institutions tend to fall into one category or the other. For instance, hedge funds, which rely heavily on borrowing, are typically debt constrained, whereas commercial banks (the focus of the present study) are more often equity constrained. In times of economic contraction, these differences in constraints lead to opposite leverage responses. When hedge funds experience tighter borrowing limits, they are forced to reduce leverage by selling assets, which often end up in the hands of commercial banks. As a result, leverage moves in opposite directions for these two groups of intermediaries.

Equity-constrained financial institutions, as modeled in studies such as Bernanke and Gertler (1989), Holmstrom and Tirole (1997), and Brunnermeier and Sannikov (2014), see their equity capital decline in a downturn, which reduces their overall risk-bearing capacity. Although they may respond by cutting back on debt financing, the reduction in equity capital is typically larger than the decrease in debt, leading to an overall rise in leverage.

This dynamic explains why leverage tends to be countercyclical for these institutions.

By contrast, models developed by Brunnermeier and Pedersen (2009), Adrian, Etula, and Muir (2014), and Adrian and Shin (2014) suggest that intermediaries facing strict debt constraints exhibit procyclical leverage. Hedge funds, for example, often operate under borrowing limits that tighten during economic downturns, forcing them to liquidate assets in order to meet margin requirements. This process of deleveraging is so strong that it outweighs the drop in equity, causing their leverage to decline alongside the broader economy. Since these institutions offload assets rapidly, equilibrium prices fall, further reinforcing the procyclical pattern of leverage adjustments.[7]

5.2 Cross-Sectional Analysis

The IRFs above display an interesting pattern — substantial reductions in lending in wake of a contractionary shock, paired with a jump in bank leverage; while expansionary shocks produce virtually no change in lending until later horizons. I argue that a sufficient condition for this behavior and a major driving factor is the interaction with capital requirements and bank balance sheets. Basel III requires a minimum Tier-1 capital ratio of 6%. When banks are pushed up against this threshold, they have no choice but do de-lever, which will force them to contract credit issuance.

Given the asymmetric movements in leverage, it stands to reason that contractionary shocks push some banks closer to the capital threshold, which forces behaviors in banks that we don't see in an expansionary environment. I argue that we have the following chain of effects: the Fed surprises markets with an announcement about the future path of interest rates, market participants react more strongly to bad news than to good news and this shows up in asset prices. Bank equity falls strongly after a contractionary, but rises mildly after an expansionary shock. This creates the asymmetric patterns in leverage and, therefore, credit.

To test this hypothesis I run a few tests. Figure 10 displays, as predicted, the asymmetric responses of bank shareholder equity using the same LP framework as above. A strong and statistically significant drop in shareholder equity follows a contractionary forward guidance shock, while an expansionary shock produces little to no response in equity.

[7] He, Kelly, Manela (2017), 23.

The next thing I want to look at is how sensitive lending it to the capital ratio — do changes in regulatory capital predict changes in lending? I run the following regression:

$$\Delta \log(\text{Loans}_{i,t}) = \alpha_i + \delta_t + \beta\,\text{Tier1Ratio}_{i,t-1} + \Gamma' Z_{i,t-1} + \varepsilon_{i,t},$$

Where α_i is bank fixed effects and δ_t is quarter fixed effects. Standard errors $\varepsilon_{i,t}$ are clustered at the bank level. $Z_{i,t-1}$ is a vector of controls. Table 4 establishes a positive relationship between bank capitalization and subsequent loan growth. In bank and quarter fixed-effects specifications, a higher Tier 1 capital ratio is associated with faster growth in lending, controlling for bank size, deposit funding, risk-weighted asset intensity, and loan-performance measures. The estimated coefficient on the lagged Tier 1 ratio is positive and statistically significant in the baseline specification ($\beta = 0.21$, s.e. $= 0.075$), and remains essentially unchanged when controlling for AOCI relative to assets ($\beta = 0.210$, s.e. $= 0.075$). When I also include equity-to-assets as a further balance-sheet control, the Tier 1 estimate is attenuated but remains positive and statistically significant ($\beta = 0.184$, s.e. $= 0.082$). Overall, these results provide evidence that bank capital positions predict lending dynamics in the cross section, which is consistent with the view that capital constraints are indeed relevant for credit supply. Importantly, Table 4 is a benchmark; next I test whether the capitalization–lending relationship becomes substantially stronger when banks are close to binding regulatory capital requirements.

Table 5 shows the results of a test that determines whether regulatory capital constraints amplify the sensitivity of lending to capitalization. I estimate a piecewise specification that allows the slope of lending in response to bank capitalization to differ depending on whether a bank is above or below a regulatory capital threshold. Specifically, I estimate

$$\Delta \log(\text{Loans}_{i,t}) = \alpha_i + \delta_t + \beta_{\text{below}}\, d^-_{i,t-1} + \beta_{\text{above}}\, d^+_{i,t-1} + \Gamma' Z_{i,t-1} + \varepsilon_{i,t},$$

where the dependent variable is quarterly loan growth, $\Delta \log(\text{Loans}_{i,t}) \equiv \log(\text{Loans}_{i,t}) - \log(\text{Loans}_{i,t-1})$, α_i denotes bank fixed effects, and δ_t denotes quarter fixed effects.

The key regressors are constructed from the bank's Tier 1 capital ratio relative to a regulatory threshold τ. Define Tier 1 distance to the requirement:

$$d_{i,t-1} \equiv \text{Tier1Ratio}_{i,t-1} - \tau.$$

Where $\tau = 0.06$. I then decompose this distance into its negative and positive parts:

$$d^{-}_{i,t-1} \equiv \max\{-d_{i,t-1}, 0\}, \qquad d^{+}_{i,t-1} \equiv \max\{d_{i,t-1}, 0\}.$$

The coefficient β_{below} captures the sensitivity of lending to capitalization when banks operate at or below the requirement , while β_{above} captures the corresponding sensitivity when banks hold capital buffers above the requirement. In this regression, if my hypothesis about the aysmmetries laid out above is correct, then we'll have:

$$|\beta_{\text{below}}| > |\beta_{\text{above}}|,$$

Meaning that lending growth becomes substantially more sensitive to Tier-1 capitalization when banks are near the regulatory constraints.

The controls $Z_{i,t-1}$ include the same lagged bank characteristics as the previous regression. Standard errors are clustered at the bank level.

Table 5 shows that the relationship between bank capitalization and lending is positive: as bank approach the capital constraint, they contract credit. The dependent variable Low capital$_{i,t-1}$(Tier 1 $\leq$ p25) is an indicator variable for whether a particular bank i is in the bottom 25th percentile of capitalization in the sample at time $t-1$. I find a statistically significant and negative relationship between this indicator and the dependent variable: banks contract credit by about 4.7% when their capitalization falls to this level (SE: 1.7%). The interaction term tells us that as these banks' capitalization improves by one standard deviation, they expand credit by roughly 43%.

Overall then, Table 5 provides evidence that lending becomes much more sensitive to capitalization when banks operate close to regulatory requirements.

Table 6 tests whether the lending response to forward-guidance (FG) surprises varies systematically with banks' Tier 1 capital buffers. The specification is as follows:

$$\Delta \log(\text{Loans}_{i,t}) = \alpha_i + \delta_t + \sum_{b \in \mathcal{B}} \beta_b \Big(FG_t^{\text{contr}} \times \mathbf{1}\{\text{BufferBin}_{i,t-1} = b\} \Big) + \Gamma' Z_{i,t-1} + \varepsilon_{i,t},$$

$$\Delta \log(\text{Loans}_{i,t}) = \alpha_i + \delta_t + \sum_{b \in \mathcal{B}} \gamma_b \Big(FG_t^{\text{exp}} \times \mathbf{1}\{\text{BufferBin}_{i,t-1} = b\} \Big) + \Gamma' Z_{i,t-1} + \varepsilon_{i,t}.$$

These regressions estimate whether the lending response to forward-guidance (FG) surprises depends on banks' regulatory capital buffers. The dependent variable, $\Delta \log(\text{Loans}_{i,t})$, is quarterly loan growth for bank i in quarter t. The term α_i denotes bank fixed effects, which absorb time-invariant differences across banks, and δ_t denotes quarter fixed effects, which absorb aggregate conditions affecting all banks in a given quarter.

The key regressors interact the aggregate FG shock in quarter t with indicator variables for the bank's Tier 1 *capital buffer bin* in the previous quarter. Let $\mathcal{B}$ denote the set of buffer bins: below requirement, $[0, 1)$pp, $[1, 2)$pp, and $[2, 4)$pp; with ($\geq$ 4pp) used as the reference group. For each bank-quarter, $\mathbf{1}\{\text{BufferBin}_{i,t-1} = b\}$ equals one if bank i was in bin b at $t-1$, and zero otherwise.

One buffer bin b_0 is designated as the reference group and is not interacted with the FG shock in the summation. In this regression, the reference group is the highest-buffer bin (banks with at least 4 percentage points of Tier 1 capital buffer above the regulatory requirement). As a result, each coefficient β_b (or γ_b) measures how the sensitivity of lending to FG shocks differs for banks in buffer bin b relative to high-buffer banks.

With quarter fixed effects, this specification identifies differences in FG sensitivity across capital-buffer bins. Each coefficient β_b measures the incremental FG sensitivity for banks in buffer bin b, relative to the sensitivity of the highest-buffer bin.

Once again, I split the regressions into contractionary FG_t^{contr} versus expansionary shocks first equation uses the contractionary FG surprise FG_t^{exp}. Lagged bank controls are the same as before and standard errors are clustered at the bank level.

Table 6 presents evidence that the credit response to forward-guidance (FG) shocks does in fact depend on banks' Tier-1 capital ratios. For contractionary FG surprises, the lending response is state-dependent: banks operating below the Tier-1 requirement exhibit the largest decline in lending, with an estimated sensitivity of -0.007 (s.e.$=0.002$). As banks' capitalization improves, their sensitivity to contractionary FG becomes gradually smaller. On the other hand, expansionary FG shocks generate fairly weak lending responses across buffer bins, with coefficients that are not only small in magnitude, but largely statistically insignificant (with the exception of a modest effect in the $[1,2)$pp bin). Overall then, Table 6 implies that contractionary FG shocks reduce bank lending primarily when banks have limited capital buffers, consistent with a capital-constraint channel in which credit supply contracts most strongly when regulatory capital requirements are close to binding, and there is an asymmetry here between contractionary versus expansionary shocks.

6 Model with a Banking Sector

To analyze the empirical findings of the previous section, I put together a quantitative model that incorporates both a banking sector and forward guidance shocks. The banking sector is largely borrowed from Benigno and Benigno (2021). In my banking sector, however, I incorporate an adjustment cost for loans. The banking sector is interconnected with the production side of the economy via intermediate-goods firms' financing of their inputs through loans, which they repay the banks with interest. There is an endogenously determined probability that the firms will not repay the loans, meaning they default.

The central bank uses the interest rate on reserves in order to control inflation. The interest rate on deposits and risk-free bonds are what drives changes in the household's consumption and saving patterns. Deposits and treasury notes are two instruments that the household can use for liquidity services. The model also includes various standard frictions, such as Calvo price-stickiness. The formulation of the forward guidance shock follows Campbell et al. (2019). Figure 5 provides an illustration of how the various ingredients of the model interact with one another.

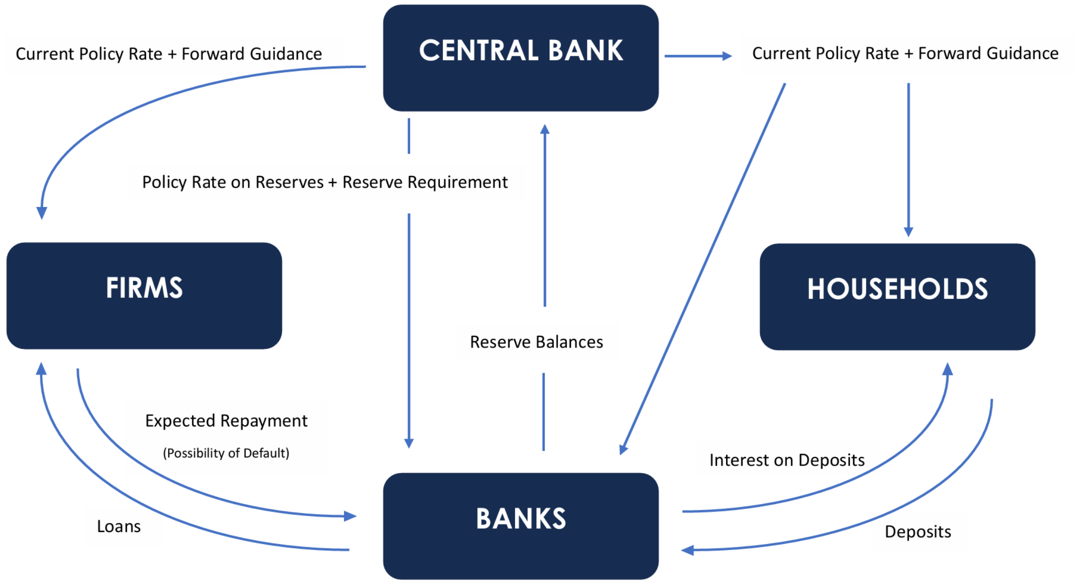


Figure 5: Model Structure

6.1 Households

The representative household maximizes lifetime utility:

$$\max_{\{C_t, N_t, B_{t+1}, D_t\}} E_0 \sum_{t=0}^{\infty} \beta^t \left(\frac{(C_t - \varphi H_t)^{1-\sigma}}{1-\sigma} - \theta \frac{N_t^{1+\eta}}{1+\eta} + \phi \ln \left(\frac{D_t + B_t^T}{P_t} \right) \right) \tag{1}$$

subject to the budget constraint:

$$P_t C_t + B_{t+1} + D_t + B_t^T \leq W_t N_t + \Psi_t + \Phi_t + (1 + i_{t-1}^B) B_t + (1 + i_{t-1}^D)(D_{t-1} + B_{t-1}^T) - P_t T_t$$

Where E_0 is the expectation operator at time 0, β is the discount factor and $0 < \beta < 1$. The household gets utility from consumption C at price P, and disutility from labor N, which pays a wage of W. The household gets liquidity services from deposits D and treasury notes B^T. The firm also has access to the privately issued risk-free bond B, which is illiquid, unlike deposits and treasury notes. T is the lump sum tax paid to the government.

The household owns the final goods firm, from which it receives profits Ψ_t. The household also own the bank, which yields the household profits Φ_t.

6.2 Intermediate Goods Producers

In the model, there are both intermediate and final goods producers. The setup for the final goods producer is standard. However, the intermediate good firm has a particular aspect about it that allows us to connect it to the banking sector.

Each intermediate goods producer $j \in [0,1]$ operates a constant returns to scale production function:

$$Y_t(j) = A_t N_t(j),$$

where Y_t and A_t are output, and an aggregate productivity shock, respectively.

The firm's profit function is given by:

$$\Psi_t(j) = P_t(j)Y_t(j) - (1 + i_t^L)\left[1 - \phi_{d,t+1}(j)\right] W_t N_t(j).$$

This is where we connect the banking sector and the production side of the economy. The firms finance their inputs via loans from the bank:

$$W_t N_t(j) = L_t(j)$$

The idea is that firms finance their inputs via loans that they must repay with interest to the bank. However, there is a risk that the firms will not repay the loans that is captured in the default variable $\phi_{d,t+1}$ that depends on both loans and the interest rate on loans.

So, we get:

$$\Psi_t(j) = P_t(j)Y_t(j) - (1 + i_t^L)\left[1 - \phi_{d,t+1}(j)\right] L_t(j).$$

which allows us to endogenize default:

$$\phi_{d,t+1} = \max\left(1 - \frac{Y_t}{(1 + i_t^L)\ell_t}, 0\right) \tag{2}$$

This shows that the default rate is bounded between 0 and 1, and is increasing in loans ℓ_t and the interest rate on loans i_t^L. The default rate is also decreasing in output.

6.3 Bank Sector

The banking sector setup comes from Benigno and Benigno (2021). I add an adjustment cost for loans to their setup and then derive equations for bank balance sheet variables like loans, deposits, reserves, etc. The Beningo et al. paper does not derive or look at IRFs for these variables in response to policy shocks. I show how to derive these equations in the appendix.

The bank chooses $\{L_t, B_t, R_t, D_t, X_t\}$ to maximize:

$$\Phi_t = E_t\Big\{\Lambda_{t+1}\Big[(1+i_t^L)(1-\phi_d)L_t+(1+i_t^B)B_t+(1+i_t^R)R_t-(1+i_t^D)D_t\Big]\Big\}-X_t-\frac{\phi_x}{2}(L_t-L_{t-1})^2 \tag{3}$$

subject to:

$$L_t + B_t + R_t = D_t + (1 - f(\delta_t))X_t, \quad \text{where} \quad \delta_t = \frac{L_t}{X_t}, \tag{4}$$

$$f(\delta_t) = \frac{\alpha}{2}\delta_t^2, \tag{5}$$

$$R_t \geq \rho D_t, \quad 0 \leq \rho < 1. \tag{6}$$

Λ_{t+1} is a stochastic discount factor equal to $\beta\left(\frac{C_{t+1}}{C_t}\right)^{-\sigma}\frac{P_t}{P_{t+1}}$. The bank supplies loans L and charges interest rate i^L for said loans. It also holds privately issued bonds B, earning interest rate i^B. The bank also keeps reserve balances R with the central bank that are remunerated at the policy rate i^R. The household holds deposits D with the bank, which the bank remunerates the household for at a rate i^D.

The bank is also able to raise equity X, subject to a cost $f(\delta)$, where δ denotes bank leverage, and the cost of raising equity is increasing in leverage. Lastly, the bank is subject to a reserve requirement: $R > \rho D$, meaning its reserves must exceed some specified fraction of its deposits. The banks profit function incorporates an adjustment cost for loans via the final term: $\frac{\phi}{2}(L_t - L_{t-1})^2$. In deriving the loan supply equation, this adjustment cost enables us to get a sluggishness in the response of loans to monetary policy shocks, which is consistent with the data.

As we will see with on the next page, the monetary policy shock will enter the bank's balance sheet via its effects on the interest rate the central bank offers on reserves balances. The effects of the shock to the interest rate on reserves will ripple through the banking system, affecting all other interest rates to varying degrees.

6.4 Forward Guidance Shock

The central bank follows a standard Taylor Rule, adjusting the nominal interest rate in response to inflation and output deviations:

$$1 + i_t^R = (1 + i^R)^\rho \left(\frac{\Pi_t}{\Pi^*}\right)^{\phi_\pi} \left(\frac{Y_t}{Y^*}\right)^{\phi_Y} e^{\phi_t}. \tag{7}$$

Where i^R, Π^*, and Y^* are the steady state values of the central bank's policy rate, inflation, and output, respectively. Shocks to the Fed's policy rate enter in through ϕ_t.

The central bank communicates policy deviation new up to 20 periods before the policy shock manifests itself in reality. Deviations in the policy rate can be characterized by news shocks according to:

$$\phi_t = \sum_{i=0}^{20} \hat{\psi}_{r,t-i}^i \tag{8}$$

Meaning that forward guidance can extend 20 quarters ahead, which is consistent with the time frame I use to calculate my IRFs from the data.

w_t is a weight that decays geometrically over time, meaning it assigns ever smaller weights to more distant quarters. Therefore, agents will place less weight on distant forward guidance shocks when it comes to their current decision making. w_t is specified as: $w_t = (1 - \rho_w)\rho_w^t$. The calibration for ρ_w is provided in the next section.

Let $\hat{\psi}_{r,t}$ denote one's belief (or prior) about the true value of $\psi_{r,t}$, which represents the true policy innovation at time t. $\hat{\psi}_{r,t}$ is defined as follows:

$$\hat{\psi}_{r,t}^j = \hat{\psi}_{r,t-1}^j + \kappa_j(s_t^j - \hat{\psi}_{r,t-1}^j), \quad j = 1, ..., 20. \tag{9}$$

Here, κ_j represents the Kalman gain with respect to horizon j, and $s_t^j - \hat{\psi}_{r,t-1}^j$ is the forecast error.

The forward guidance shock ψ_t^{FG} is defined as a set of signals:

$$\psi_t^{FG} = [s_t^0 \ \ s_t^1 \dots s_t^{20}]$$

The current policy rate is perfectly observed:

$$s_t^0 = \psi_{r,t}^0$$

While future deviations are unobserved, i.e. for $j \geq 1$

$$s_t^j = \psi_{r,t}^j + \nu_t, \qquad \nu_t \sim N(0, \sigma_\nu^2) \tag{10}$$

Hence, the Kalman gain $\kappa = \frac{\sigma_\psi^2}{\sigma_\psi^2 + \sigma_\nu^2}$, where σ_ψ^2 is the variance of the agent's prior. Importantly, the agent does not know σ_ν^2, rather, they believe it to be somewhere in the range of $\sigma_\nu^2 \in [\underline{\sigma}^2, \overline{\sigma}^2]$. The value of σ_ν^2 that the agent ends up entertaining depends upon the realized value of s_t.

Let the signal about horizon-j policy rates observed at time t be

$$s_t^j \ = \ \psi_{r,t}^j + \nu_t, \qquad \nu_t \sim \mathcal{N}\big(0, \ \sigma_\nu^2(s_t^j)\big)\,,$$

and let the prior variance of $\psi_{r,t}^j$ be $\sigma_\psi^2 > 0$. The Kalman gain is

$$\kappa_t^j(s_t^j) \ = \ \frac{\sigma_\psi^2}{\sigma_\psi^2 + \sigma_\nu^2(s_t^j)}.$$

The perceived noise variance is differentiable in the realized signal and strictly decreasing:

$$\frac{d}{ds}\,\sigma_\nu^2(s) \ < \ 0 \quad \text{for all } s \in R.$$

By differentiation,

$$\frac{d}{ds}\,\kappa_t^j(s) \;=\; \frac{\sigma_\psi^2}{\big(\sigma_\psi^2+\sigma_\nu^2(s)\big)^2}\Big(-\,\frac{d}{ds}\sigma_\nu^2(s)\Big)\;>\;0,$$

so $\kappa_t^j(\cdot)$ is strictly increasing in s.

Define *hawkish* news by $s_t^j > 0$ and *dovish* news by $s_t^j < 0$. Then, under the assumption above,

$$s_t^j > 0 \;\Rightarrow\; \sigma_\nu^2(s_t^j) \text{ smaller} \;\Rightarrow\; \kappa_t^j(s_t^j) \text{ larger}, \qquad s_t^j < 0 \;\Rightarrow\; \sigma_\nu^2(s_t^j) \text{ larger} \;\Rightarrow\; \kappa_t^j(s_t^j) \text{ smaller}.$$

Thus hawkish signals are absorbed with higher effective precision than dovish signals, generating asymmetric responses even under a symmetric policy rule.

When a shock occurs to equation 10, either through ν_t or $\psi_{r,t}^j$, this feeds into equation 9, forcing the agent to update their beliefs about $\hat{\psi}_{r,t}^j$.The agent starts off period t with some belief about $\psi_{r,t}^j$. After observing the signal s_t^j, the agent compares it to their prior: $s_t^{20} - \hat{\psi}_{r,t-1}^{20}$. Any error in their forecast will, after being scaled by the Kalman filter, feed into their new best guess during current period t of horizon 20's true policy innovation, $\hat{\psi}_{r,t}^{20}$.

This update to the agent's belief then works itself into equation 8, which directly affects the current period's determination of the policy rate i_t^R. This suggests that the central bank, in setting its policy rate, responds to how agents *perceive* the effects of their forward guidance, meaning that agents' belief themselves feed back into the current policy stance.

6.5 Government

One final set of ingredients involved in the model is a central bank with the following budget constraint:

$$B_t^T = (1+i_t^D)B_{t-1}^T - T_t \tag{11}$$

Which denotes the government's primary surplus. Further, assume that the government sets the tax policy in the following manner:

$$T_t = \tau Y_t, \qquad 0<\tau<1 \tag{12}$$

So that total lump sum taxes are proportional to output.

The remainder of the model can be found in the appendix. The remaining ingredients are standard, with a final goods firm that combines a continuum of differentiated intermediate goods according to a Dixit-Stiglitz aggregator. As shown above, each intermediate good producer uses labor to produce their output. The wages paid to laborers are financed via loans from the bank, plus interest. There is an endogenously determined probability of default that is dependent upon the existing level of output, loans, and interest owed on loans.

Prices are also made to be sticky via the classic Calvo pricing setup. The appendix also shows how the equations for bank balance sheet items like loans, bonds, and reserve balances are derived. Before presenting the model simulation results, I provide details on parameter calibration.

6.6 Model Calibration

I use Bayesian methods à la Smets and Wouters (2007) to estimate the model. I estimate several parameters following adjacent strands of literature with relevant citations. Then I present the priors and their posterior estimates. I use 16 observables from FRED to estimate the model, which includes: real GDP, real consumption, consumer price inflation, median usual weekly real earnings, nonfarm employment, bank equity capital, reserve balances with Federal Reserve banks, 3-month rates and yields on certificates of deposit, tier 1 leverage capital, total loans and leases for commercial banks, commercial bank holdings of treasury and agency securities, deposits for commercial banks, bank-prime loan rate, nonfarm labor productivity, the federal funds rate, and the net charge-off rate on total loans and leases.

Table 1: Calibrated Parameters

Parameter	Value	Description	Source
β	0.99	Discount Factor	–
σ	2	Risk Aversion	–
η	2	Frisch Elasticity of Labor Supply	–

Parameter	Value	Description	Source
θ	1	Labor Disutility Weight	–
ϕ	0.1	Liquidity Services Weight	–
ρ	0.1	Reserve Ratio	Benigno & Benigno (2021)
κ	0.5	Kalman Gain	Coibion & Gorodnichenko (2015)
τ	0.3	Tax Rate	OECD Centre for Tax Policy & Administration

Table 2: Prior and Posterior Distribution of Structural Parameters

Parameter	**Prior distribution**		**Posterior distribution**			
	Dist.	Mean / Std. dev.	Mean	5%	Median	95%
Model Parameters						
ρ_A	Beta	0.800 / 0.150	0.8590	0.8022	0.9201	
ϕ_π	Normal	1.500 / 1.000	0.3155	-1.3936	2.0172	
ϕ_y	Normal	0.500 / 0.600	1.3405	0.3804	2.3038	
ξ	Beta	0.550 / 0.250	0.7824	0.7189	0.8538	
ϕ_w	Beta	0.750 / 0.150	0.4930	0.4535	0.5353	
ρ_b	Beta	0.850 / 0.080	0.9426	0.9036	0.9838	
ϕ_x	Gamma	1.200 / 0.600	0.3670	0.0939	0.6319	
γ_b	Gamma	0.100 / 0.050	0.1372	0.0718	0.2011	
λ_h	Beta	0.900 / 0.050	0.9554	0.9274	0.9848	
ε	Normal	6.000 / 2.000	6.0186	2.7377	9.2301	
ε_w	Normal	4.500 / 1.000	3.1864	2.3972	4.1106	

Table 3: Prior and Posterior Distribution of Parameters — Shocks

Parameter	Prior distribution		Posterior distribution			
	Dist.	Mean / Std. dev.	Mean	5%	Median	95%
Standard deviations of shocks						
σ_l	Gamma	0.150 / 0.060	0.1606	0.1276	0.1941	
σ_d	Gamma	0.150 / 0.060	0.3878	0.3392	0.4366	
σ_ϕ	Gamma	0.120 / 0.050	0.0350	0.0178	0.0517	
σ_A	Inv. Gamma	0.300 / 0.050	0.2151	0.1903	0.2388	
σ_{FG}	Inv. Gamma	0.100 / 0.010	0.1315	0.1177	0.1453	
σ_y	Inv. Gamma	0.200 / 0.080	0.2274	0.1851	0.2689	
σ_c	Inv. Gamma	0.200 / 0.080	0.1822	0.1632	0.2009	
σ_π	Inv. Gamma	2.000 / 0.250	2.2134	2.0055	2.4167	
σ_{iL}	Inv. Gamma	2.500 / 0.500	2.3492	2.1166	2.5724	
σ_{iD}	Inv. Gamma	3.000 / 0.500	2.5530	2.3001	2.8017	
σ_b	Inv. Gamma	0.004 / 0.002	0.0047	0.0025	0.0070	
σ_{π_w}	Inv. Gamma	0.180 / 0.070	0.1337	0.1173	0.1498	
σ_{iR}	Inv. Gamma	0.180 / 0.080	0.1042	0.0740	0.1335	

Tables 2 and 3 present the parameter estimates using the Metropolis algorithm, running four chains, each with 250,000 draws. The calibration for the parameters listed in the table 1 above are standard as these are very conventional modeling parameters. However, beginning with ϕ_x, we encounter parameters that are more difficult to calibrate. The parameter ϕ_X is an adjustment cost parameter for loans. Although the specific adjustment cost for loans, $\frac{\phi_x}{2}(L_t - L_{t-1})^2$, is unique to this paper, I inform my choice of ϕ_x through other papers that incorporate financial market frictions, such as Christiano et al. (2014).

We know that the cost of raising equity, $f(\delta_t)$ in my model, is increasing in leverage. Since I specify this function as $\frac{\alpha}{2}\delta_t^2$, knowing how much each increase in leverage affects equity costs will inform us as to the calibration of α. Corbae and D'Erasmo (2019) calibrate a banking model where large banks face a marginal cost of equity issuance of about 2.5% of the funds raisedy. A 2.5–5% issuance cost means that for each \$1 of new equity capital raised, the bank forfeits \$0.025–\$0.05 in fees, higher capital costs, and dilution costs. If a bank with, say, a 10:1 leverage ratio wants to reduce leverage by one unit, it must raise roughly 10% of its existing equity as new capital – incurring an issuance cost of about 0.5% of its pre-issue equity value under these parameters. In terms of what this means for our calibration, if we assume an equity issuance cost of roughly 2.5%, then using $f(\delta_t) = \frac{\alpha}{2}\delta_t^2$ and normalizing $\delta_t = 1$, we can set $\frac{\alpha}{2} \approx 0.025$, which yields $\alpha \approx 0.05$.

The reserve ratio is set at 10%. This is consistent with what the reserve ratio in the U.S. banking system has been historically.[8] Benigno and Benigno (2021) experiment with varying levels of reserve requirements, with 10% being the lowest level they model with.

The parameters associated with the Taylor rule are fairly standard, but are taken directly from Campbell et al. (2019). The last parameter source is the Kalman Gain κ, which is calibrated to 0.5. This is consistent with similar calibrations in the literature, as in Coibion and Gorodnichenko (2015) who compute $\kappa = 0.46$.

7 Model Results

I now present a series of impulse response function (IRFs) that are generated by a one standard deviation contractionary forward guidance shock. The shock feeds directly into the central bank's policy rate, which also corresponds to what the central bank pays in interest on reserve balances, specified by the Taylor Rule.

In Figure 6, the solid blue line is the IRF produced by the data, which we presented earlier in Figures 2 & 3. The outer dashed lines correspond to the 68% bands - the outer solid bands the 90% bands. Each of the blue IRFs and their confidence bands are generated by the local projections process described in section five. The red lines represent the IRFs of produced by the quantitative model in section six. On the top row is displayed the response

[8] From about 1993 until March 2020, the required reserve ratio, set by the Fed, was 10%. Since the onset of the pandemic, the reserve ratio has been dropped to zero.

of loans to both contractionary (left side) and expansionary (right side) forward guidance shocks. The same is true of leverage in the bottom row.

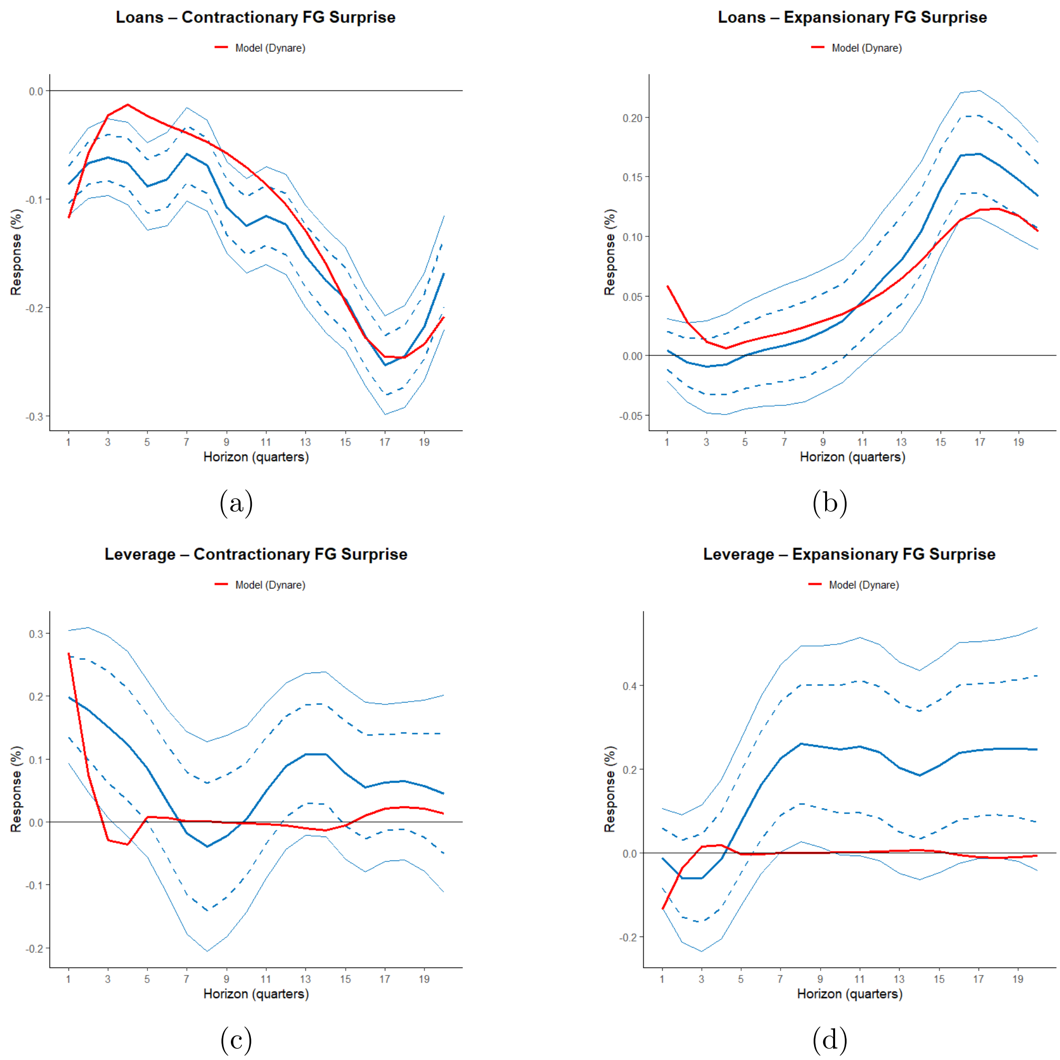


Figure 6: Empirical IRFs (blue) and model (red). Top: loans. Bottom: leverage. Left: contractionary. Right: expansionary.

The quantitative model's key IRFs (red) track the data nicely, capturing the important curvatures in the data. For lending in wake of a contraction, the model tracks the data especially well on impact and across many later horizons. In panel b, the model also fits nicely with the data across most periods, which means that the model successfully captures the asymmetric dynamics that follow from contractionary versus expansionary shocks. The model also fits the leverage data nicely. We see a much larger jump in leverage on impact after a surprise tightening, which the model captures well. For panel d, the model hovers at the zero-trend line for most periods, which lines up with what the data tells us, because most of the point estimates of the LP IRF in panel d are statistically indistinguishable from zero.

In terms of the quantitative model, the factors driving the dynamics are the following: in the immediate aftermath of the shock, the probability of intermediate goods producers defaulting on bank loans spikes above trend. We also see that bank leverage jumps above trend. These two factors, the spike in leverage and the increase in default likelihood, immediately drive lending and reserve balances held at the central bank down. The spike in bank leverage following the policy tightening is consistent with the logic described in section 4: bank equity drops faster than assets (in this case loans). As a result, the leverage ratio increases in the immediate wake of a contractionary monetary policy shock. My model also replicates the countercyclicality of leverage found in the data.

In wake of these adjustments, the default likelihood begins to quickly fall below trend as banks reduce leverage and loan issuance. The reduction in loans leads to a fall in deposits since loans drive deposits, both empirically and in the model, creating an amplification and feedback effect in driving both down over a prolonged period.

Various policy exercises can be examined with our model. In the appendix I show how bank balance sheets adjust to a contractionary forward guidance shock with varying levels of reserve ratio requirements. Unsurprisingly, as the fed increases the reserve requirements for banks, they react more strongly to the forward guidance shock.

7.1 ZLB Periods

Of particular interest when examining the effects of forward guidance is how forward guidance can affect economic activity at the zero-lower-bound (ZLB). Figure 6 shows the responses of bank balance sheet items in the case of a ZLB episode, where the bank makes an announcement that signals its intention to hold interest rates down for longer.

It turns out that it is difficult to implement an expansionary forward guidance shock at the ZLB in a quantitative model. Given that the policy rate cannot drop below zero, some kind of workaround is needed to obtain the results that this kind of experiment would generate. I now describe how I simulate an expansionary forward guidance shock at the

ZLB.

First, I implement the zero lower bound environment by shutting off the policy rate's response to output and inflation. This means that I take the log-linearized Taylor rule from section 6.4 and set $\phi_\pi = \phi_Y = 0$. Here, the policy rate simply becomes $i_t^R = m_t$, where m_t is the variable that houses the contemporaneous and forward guidance shocks. Therefore, if there are no shocks, $i_t^R = 0$. In the appendix (figure 12), I show how i_t^R responds to a *contractionary* forward guidance shock to demonstrate that the policy rate *itself* does not respond until the actual monetary policy change is implemented - meaning the policy rate stays at zero and doesn't respond to forward guidance shocks.

Next, I introduce a four-quarter-ahead *contractionary* forward guidance shock into the model. Then, separately, I introduce an eight-quarter-ahead contractionary FG shock. I then take the differences of the impulse response estimates across each horizon between that were generated by the later and earlier forward guidance shocks. I call the shock that generates the resulting IRFs an *expansionary* FG shock at the ZLB.

Specifically, we have:

$$\Delta Y_{8,4} = Y_{t,\varepsilon_t^8} - Y_{t,\varepsilon_t^4} \equiv Y_{t,\varepsilon_t^{FG}}^{ZLB}$$

Where Y_{t,ε_t^8} is the impulse response at time t to an eight-period-ahead contractionary FG shock ε_t^8.

The reason it makes sense to call this an expansionary forward guidance shock at the ZLB is because, in this experiment, we are looking at what happens to our economy when the agents expect the policy rate to remain at the zero lower bound for longer. The agents go from expecting a policy contraction a year from now, to expecting the policy rate to remain at the ZLB for the next two years. The above procedure captures the reaction of the economy to the changes in expectations that follow from this surprise.

Figure 7 captures what happens to policy rate expectations after the change. Again, we are at the ZLB, so interest rates cannot change. However, in this experiment under the eight-period-ahead contraction, i_t^R remains anchored at 0, whereas it rises at period four under the four-period-ahead contraction. Therefore, by construction, this IRF shows a negative percentage change in the policy rate, which, to reiterate, doesn't mean the policy rate is becoming negative. Instead, what this reflects is the adjustment in agents *expectations* about what is supposed to happen to interest rates four quarters from now.

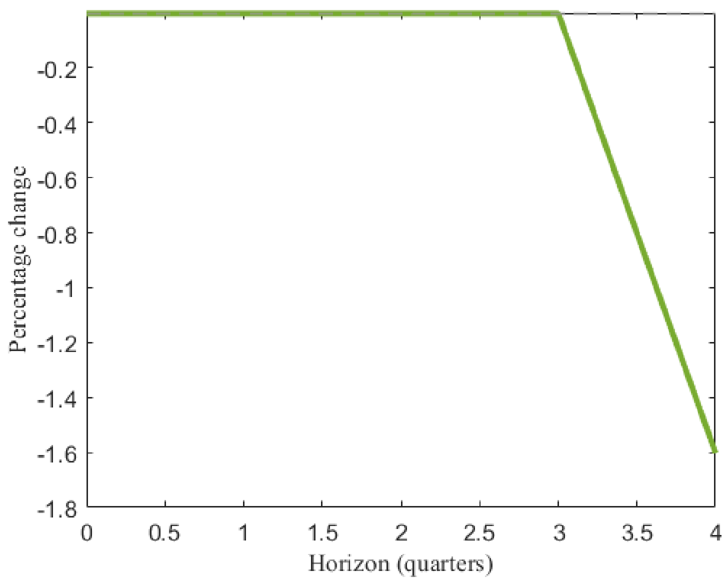


Figure 7: Policy Rate in Response to a FG Shock at ZLB

Recall that this is generated by taking the difference between the policy rate given a 10 quarter ahead tightening and a five quarter ahead tightening, which is why the IRF responds negatively.

Below, I plot what happens to output and lending in response to this expansionary forward guidance shock at the ZLB. In Figure 8, both output and lending, as expected, increase on impact. However, as is consistent with McKay et al. (2016), the magnitude of the responses are modest. There is an immediate jump in lending by about 4.5 basis points on impact (along with a 4 basis point jump in output), that quickly tapers off. After quarter 4, both variables increase again. However, we are only interested in what happens between periods 0 and 4 since that is when the policy rate remains at zero in both cases and is therefore what's relevant for the ZLB experiment.

The small magnitudes of these responses are fairly informative about the power of forward guidance at the zero bound — expansionary forward guidance *does* stimulate real economic activity at the ZLB, but only weakly. This is owing to the fact that the primary driver of economic activity in this scenario is the financial sector.

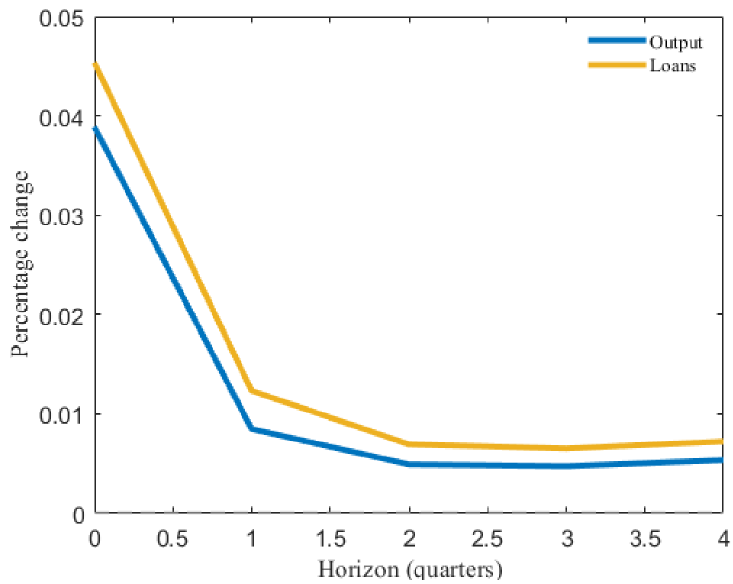


Figure 8: Expansionary FG Shock at ZLB

These are the impulse responses of loans and output in going from a an environment where agents expect credit tightening a year into the future to two years into the future.

More specifically, the principal transmission channel is the increase in bank equity, corresponding to a drop in bank leverage, which is coupled with a temporary credit expansion. However, the jump in credit is very modest and, therefore, so are the effects on output. This highlights a major finding of this paper, which is that, not only are bank balance sheets a major economic driver at the zero bound, but that they constraint the effects of expansionary forward guidance at the ZLB, which suggests that forward guidance alone is unlikely to generate large effects in a liquidity trap.

The final plot, Figure 9, shows the reason why lending and, in addition, bank balance sheets are of interest when it comes to forward guidance. In wake of the expansionary forward guidance shock at the ZLB, the primary drivers of output's immediate response are bank equity and leverage. Since leverage is constructed as loans/equity and equity increases by more than one-for-one with loans, leverage as a whole falls, enabling banks to further expand credit - hence the jump in lending in figure 6.

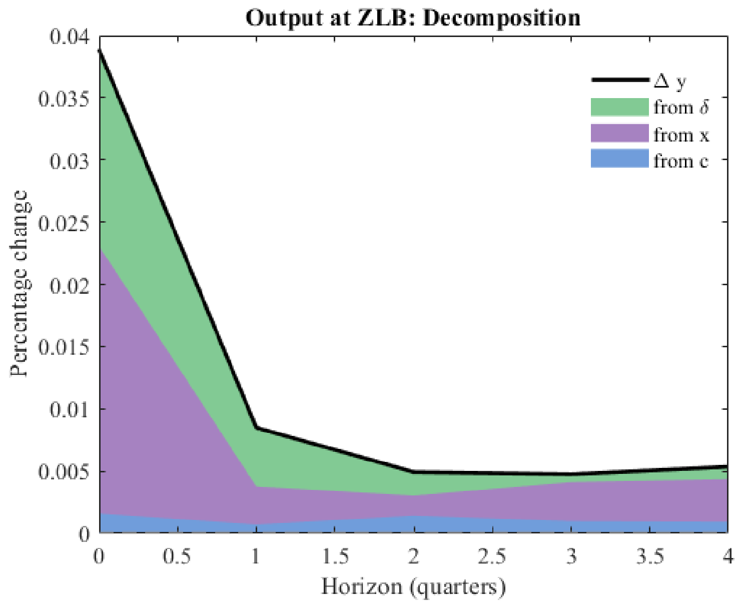


Figure 9: Expansionary FG shock at the ZLB

Here is decompose the response of output to the expansionary FG shock at the ZLB by relative contribution of the relevant variables to the overall change in output.

After the expansionary shock, the policy rate remains fixed. Nevertheless, the interest rate of loans falls, which reduces marginal costs for firms, which increases production and therefore consumption. However, the financial sector remains the dominant force in driving changes in output.

This elucidates the fact that the primary driver of macro aggregates like output and inflation in response to forward guidance shocks at the ZLB are adjustments made by the financial sector, particularly adjustments of the balance sheets of intermediaries, to these shocks. These shocks loosen bank balance sheets by boosting their equity, lowering their leverage, and thereby enabling them to expand credit, stimulating output as a result. Therefore, the bank balance sheet channel is key in the transmission of forward guidance to the real economy.

8 Conclusion

Forward guidance has become an increasingly important tool of central banks around the world. In countries with credible central banking systems, forward guidance can be a particularly effective tool in stimulating the economy. This paper has analyzed the effect that forward guidance has on commercial bank balance sheets. I've analyzed the effects of both expansionary and contractionary forward guidance shocks.

I find that banks' balance sheets are much slower to respond to expansionary forward guidance than they are to contractionary forward guidance, even when the shocks are of the same magnitude (absolute value). Second, the magnitude of the adjustments themselves are smaller during an expansion than during a contraction, which indicates that expansionary forward guidance is less effective in stimulating bank activity than contractionary forward guidance is in tightening bank balance sheets. I provide evidence that this is owing ultimately to capital requirements. Contractionary forward guidance shocks cause asset prices, and therefore, bank equity to fall in an absolute magnitude that is greater than their rise following an expansionary forward guidance surprise. When asset prices fall, banks also become less well-capitalized. As they inch closer to minimum capital requirements, they're forced to substantially reduce credit. In wake of expansionary shocks, these requirements do not force behaviors on the part of banks in the way that they do in a contraction. Therefore we get this asymmetry in credit.

This finding is significant because one of the principal interests that people have in forward guidance policy is its ability to *stimulate* the economy, especially in the case of a liquidity trap. My findings show that although the central bank appears capable of stimulating credit expansions and output during the ZLB period, the responsiveness of banks to this kind of stimulus is fairly muted, much more so than what we observe in response to contractionary forward guidance shocks. Therefore, forward guidance is very effective at contracting credit, but weak at stimulating it, which is precisely when forward guidance is supposed to be of greatest use.

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Cross-Sectional Analysis

Table 4: Tier 1 Capital Tightness and Bank Lending Growth

	(1) Baseline	(2) + AOCI	(3) + AOCI & Equity
Dependent variable:	$\Delta\log(\text{Loans}_{i,t})$		
Tier 1 Ratio$_{i,t-1}$	0.210**	0.210**	0.184*
	(0.075)	(0.075)	(0.082)
log(Assets$_{i,t-1}$)	-0.045***	-0.044***	-0.029***
	(0.009)	(0.009)	(0.005)
Deposits/Assets$_{i,t-1}$	-0.040	-0.048	0.047
	(0.065)	(0.067)	(0.027)
RWA/Assets$_{i,t-1}$	-0.007	-0.007	-0.027
	(0.034)	(0.034)	(0.040)
Nonaccrual Loans/Loans$_{i,t-1}$	-0.307**	-0.300**	-0.304**
	(0.103)	(0.104)	(0.105)
Past Due Loans/Loans$_{i,t-1}$	-0.296*	-0.290*	-0.300*
	(0.139)	(0.138)	(0.130)
AOCI/Assets$_{i,t-1}$		-0.165**	-0.628*
		(0.051)	(0.260)
Equity/Assets$_{i,t-1}$			0.518*
			(0.261)
Bank fixed effects	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes
Observations	118,496	117,558	117,143
R^2	0.243	0.243	0.249
Within R^2	0.109	0.109	0.116

Notes: The dependent variable is quarterly loan growth, measured as $\Delta\log(\text{Loans}_{i,t})$. All specifications include bank fixed effects and quarter fixed effects. Standard errors are clustered at the bank level and are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Tier 1 Capital Tightness and Lending: Evidence of Binding Constraints

	(1) Linear baseline	(2) Low-capital interaction
Dependent variable:	$\Delta \log(\text{Loans}_{i,t})$	
Tier 1 Ratio$_{i,t-1}$	0.210**	0.210**
	(0.075)	(0.075)
Low capital$_{i,t-1}$ (Tier 1 $\leq$ p25)		-0.047**
		(0.017)
Tier 1 Ratio$_{i,t-1}$ $\times$ Low capital$_{i,t-1}$		0.434**
		(0.153)
Controls	Yes	Yes
Bank fixed effects	Yes	Yes
Quarter fixed effects	Yes	Yes
Observations	117,558	117,558
R^2	0.243	0.243
Within R^2	0.109	0.109

Notes: The dependent variable is quarterly loan growth measured as $\Delta \log(\text{Loans}_{i,t})$. All specifications include the baseline balance-sheet and loan quality controls: log(Assets), Deposits/Assets, RWA/Assets, Nonaccrual Loans/Loans, Past Due Loans/Loans, and AOCI/Assets, all lagged one quarter. Column (2) allows the marginal effect of Tier 1 capital to differ for banks in the bottom quartile of the lagged Tier 1 ratio distribution. Standard errors are clustered at the bank level and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Forward Guidance Shocks and Bank Lending: Heterogeneity by Tier 1 Capital Buffer Bins

	(1) Contractionary FG	(2) Expansionary FG
Dependent variable:	$\Delta \log(\text{Loans}_{i,t})$	
FG × Below requirement	-0.007^{**}	-0.001
	(0.002)	(0.001)
FG × Buffer bin $[0, 1)$ pp	-0.003	-0.002
	(0.002)	(0.001)
FG × Buffer bin $[1, 2)$ pp	-0.001	-0.001^{*}
	(0.001)	(0.000)
FG × Buffer bin $[2, 4)$ pp	-0.000	-0.000
	(0.000)	(0.000)
Controls	Yes	Yes
Bank fixed effects	Yes	Yes
Quarter fixed effects	Yes	Yes
Observations	117,558	117,558
R^2	0.175	0.174
Within R^2	0.028	0.028

Notes: This table reports heterogeneity in the lending response to forward-guidance (FG) surprises by banks' Tier 1 *capital buffer*, measured relative to the regulatory requirement. The dependent variable is quarterly loan growth, $\Delta \log(\text{Loans}_{i,t})$. The contractionary shock is defined as the positive part of the quarterly FG surprise (FG_t^{contr}), and the expansionary shock is defined as the positive magnitude of the negative FG surprise (FG_t^{exp}). Each coefficient corresponds to an interaction between the shock and an indicator for the bank's Tier 1 capital-buffer bin at $t - 1$, with the omitted category being banks with at least 4 percentage points of Tier 1 capital buffer (i.e., Tier 1 ratio $\geq \tau + 4$pp). All specifications include bank and quarter fixed effects and the baseline lagged bank controls (log assets, deposits/assets, RWA/assets, nonaccrual loans/loans, past due loans/loans, and AOCI/assets). Standard errors clustered at the bank level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

A Appendix

A.1 Empirical Design

Federal funds rate futures are a financial instrument whose payout is calculated by comparing the contract price to the average federal funds effective rate over the month preceding expiration of the contract. The price of the contract is calculated, simply, as 100 - Expected Federal Funds Rate. If the expected federal funds rate at the end of the month is lower than anticipated when the contract was written, then the holder profits (the holder loses money if rates end up higher than expected at origination of the contract).

The surprise captured by the change in the federal funds rate target in the aftermath of an FOMC announcement can be specified as[9]:

$$mp1_t = (ff1_t - ff1_{t-\Delta t})\frac{T_1}{T_1 - \tau_1}$$

where T_1 is number of days in the expiration month, and τ_1 is the day of the FOMC announcement in month T_1. $ff1_t$ can simply be calculated as $ff1_t = 100 - P_{ff,t}$ Where $P_{ff,t}$ is the price at time t of federal funds futures contract. $ff1_{t-\Delta t}$ is specified as:

$$ff1_{t-\Delta t} = \frac{\tau_1}{T_1}p_0 + \frac{T_1 - \tau_1}{T_1}E_{t-\Delta t}p_1 + \xi_{t-\Delta t}$$

Here, p_0 denotes the the federal funds that that has prevailed up to the current point of month, and p_1 is the expected rate for the remainder of the month. $\xi_{t-\Delta t}$ is a risk premium.

A similar set of procedures allows one to identify the revision in expectations about what the federal funds rate target will be following the next FOMC announcement[10]:

$$mp2_t = \left[(ff2_t - ff2_{t-\Delta t}) - \frac{\tau_2}{T_2}mp1_t\right]\frac{T_2}{T_2 - \tau_2}$$

[9]All of the following mathematical details can be found in Gurkaynak et al. (2005) and are derived from there.

[10]The remainder of the details about the construction of Eurodollar and Treasury Futures can be found in GSS (2005)

In identifying the factors one uses the following factor specification:

$$X = F\Lambda + e$$

Where Λ is a 2 x n matrix of factor loadings, F is a 204 x 2 matrix of unobserved factors. The e term denotes white noise.

In performing the rotation of the two factors, I define the 204 x 2 matrix Γ:

$$\Gamma = F\Upsilon$$

where

$$\Upsilon = \begin{bmatrix} \rho_1 & \lambda_1 \\ \rho_2 & \lambda_2 \end{bmatrix}$$

Here, columns are normalized to unit length. Then one restricts the two factors Γ_1 and Γ_2 to be orthogonal:

$$E(\Gamma_1\Gamma_2) = \rho_1\lambda_1 + \rho_1\lambda_1$$

After this, it is ensured that Γ_2 has no influence on the surprise to the current federal funds rate in the following way: denote α_1 and α_2 as the loadings of the current federal funds rate surprise on F_1 and F_2, respectively. Then, since

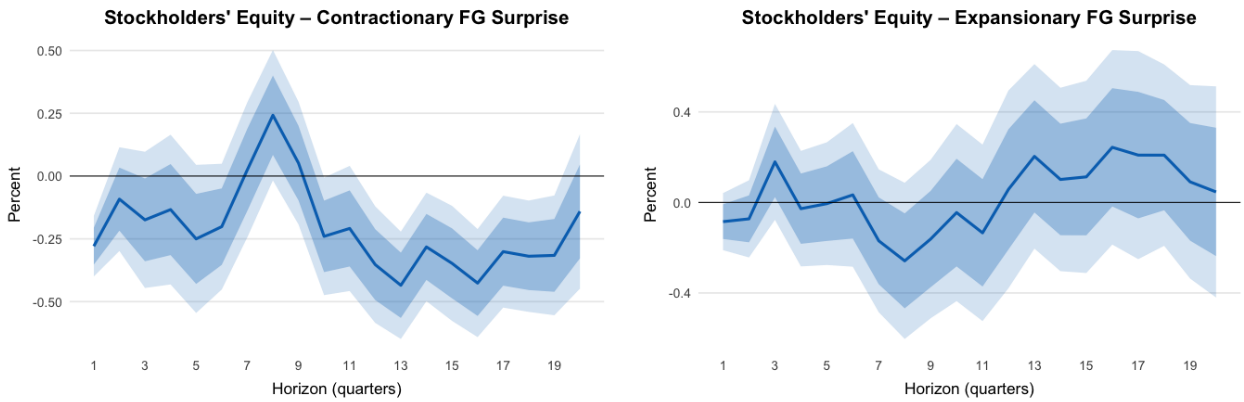
$$F_1 = \frac{1}{\rho_1\lambda_2 - \rho_2\lambda_1}[\lambda_2\Gamma_1 - \rho_2\Gamma_2]$$
$$F_2 = \frac{1}{\rho_1\lambda_2 - \rho_2\lambda_1}[\rho_1\Gamma_2 - \lambda_1\Gamma_1]$$

which yields:

$$\alpha_2\rho_1 - \alpha_1\rho_2 = 0$$

At which point, one can identify Υ.

A.2 Additional IRFs



(a) Contractionary FG surprise (b) Expansionary FG surprise

Figure 10: Impulse responses of stockholders' equity to forward-guidance surprises

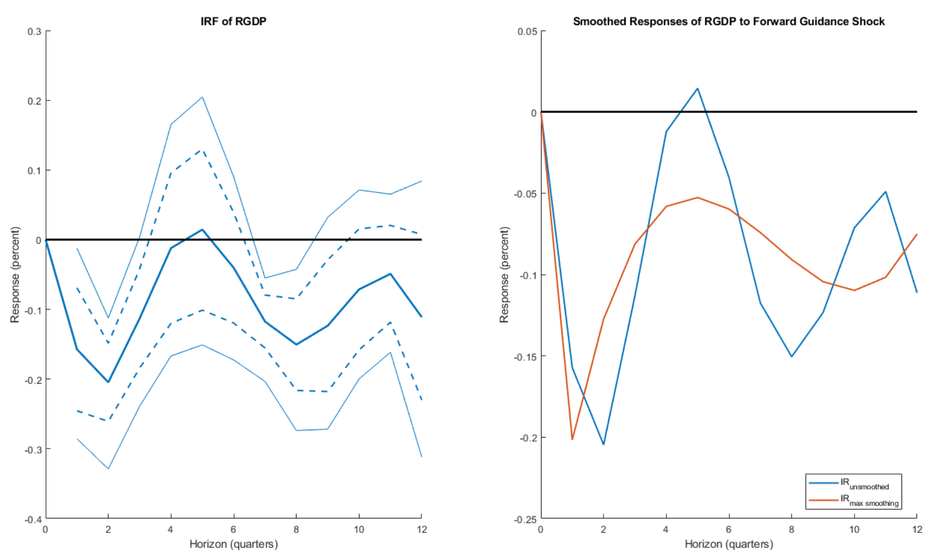


Figure 11: Real GDP Response to a Contractionary Forward Guidance Shock

The figures respresent the impulse response of real GDP to a one standard deviation contractionary forward guidance shock. For the left hand figure, the inner dashed band corresponds to the 68% confidence band, while the outer solid band corresponds to the 90% confidence band. The right hand figure shows how the impulse response dynamics change as we go from a local projections IRF (IR_{lp}), to a smoothed local projections plot (IR_{slp}), and maximally smoothed response ($IR_{slp,maxpen}$).

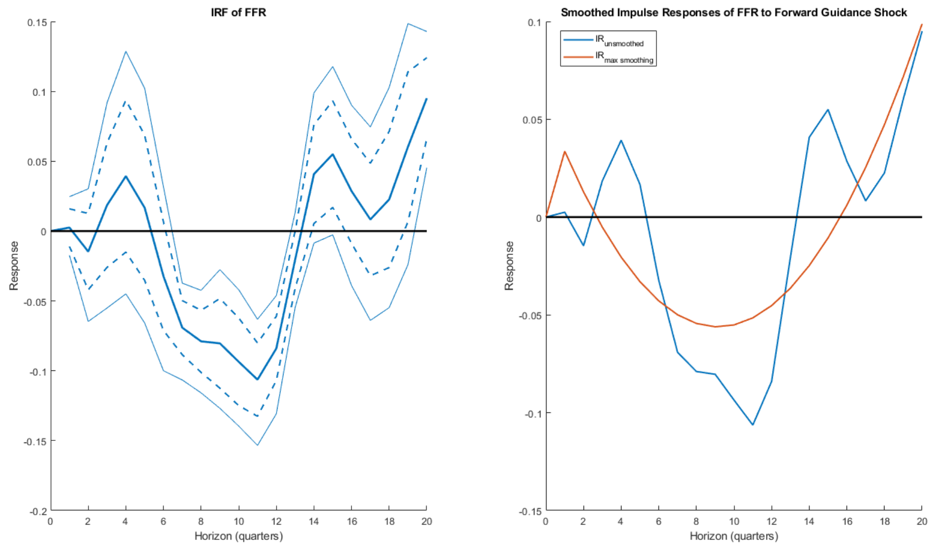


Figure 12: Federal Funds Rate Response to a Contractionary Forward Guidance Shock

Model

Household's Problem

The representative household maximizes lifetime utility:

$$\max_{\{C_t,N_t,B_{t+1},D_t\}} E_0 \sum_{t=0}^{\infty} \beta^t \left(\frac{C_t^{1-\sigma}}{1-\sigma} - \theta \frac{N_t^{1+\eta}}{1+\eta} + \phi \ln \left(\frac{D_t + B_t^T}{P_t} \right) \right) \tag{A.1}$$

subject to the budget constraint:

$$P_tC_t + B_{t+1} + D_t + B_t^T \leq W_tN_t + \Psi_t + \Phi_t + (1+i_{t-1}^B)B_t + (1+i_{t-1}^D)(D_{t-1} + B_{t-1}^T) - P_tT_t \tag{A.2}$$

Lagrangian Formulation

Define the Lagrangian:

$$\mathcal{L} = E_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{C_t^{1-\sigma}}{1-\sigma} - \theta \frac{N_t^{1+\eta}}{1+\eta} + \phi \ln \left(\frac{D_t + B_t^T}{P_t} \right) \right.$$
$$\left. + \lambda_t \left(W_t N_t + \Psi_t + \Phi_t + (1 + i_{t-1}^B) B_t + (1 + i_{t-1}^D)(D_{t-1} + B_{t-1}^T) - P_t T_t - P_t C_t - B_{t+1} - D_t - B_t^T \right) \right] \quad \text{(A.3)}$$

First-Order Conditions

FOC for Consumption C_t

$$C_t^{-\sigma} = \lambda_t P_t \quad \text{(A.4)}$$

FOC for Labor Supply N_t

$$\theta N_t^{\eta} = \lambda_t W_t \quad \text{(A.5)}$$

FOC for Bonds B_{t+1}

$$\lambda_t = \beta E_t[\lambda_{t+1}(1 + i_t^B)] \quad \text{(A.6)}$$

FOC for Deposits D_t

$$\frac{\phi}{D_t + B_t^T} = \lambda_t - \beta E_t[\lambda_{t+1}(1 + i_t^D)] \quad \text{(A.7)}$$

Labor Supply Condition

$$N_t = \left(\frac{w_t}{\theta} C_t^{-\sigma} \right)^{\frac{1}{\eta}} \quad \text{(A.8)}$$

Euler Equation for Bonds

$$1 = \beta E_t \left[\frac{C_{t+1}^{-\sigma}}{C_t^{-\sigma}} \frac{P_t}{P_{t+1}} (1 + i_t^B) \right] \tag{A.9}$$

Which can be simplified to:

$$\frac{1}{1 + i_t^B} = E_t\{\Lambda_{t+1}\} \tag{A.10}$$

Implicit Demand for Real Balances

Combining equations 6 and 7 we get

$$\frac{\phi}{D_t + B_t^T} = \beta E_t[\lambda_{t+1}(1 + i_t^B)] - \beta E_t[\lambda_{t+1}(1 + i_t^D)] \tag{A.11}$$

which simplifies to

$$\frac{\phi}{D_t + B_t^T} = \beta E_t \lambda_{t+1}(i_t^B - i_t^D) \tag{A.12}$$

using equation 6 again, we can get:

$$\frac{\phi}{D_t + B_t^T} = \frac{\lambda_t}{(1 + i_t^B)}(i_t^B - i_t^D) \tag{A.13}$$

plugging in the relation from equation 4 for lambda we obtain:

$$\frac{\phi}{D_t + B_t^T} = \frac{C_t^{-\sigma}}{P_t(1 + i_t^B)}(i_t^B - i_t^D) \tag{A.14}$$

some algebra eventually leads to our demand for real balances in terms of deposits:

$$d_t = \phi C_t^{\sigma} \frac{(1 + i_t^B)}{(i_t^B - i_t^D)} - b_t^T \tag{A.15}$$

Stochastic Discount Factors

We define the one-period stochastic discount factor as:

$$\Lambda_{t+1} = \beta \left(\frac{C_{t+1}}{C_t} \right)^{-\sigma} \frac{P_t}{P_{t+1}}. \tag{A.16}$$

More generally, the j-period stochastic discount factor is defined as:

$$\Lambda_{t+j} = \beta^j \left(\frac{\lambda_{t+j}}{\lambda_t} \right). \tag{A.17}$$

Final Goods Sector

The final goods sector combines a continuum of differentiated intermediate goods $Y_t(j)$ according to a Dixit-Stiglitz aggregator:

$$Y_t = \left(\int_0^1 Y_t(j)^{\frac{\epsilon-1}{\epsilon}} dj \right)^{\frac{\epsilon}{\epsilon-1}}, \quad \epsilon > 1 \tag{A.18}$$

where ϵ represents the elasticity of substitution between intermediate goods.

Profit Maximization Problem

The final goods firm takes P_t as given and chooses $Y_t(j)$ to maximize profits:

$$\max_{\{Y_t(j)\}} P_t \left(\int_0^1 Y_t(j)^{\frac{\epsilon-1}{\epsilon}} dj \right)^{\frac{\epsilon}{\epsilon-1}} - \int_0^1 P_t(j) Y_t(j) dj \tag{A.19}$$

Aggregate Price Level

The aggregate price level P_t is given by:

$$P_t = \left(\int_0^1 P_t(j)^{1-\epsilon} dj \right)^{\frac{1}{1-\epsilon}} \tag{A.20}$$

Intermediate Goods Firm's Problem

Each intermediate goods producer $j \in [0, 1]$ operates a constant returns to scale production function:

$$Y_t(j) = A_t N_t(j), \tag{A.21}$$

where A_t is the aggregate productivity shock.

The firm's profit function is given by:

$$\Psi_t(j) = P_t(j)Y_t(j) - (1 + i_t^L)(1 - \phi_{d,t+1})W_t N_t(j). \tag{A.22}$$

Where firms finance their inputs via loans from the bank:

$$W_t N_t(j) = L_t(j) \tag{A.23}$$

So, we get:

$$\Psi_t(j) = P_t(j)Y_t(j) - (1 + i_t^L(j))(1 - \phi_{d,t+1}(j))L_t(j). \tag{A.24}$$

which allows us to endogenize default:

$$\phi_{d,t+1} = \max\left(1 - \frac{Y_t(j)P_t(j)}{(1 + i_t^L(j))L_t(j)}, 0\right) \tag{A.25}$$

which in aggregated terms is:

$$\phi_{d,t+1} = \max\left(1 - \frac{Y_t}{(1 + i_t^L)\ell_t}, 0\right) \tag{A.26}$$

Substituting for $N_t(j)$

Using the production function, we substitute $N_t(j) = \frac{Y_t(j)}{A_t}$ into the profit function:

$$\Psi_t(j) = P_t(j)Y_t(j) - (1 + i_t^L)(1 + \phi_{t+1})\frac{W_t}{A_t}Y_t(j). \tag{A.27}$$

Demand Constraint

The firm's demand function is derived from the final goods sector:

$$Y_t(j) = \left(\frac{P_t(j)}{P_t}\right)^{-\epsilon} Y_t. \tag{A.28}$$

Profit Function with Demand Substituted

Substituting $Y_t(j) = \left(\frac{P_t(j)}{P_t}\right)^{-\epsilon} Y_t$ into the profit function:

$$\Psi_t(j) = P_t(j)\left(\frac{P_t(j)}{P_t}\right)^{-\epsilon} Y_t - (1+i_t^L)(1+\phi_{t+1})\frac{W_t}{A_t}\left(\frac{P_t(j)}{P_t}\right)^{-\epsilon} Y_t. \tag{A.29}$$

Factor out $\left(\frac{P_t(j)}{P_t}\right)^{-\epsilon} Y_t$:

$$\Psi_t(j) = \left(\frac{P_t(j)}{P_t}\right)^{-\epsilon} Y_t \left[P_t(j) - (1+i_t^L)(1+\phi_{t+1})\frac{W_t}{A_t}\right]. \tag{A.30}$$

Profit Maximization Problem

Each intermediate goods firm chooses $P_t(j)$ to maximize:

$$\max_{P_t(j)} \quad \left(\frac{P_t(j)}{P_t}\right)^{-\epsilon} Y_t \left[P_t(j) - (1+i_t^L)(1+\phi_{t+1})\frac{W_t}{A_t}\right]. \tag{A.31}$$

Sticky Prices: Calvo Pricing

We assume price rigidity following Calvo (1983), where intermediate firms can reset prices with probability $1-\xi$, and keep the previous price with probability ξ.

Firm's Pricing Problem

Each intermediate firm j maximizes expected discounted profits:

$$\max_{P_t(j)} X_t \sum_{s=0}^{\infty} \xi^s \Lambda_{t,t+s}\left[\frac{P_t(j)}{P_{t+s}}\left(\frac{P_t(j)}{P_{t+s}}\right)^{-\epsilon} Y_{t+s} - (1+i_t^L)(1+\phi_{t+1})\frac{w_{t+s}}{A_{t+s}}\left(\frac{P_t(j)}{P_{t+s}}\right)^{-\epsilon} Y_{t+s}\right]. \tag{A.32}$$

subject to the demand function:

$$Y_{t+s}(j) = \left(\frac{P_t(j)}{P_{t+s}} \right)^{-\epsilon} Y_{t+s}. \tag{A.33}$$

Reset Price under Calvo Pricing

Under the Calvo pricing assumption, a firm that updates its price at time t chooses $P_t(j)$ to maximize expected discounted profits. The optimal price-setting equation is:

$$P_t(j) = \frac{\epsilon}{\epsilon - 1} \frac{X_t \sum_{s=0}^{\infty} \xi^s \Lambda_{t,t+s} mc_{t+s} P_{t+s}^{\epsilon} Y_{t+s}}{X_t \sum_{s=0}^{\infty} \xi^s \Lambda_{t,t+s} P_{t+s}^{\epsilon-1} Y_{t+s}}. \tag{A.34}$$

Since nothing on the right-hand side depends on j, all updating firms choose the same price. We define this common reset price as $P_t^{\#}$, leading to:

$$P_t^{\#} = \frac{\epsilon}{\epsilon - 1} \frac{X_{1,t}}{X_{2,t}}, \tag{A.35}$$

where the two auxiliary variables $X_{1,t}$ and $X_{2,t}$ evolve recursively as:

$$X_{1,t} = mc_t P_t^{\epsilon} Y_t + \xi X_t \Lambda_{t,t+1} X_{1,t+1}, \tag{A.36}$$

$$X_{2,t} = P_t^{\epsilon-1} Y_t + \xi X_t \Lambda_{t,t+1} X_{2,t+1}. \tag{A.37}$$

Key Properties

- Since the right-hand side does not depend on j, all updating firms set the same **reset price** $P_t^{\#}$.
- $X_{1,t}$ represents the expected future discounted marginal cost-weighted demand.
- $X_{2,t}$ represents the expected future discounted nominal demand.

Real Marginal Cost

The firm's real marginal cost is given by:

$$mc_t = (1 + i_t^L)(1 - \phi_{t+1})\frac{w_t}{A_t}. \tag{A.38}$$

Sticky Wages

We have a labor unions of unit mass, indexed by $i \in [0, 1]$. The unions employ household labor and remunerate them at a rate w_t. The unions then turnaround and sell this labor to a "labor packer" at a price of $U_t(h)$. This labor is then transformed by the packer into a a final labor item that firms can employ in the form of a CES technology:

$$N_{d,t} = \left[\int_0^1 N_t(i)^{\frac{\epsilon_w - 1}{\epsilon_w}} di\right]^{\frac{\epsilon_w}{\epsilon_w - 1}} \tag{A.39}$$

We end up with the following wage index and individual union labor demand after profit maximizaiton:

$$U_t^{1-\epsilon_w} = \int_0^1 U_t(i)^{1-\epsilon_w} di$$
$$N_t(i) = \left(\frac{U_t(i)}{U_t}\right)^{-\epsilon_w} N_{d,t}$$

With probability $1 - \phi_w$, the unions can adjust the wage. They face the following problem:

$$\max_{N_t(i)} E_t \sum_{j=0}^{\infty} \phi_w^j \Lambda_{t,t+j} \left\{U_t(i)^{1-\epsilon_w} U_{t+j}^{\epsilon_w} P_{t+j}^{-1} N_{d,t+j} - w_{t+j} U_t(i)^{-\epsilon_w} U_{t+j}^{\epsilon_w} N_{d,t+j}\right\}$$

After taking the FOC, we can rearrange to get the optimal reset wage $U_t^{\#}$:

$$U_t^{\#} = \frac{\epsilon_w}{\epsilon_w - 1} \frac{E_t \sum_{j=0}^{\infty} \phi_w^j \Lambda_{t,t+j} w_{t+j} U_{t+j}^{\epsilon_w} N_{d,t+j}}{E_t \sum_{j=0}^{\infty} \phi_w^j \Lambda_{t,t+j} P_{t+j}^{-1} U_{t+j}^{\epsilon_w} N_{d,t+j}}$$

Defining $f_{1,t} = \frac{F_{1,t}}{P_t^{\epsilon_w}}$ and $f_{2,t} = \frac{F_{2,t}}{P_t^{\epsilon_w - 1}}$, we derive:

$$u_t^{\#} = \frac{\epsilon_w}{\epsilon_w - 1} \frac{f_{1,t}}{f_{2,t}} \tag{A.40}$$

Where we define $f_{1,t}$ and $f_{2,t}$ recursively:

$$f_{1,t} = w_t u_t^{\epsilon_w} N_{d,t} + \phi_w E_t \Lambda_{t,t+1} \Pi_{t+1}^{\epsilon_w} f_{1,t+1} \tag{A.41}$$

$$f_{2,t} = u_t^{\epsilon_w} N_{d,t} + \phi_w E_t \Lambda_{t,t+1} \Pi_{t+1}^{\epsilon_w - 1} f_{2,t+1} \tag{A.42}$$

Aggregate real wage evolution is expressed as follows (which follows a similar derivation as the inflation rate evolution):

$$u_t^{1-\epsilon_w} = (1-\phi_w)(u_t^{\#})^{1-\epsilon_w} + \phi_w \Pi_t^{\epsilon_w - 1} u_{t-1}^{1-\epsilon_w} \tag{A.43}$$

Since labor supply must equal that demanded by the unions:

$$N_t = \int_0^1 N_{d,t}(i) di$$

We end up with:

$$N_t = N_{d,t} v_t^w$$

With v_t^w representing wage dispersion:

$$v_t^w = (1-\phi_w) \left(\frac{u_t^{\#}}{u_t} \right)^{-\epsilon_w} + \phi_w \Pi_t^{\epsilon_w} \left(\frac{u_t}{u_{t-1}} \right)^{\epsilon_w} v_{t-1}^w$$

B Bank's Problem

The bank chooses $\{L_t, B_t, R_t, D_t, X_t\}$ to maximize:

$$\Phi_t = E_t \Big\{ \Lambda_{t+1} \Big[(1+i_t^L)(1-\phi_d) L_t + (1+i_t^B) B_t + (1+i_t^R) R_t - (1+i_t^D) D_t \Big] \Big\} - X_t - \frac{\phi_x}{2} (L_t - L_{t-1})^2 \tag{B.1}$$

subject to:

$$L_t + B_t + R_t = D_t + (1 - f(\delta_t)) X_t, \quad \text{where} \quad \delta_t = \frac{L_t}{X_t}, \tag{B.2}$$

$$f(\delta_t) = \frac{\alpha}{2}\delta_t^2, \tag{B.3}$$

$$R_t \geq \rho D_t, \quad 0 \leq \rho < 1. \tag{B.4}$$

C Lagrangian Formulation

Defining multipliers:

- μ_t for the balance-sheet constraint,
- $\alpha_t \geq 0$ for the reserve requirement.

The Lagrangian is:

$$\mathcal{L} = E_t\Big[\Lambda_{t+1}\big((1+i_t^L)(1-\phi_d)L_t + (1+i_t^B)B_t + (1+i_t^R)R_t - (1+i_t^D)D_t\big)\Big]$$
$$-X_t - \frac{\phi_x}{2}(L_t - L_{t-1})^2 - \mu_t\Big(L_t + B_t + R_t - D_t - \Big(1 - \frac{\alpha}{2}\delta_t^2\Big)X_t\Big) - \alpha_t(R_t - \rho D_t).$$

D First-Order Conditions (FOCs)

D.1 FOC with respect to B_t

$$E_t[\Lambda_{t+1}(1+i_t^B)] - \mu_t = 0. \tag{D.1}$$

D.2 FOC with respect to R_t

$$E_t[\Lambda_{t+1}(1+i_t^R)] - \mu_t - \alpha_t = 0. \tag{D.2}$$

D.3 FOC with respect to D_t

$$-E_t[\Lambda_{t+1}(1+i_t^D)] + \mu_t + \rho\alpha_t = 0. \tag{D.3}$$

D.4 FOC with respect to L_t

$$E_t[\Lambda_{t+1}(1+i_t^L)(1-\phi_d)] - \phi_x(L_t - L_{t-1}) - \mu_t(1+\alpha\delta_t) = 0. \tag{D.4}$$

D.5 FOC with respect to X_t

Using the chain rule for the balance-sheet constraint:

$$-1 + \mu_t(1 - \frac{\alpha}{2}\delta_t^2) = 0 \tag{D.5}$$

Solving for μ_t:

$$\mu_t = \frac{1}{(1-\frac{\alpha}{2}\delta_t^2)}. \tag{D.6}$$

E Loan - Bond Spread Condition

Given our FOC conditions, we can derive the interest rate spread between loans and bonds. Substitute the value of μ_t from (44) into the FOC for L:

$$\Lambda_{t+1}(1+i_t^L)(1-\phi_d) - \phi_x\big(L_t - L_{t-1}\big) - \Lambda_{t+1}(1+i_t^B)\Big[1+\alpha\,\delta_t\Big] = 0. \tag{E.1}$$

Dividing the entire equation by Λ_{t+1} (which is positive) yields

$$(1+i_t^L)(1-\phi_d) = (1+i_t^B)(1+\alpha\,\delta_t) + \frac{\phi_x}{\Lambda_{t+1}}\big(L_t - L_{t-1}\big). \tag{E.2}$$

I wish to express the gross spread $\frac{1+i_t^L}{1+i_t^B}$. Divide both sides of (2) by $1+i_t^B$:

$$\frac{1+i_t^L}{1+i_t^B}(1-\phi_d) = 1+\alpha\,\delta_t + \frac{\phi_x}{\Lambda_{t+1}(1+i_t^B)}\big(L_t - L_{t-1}\big). \tag{E.3}$$

Finally, divide both sides by $1-\phi_d$ to obtain:

$$\frac{1+i_t^L}{1+i_t^B} = \frac{1+\alpha\,\delta_t}{1-\phi_d} + \frac{\phi_x}{\Lambda_{t+1}(1+i_t^B)(1-\phi_d)}\big(L_t - L_{t-1}\big). \tag{E.4}$$

Final Result

Equation (53) is the stand-alone interest rate spread condition that results from the bank's optimization problem with adjustment costs:

$$\frac{1+i_t^L}{1+i_t^B} = \frac{1+\alpha\,\delta_t}{1-\phi_d} + \frac{\phi_x}{\Lambda_{t+1}(1+i_t^B)(1-\phi_d)}\big(L_t - L_{t-1}\big)$$

This equation shows that, in addition to the baseline spread $\frac{1+\alpha\,\delta_t}{1-\phi_d}$ (which would arise in the absence of adjustment costs), there is an extra term that accounts for the cost of adjusting the loan portfolio.

F Equity

My specification for the evolution of bank equity is based on that employed by Benigno and Benigno (2021). Equity has the following specification:

$$x_t = \left[1 - \frac{(1+i_t^L)}{(1+i_t^B)}(1-\phi_{d,t+1})\right]\ell_t + \frac{i_t^D - i_t^B}{1+i_t^B}d_t + \frac{i_t^B - i_t^R}{1+i_t^B}r_t \tag{F.1}$$

G Treasury Bond Issuance and Tax Rule

Let there be a central bank with the following budget constraint:

$$B_t^T = (1+i_t^D)B_{t-1}^T - T_t \tag{G.1}$$

Further, assume that the government sets the tax policy in the following manner:

$$T_t = \tau Y_t, \qquad 0 < \tau < 1 \tag{G.2}$$

H Taylor Rule (Monetary Policy)

The central bank follows a Taylor Rule, adjusting the nominal interest rate in response to inflation and output deviations:

$$1 + i_t^R = (1 + i^R)^{\rho} \left(\frac{\Pi_t}{\Pi^*}\right)^{\phi_\pi} \left(\frac{Y_t}{Y^*}\right)^{\phi_Y} e^{\phi_t}. \tag{H.1}$$

Where i^R, Π^*, and Y^* are the steady state values of the interest rate on reserve balances, inflation, and output, respectively. Shocks to the interest rate on reserves enter in through ϕ_t.

The shock to the policy rate is specified as:

$$\phi_t = \sum_{i=0}^{20} \psi_{r,t-i}^{i} \tag{H.2}$$

w_t is a weight that decays geometrically over time.

Let $\hat{\psi}_{r,t}$ denote one's belief (or prior) about the true value of $\psi_{r,t}$, which represents the true policy innovation at time t. $\hat{\psi}_{r,t}$ is defined as follows:

$$\hat{\psi}_{r,t}^{j} = \hat{\psi}_{r,t-1}^{j} + \kappa_j (s_t^j - \hat{\psi}_{r,t-1}^{j}), \quad j = 1, ..., 20. \tag{H.3}$$

Here, κ_j represents the Kalman gain with respect to horizon j, and $s_t^j - \hat{\psi}_{r,t-1}^{j}$ is the forecast error.

The forward guidance shock ψ_t^{FG} is defined as a set of signals:

$$\psi_t^{FG} = [s_t^0 \;\; s_t^1 \ldots s_t^{20}]$$

The current policy rate is perfectly observed:

$$s_t^0 = \psi_{r,t}^0$$

While future deviations are unobserved, i.e. for $j \geq 1$

$$s_t^j = \psi_{r,t}^j + \nu_t, \qquad \nu_t \sim N(0, \sigma_\nu^2) \tag{H.4}$$

Hence, the Kalman gain $\kappa = \frac{\sigma_\psi^2}{\sigma_\psi^2 + \sigma_\nu^2}$, where σ_ψ^2 is the variance of the agent's prior.

I Equilibrium Conditions

$$E_t\{\Lambda_{t+1}(1+i_t^B)\} = 1 \tag{I.1}$$

$$\theta N_t^\eta = (C_t - \varphi H_t)^{-\sigma} w_t \tag{I.2}$$

$$d_t = \phi(C_t - \varphi H_t)^\sigma \frac{(1+i_t^B)}{(i_t^B - i_t^D)} - b_t^T \tag{I.3}$$

$$\Lambda_t = \beta \left(\frac{C_t - \varphi H_t}{C_{t-1} - \varphi H_{t-1}} \right)^{-\sigma} \Pi_t^{-1} \tag{I.4}$$

$$1 = (1-\xi)(p_t^\#)^{1-\epsilon} + \xi \Pi_t^{\epsilon-1} \tag{I.5}$$

$$u_t^{1-\epsilon_w} = (1-\phi_w)(u_t^\#)^{1-\epsilon_w} + \phi_w \Pi_t^{\epsilon_w - 1} u_{t-1}^{1-\epsilon_w} \tag{I.6}$$

$$p_t^\# = \frac{\epsilon}{\epsilon - 1} \frac{\hat{X}_{1,t}}{\hat{X}_{2,t}} \tag{I.7}$$

$$u_t^\# = \frac{\epsilon_w}{\epsilon_w - 1} \frac{f_{1,t}}{f_{2,t}} \tag{I.8}$$

$$\hat{X}_{1,t} = mc_t Y_t + \xi E_t \Lambda_{t+1} \Pi_{t+1}^\epsilon \hat{X}_{1,t+1} \tag{I.9}$$

$$\hat{X}_{2,t} = Y_t + \xi E_t \Lambda_{t+1} \Pi_{t+1}^{\epsilon-1} \hat{X}_{2,t+1} \tag{I.10}$$

$$f_{1,t} = w_t u_t^{\epsilon_w} N_{d,t} + \phi_w E_t \Lambda_{t+1} \Pi_{t+1}^{\epsilon_w} f_{1,t+1} \tag{I.11}$$

$$f_{2,t} = u_t^{\epsilon_w} N_{d,t} + \phi_w E_t \Lambda_{t+1} \Pi_{t+1}^{\epsilon_w - 1} f_{2,t+1} \tag{I.12}$$

$$u_t = mc_t A_t \tag{I.13}$$

$$mc_t = (1+i_t^L)(1-\phi_{d,t+1}) \frac{w_t}{A_t} \tag{I.14}$$

$$Y_t = C_t + \frac{\alpha}{2}\delta_t^2 X_t + \frac{\varphi_x}{2}(L_t - L_{t-1})^2 \tag{I.15}$$

$$b_t^T = (1+i_t^D) b_{t-1}^T - T_t \tag{I.16}$$

$$T_t = \tau Y_t \tag{I.17}$$

$$A_t N_t = Y_t \nu_t^P \tag{I.18}$$

$$N_t = N_{d,t} \nu_t^w \tag{I.19}$$

$$\nu_t^P = (1-\xi)(p_t^\#)^{-\epsilon} + \xi \Pi_t^\epsilon \nu_{t-1}^P \tag{I.20}$$

$$\nu_t^w = (1-\phi_w) \left(\frac{u_t^\#}{u_t} \right)^{-\epsilon_w} + \phi_w \Pi_t^{\epsilon_w} \left(\frac{u_t}{u_{t-1}} \right)^{\epsilon_w} \nu_{t-1}^w \tag{I.21}$$

$$\ln A_t = \rho_A \ln A_{t-1} + s_A \epsilon_{A,t} \tag{I.22}$$

$$1 + i_t^R = (1 + i^R)^{\rho_r} \left(\frac{\Pi_t}{\Pi^*} \right)^{\phi_\pi} \left(\frac{Y_t}{Y^*} \right)^{\phi_Y} e^{\epsilon_t^{FG}} \tag{I.23}$$

$$\phi_{d,t+1} = 1 - \frac{Y_t}{(1 + i_t^L)\ell_t} \tag{I.24}$$

$$\frac{(1 + i_t^L)}{(1 + i_t^B)} = \frac{1 + \alpha\delta_t}{1 - \phi_{d,t+1}} + \frac{\phi_x}{\Lambda_{t+1}(1 + i_t^B)(1 - \phi_{d,t+1})}(\ell_t - \ell_{t-1}) \tag{I.25}$$

$$\ell_t = \rho_\ell \ell_{t-1} + (1 - \rho_\ell) \left(\left(\frac{1}{\rho} - 1 \right) r_t + \left(1 - \frac{\alpha}{2}\delta_t^2 \right) x_t - b_t \right) \tag{I.26}$$

$$r_t = \frac{1}{1 - \rho} \left[\left(1 - \frac{\alpha}{2}\delta_t^2 \right) x_t - \left(\frac{(1 + i_t^L) + (1 + i_t^B)}{(1 + i_t^L)} \right) w_t N_t \right] \tag{I.27}$$

$$\ell_t + b_t + r_t = d_t + \left(1 - \frac{\alpha}{2}\delta_t^2 \right) x_t \tag{I.28}$$

$$x_t = \left[1 - \frac{(1 + i_t^L)}{(1 + i_t^B)}(1 - \phi_{d,t+1}) \right] \ell_t + \frac{i_t^D - i_t^B}{1 + i_t^B} d_t + \frac{i_t^B - i_t^R}{1 + i_t^B} r_t \tag{I.29}$$

$$\delta_t = \frac{\ell_t}{x_t} \tag{I.30}$$

Steady State

In deriving the Steady State, I normalize the following set of variables equal to 1:

$$Y = C = \Pi = 1$$

The steady state stochastic discount factor becomes:

$$\Lambda = \beta$$

From which it follows that our interest rate on private debt is:

$$i_B = \frac{1}{\beta} - 1$$

Since any variable $x_t = x_{t-1} = x$ in steady state, we have the following:

$$\ell = \left(\frac{1}{\rho} - 1 \right) r + \left(1 - \frac{\alpha}{2}\delta^2 \right) x - b$$

$$1 + i_L = \frac{1 + i_B}{1 - \phi_d}$$
$$\ell = \frac{1}{1 + i_B}$$

Adding an additional normalization in the form of $p^{\#} = 1$, we get:

$$mc = \frac{\epsilon - 1}{\epsilon}$$

Which follows from the fact that:

$$X1 = \frac{mc}{1 - \xi\beta}$$
$$X2 = \frac{1}{1 - \xi\beta}$$

Which comes fromt the fact that $\Lambda = \beta$, $\Pi = 1$, and $X_{1,t} = X_{1,t+1} = X_1$ in steady state. The remaining conditions are as follows:

$$\theta = w \tag{I.31}$$
$$\nu^P = 1 \tag{I.32}$$
$$mc = (1 + i_L)(1 - \phi_d)\frac{w}{A} \tag{I.33}$$
$$\phi_d = 1 - \frac{Y}{(1 + i_L)\ell} \tag{I.34}$$
$$i_D = \frac{\tau}{b_T} \tag{I.35}$$
$$d = \varphi\frac{1 + i_B}{i_B - i_D} - b_T \tag{I.36}$$
$$\ell + b + r = d + \left(1 - \frac{\alpha}{2}\delta^2\right) x \tag{I.37}$$
$$x = \left[1 - \frac{(1 + i_L)}{(1 + i_B)}(1 - \phi_d)\right] \ell + \frac{i_D - i_B}{1 + i_B} d + \frac{i_B - i_R}{1 + i_B} r \tag{I.38}$$
$$A = 1 \tag{I.39}$$
$$f1 = \frac{w}{1 - \phi_w\beta} \tag{I.40}$$

$$f2 = \frac{1}{1-\phi_w \beta} \tag{I.41}$$

$$u^{\#} = 1 \tag{I.42}$$

$$\delta = \frac{l}{x} \tag{I.43}$$

Log Linearized Conditions

$$E_t \tilde{\Lambda}_{t+1} + \tilde{i}_{B,t} = 0 \tag{I.44}$$

$$\eta \tilde{N}_t - \tilde{W}_t + \sigma \frac{C^*}{C^* - \varphi H^*} \tilde{C}_t - \sigma \frac{\varphi H^*}{C^* - \varphi H^*} \tilde{H}_t = 0 \tag{I.45}$$

$$\begin{aligned} \tilde{d}_t = & \frac{\phi (C^* - \varphi H^*)^{\sigma - 1} \sigma}{d^*} \frac{1 + i^{B*}}{i^{B*} - i^{D*}} (\tilde{C}_t - \tilde{H}_t) \\ & - \frac{\phi (C^* - \varphi H^*)^{\sigma}}{d^*} \frac{1 + i^{D*}}{(i^{B*} - i^{D*})^2} \tilde{i}^B_t + \frac{\phi (C^* - \varphi H^*)^{\sigma}}{d^*} \frac{1 + i^{B*}}{(i^{B*} - i^{D*})^2} \tilde{i}^D_t - \frac{b^{T*}}{d^*} \tilde{b}^T_t \end{aligned} \tag{I.46}$$

$$\tilde{\Lambda}_t = -\sigma \frac{C^*}{C^* - \varphi H^*} (\tilde{C}_t - \tilde{C}_{t-1}) - \sigma \frac{\varphi H^*}{C^* - \varphi H^*} (\tilde{H}_t - \tilde{H}_{t-1}) - \tilde{\Pi}_t \tag{I.47}$$

$$0 = (1-\xi)(1-\epsilon)(p^{\#*})^{1-\epsilon} \tilde{p}^{\#}_t + \xi (\epsilon - 1)(\Pi^*)^{\epsilon - 1} \tilde{\Pi}_t \tag{I.48}$$

$$\tilde{u}_t = \frac{(1-\phi_w)) u^{\# 1 - \epsilon_w *}}{u^{* 1 - \epsilon_w}} \tilde{u}^{\#}_t + \phi_w (\epsilon_w - 1) \Pi^{* \epsilon_w - 1} (\tilde{\Pi}_t - \tilde{u}_{t-1}) \tag{I.49}$$

$$\tilde{p}^{\#}_t = \tilde{X}_{1,t} - \tilde{X}_{2,t} \tag{I.50}$$

$$\tilde{u}^{\#}_t = \tilde{f}_{1,t} - \tilde{f}_{2,t} \tag{I.51}$$

$$\tilde{X}_{1,t} = \frac{mc^* Y^*}{X_1^*} (\tilde{mc}_t + \tilde{Y}_t) + \xi \Lambda^* (\Pi^*)^{\epsilon} E_t (\tilde{\Lambda}_{t+1} + \epsilon \tilde{\Pi}_{t+1} + \tilde{X}_{1,t+1}) \tag{I.52}$$

$$\tilde{X}_{2,t} = \frac{Y^*}{X_2^*} \tilde{Y}_t + \xi \Lambda^* (\Pi^*)^{-1} E_t (\tilde{\Lambda}_{t+1} - \tilde{\Pi}_{t+1} + \tilde{X}_{2,t+1}) \tag{I.53}$$

$$\tilde{f}_{1,t} = \frac{w^* u^{\epsilon_w *} N_d^*}{f_1^*} (\tilde{w}_t + \epsilon_w \tilde{u}_t + \tilde{N}_{d,t}) + \phi_w \Lambda^* \Pi^{\epsilon_w *} (\tilde{\Lambda}_{t+1} + \epsilon_w \tilde{\Pi}_{t+1} + \tilde{f}_{1,t+1}) \tag{I.54}$$

$$\tilde{f}_{2,t} = \frac{u^{\epsilon_w *} N_d^*}{f_2^*} (\tilde{u}_t + \tilde{N}_{d,t}) + \phi_w \Lambda^* \Pi^{\epsilon_w - 1 *} (\tilde{\Lambda}_{t+1} + (\epsilon_w - 1) \tilde{\Pi}_{t+1} + \tilde{f}_{2,t+1}) \tag{I.55}$$

$$\tilde{u}_t = \tilde{mc}_t + \tilde{A}_t \tag{I.56}$$

$$\tilde{mc}_t = \tilde{i}^L_t - \frac{1}{1-\phi_d^*} \tilde{\phi}_{d,t+1} + \tilde{w}_t - \tilde{A}_t \tag{I.57}$$

$$\tilde{Y}_t = \frac{C^*}{Y^*} \tilde{C}_t + \frac{\alpha (\delta^*)^2 X^*}{Y^*} (\tilde{X}_t + \tilde{\delta}_t) \tag{I.58}$$

$$\tilde{b}_t^T = (1+i^{D*})\tilde{b}_{t-1}^T + \tilde{i}_t^D - \frac{T^*}{b^{T*}}\tilde{T}_t \tag{I.59}$$

$$\tilde{T}_t = \tau \tilde{Y}_t \tag{I.60}$$

$$\tilde{A}_t + \tilde{N}_t = \tilde{Y}_t + \tilde{\nu}_t^P \tag{I.61}$$

$$\tilde{N}_t = \tilde{N}_{t,t} + \tilde{\nu}_t^w \tag{I.62}$$

$$\tilde{\nu}_t^P = \xi(\Pi^*)^{\epsilon}(\epsilon\tilde{\Pi}_t + \tilde{\nu}_{t-1}^P) - \frac{\epsilon(1-\xi)(p^{\#*})^{-\epsilon}}{\nu^{P*}}\tilde{p}_t^{\#} \tag{I.63}$$

$$\tilde{\nu}_t^w = \frac{(1-\phi_w)\epsilon_w\left(\frac{u^{\#*}}{u^*}\right)^{-\epsilon_w}}{\nu^{w*}}(\tilde{u} - \tilde{u}_t^{\#}) + \phi_w \Pi^{\epsilon_w}(\epsilon_w\tilde{\Pi}_t + \epsilon_w(\tilde{u}_t - \tilde{u}_{t-1}) + \tilde{\nu}_{t-1}^w) \tag{I.64}$$

$$\tilde{A}_t = \rho_A \tilde{A}_{t-1} + \gamma_A \varepsilon_{A,t} \tag{I.65}$$

$$\tilde{i}_t^R = (1+i^{R*})^{\rho_r}(\phi_\pi \tilde{\Pi}_t + \phi_Y \tilde{Y}_t + \tilde{\varepsilon}_t^{FG}) \tag{I.66}$$

$$\tilde{\phi}_{d,t+1} = \frac{1-\phi_d^*}{\phi_d^*}(\tilde{i}_t^L + \tilde{\ell}_t - \tilde{Y}_t) \tag{I.67}$$

$$\frac{1}{1+i^{B*}}\tilde{i}_t^L - \frac{1+i^{L*}}{(1+i^{B*})^2}\tilde{i}_t^B = \frac{\alpha\delta^*}{1-\phi_d^*}\tilde{\delta}_t + \frac{(1+\alpha\delta^*)\phi_d^*}{(1-\phi_d^*)^2}\tilde{\phi}_{d,t+1} + \frac{\phi_x l^*}{\Lambda^*(1+i^{B*})(1-\phi_d^*)}(\tilde{l}_t - \tilde{l}_{t-1}) \tag{I.68}$$

$$\tilde{\ell}_t = \rho_\ell \tilde{\ell}_{t-1} + \frac{(1-\rho_\ell)}{\ell^*}\left[\left(\frac{1}{\rho} - 1\right) r^*\tilde{r}_t + \left(1 - \frac{\alpha}{2}(\delta^*)^2\right) x^*\tilde{x}_t - \alpha\delta^*(x^*)^2\tilde{\delta}_t - b^*\tilde{b}_t\right] \tag{I.69}$$

$$\ell^*\tilde{\ell}_t + b^*\tilde{b}_t + r^*\tilde{r}_t = d^*\tilde{d}_t + \left(1 - \frac{\alpha}{2}(\delta^*)^2\right) x^*\tilde{x}_t - \alpha\delta^* x^*\tilde{\delta}_t \tag{I.70}$$

$$\tilde{r}_t = \frac{1}{r^*}\left[\left(1 - \frac{\alpha}{2}\delta^{*2}\right) x^*\tilde{x}_t - \alpha\delta^{*2}x^*\tilde{\delta}_t - \frac{w^*N^*}{1+i_L^*}\tilde{i}_t^B + \frac{1+i_B^*}{(1+i_L^*)^2}w^*N^*\tilde{i}_t^L - \left(1 + \frac{1+i_B^*}{1+i_L^*}\right) w^*N^*(\tilde{w}_t + \tilde{N}_t)\right] \tag{I.71}$$

$$\begin{aligned}\tilde{x}_t = &\left[1 - \frac{1+i_L^*}{1+i_B^*}(1-\phi_d^*)\right]\frac{l^*}{x^*}\tilde{l}_t + \frac{i_D^* - i_B^*}{1+i_B^*}\frac{d^*}{x^*}\tilde{d}_t + \frac{i_B^* - i_R^*}{1+i_B^*}\frac{r^*}{x^*}\tilde{r}_t + \\ &\frac{l^*}{x^*}\left[-\frac{(1-\phi_d^*)}{(1+i_B^*)}\tilde{i}_t^L + \frac{(1+i_L^*)(1-\phi_d^*)}{(1+i_B^*)^2}\tilde{i}_t^B + \frac{(1+i_L^*)}{(1+i_B^*)}\tilde{\phi}_{d,t+1}\right] + \frac{d^*}{x^*}\left[\frac{1}{1+i_B^*}\tilde{i}_t^D - \frac{1+i_D^* - i_B^*}{(1+i_B^*)^2}\tilde{i}_t^B\right] + \\ &\frac{r^*}{x^*}\left[\frac{1+i_R^* - i_B^*}{(1+i_B^*)^2}\tilde{i}_t^B - \frac{1}{1+i_B^*}\tilde{i}_t^R\right]\end{aligned} \tag{I.72}$$

$$\tilde{\delta}_t = \tilde{\ell}_t - \tilde{x}_t \tag{I.73}$$

Table 7: Prior and Posterior Distribution of the Structural Parameters

Parameter	**Prior distribution**		**Posterior distribution**		
	Dist.	Mean / Std. dev.	Mean	5%	95%
Model Parameters					
ρ_A	Beta	0.800 / 0.150	0.8590	0.8022	0.9201
ϕ_π	Normal	1.500 / 1.000	0.3155	−1.3936	2.0172
ϕ_y	Normal	0.500 / 0.600	1.3405	0.3804	2.3038
ξ	Beta	0.550 / 0.250	0.7824	0.7189	0.8538
ϕ_w	Beta	0.750 / 0.150	0.4930	0.4535	0.5353
ρ_b	Beta	0.850 / 0.080	0.9426	0.9036	0.9838
ϕ_x	Gamma	1.200 / 0.600	0.3670	0.0939	0.6319
γ_b	Gamma	0.100 / 0.050	0.1372	0.0718	0.2011
λ_h	Beta	0.900 / 0.050	0.9554	0.9274	0.9848
ε	Normal	6.000 / 2.000	6.0186	2.7377	9.2301
ε_w	Normal	4.500 / 1.000	3.1864	2.3972	4.1106
Standard deviations of shocks					
σ_l	Gamma	0.150 / 0.060	0.1606	0.1276	0.1941
σ_d	Gamma	0.150 / 0.060	0.3878	0.3392	0.4366
σ_ϕ	Gamma	0.120 / 0.050	0.0350	0.0178	0.0517
σ_A	Inv. Gamma	0.300 / 0.050	0.2151	0.1903	0.2388
σ_{FG}	Inv. Gamma	0.100 / 0.010	0.1315	0.1177	0.1453
σ_y	Inv. Gamma	0.200 / 0.080	0.2274	0.1851	0.2689
σ_c	Inv. Gamma	0.200 / 0.080	0.1822	0.1632	0.2009
σ_π	Inv. Gamma	2.000 / 0.250	2.2134	2.0055	2.4167
σ_{iL}	Inv. Gamma	2.500 / 0.500	2.3492	2.1166	2.5724
σ_{iD}	Inv. Gamma	3.000 / 0.500	2.5530	2.3001	2.8017
σ_b	Inv. Gamma	0.004 / 0.002	0.0047	0.0025	0.0070
σ_{π_w}	Inv. Gamma	0.180 / 0.070	0.1337	0.1173	0.1498
σ_{iR}	Inv. Gamma	0.180 / 0.080	0.1042	0.0740	0.1335

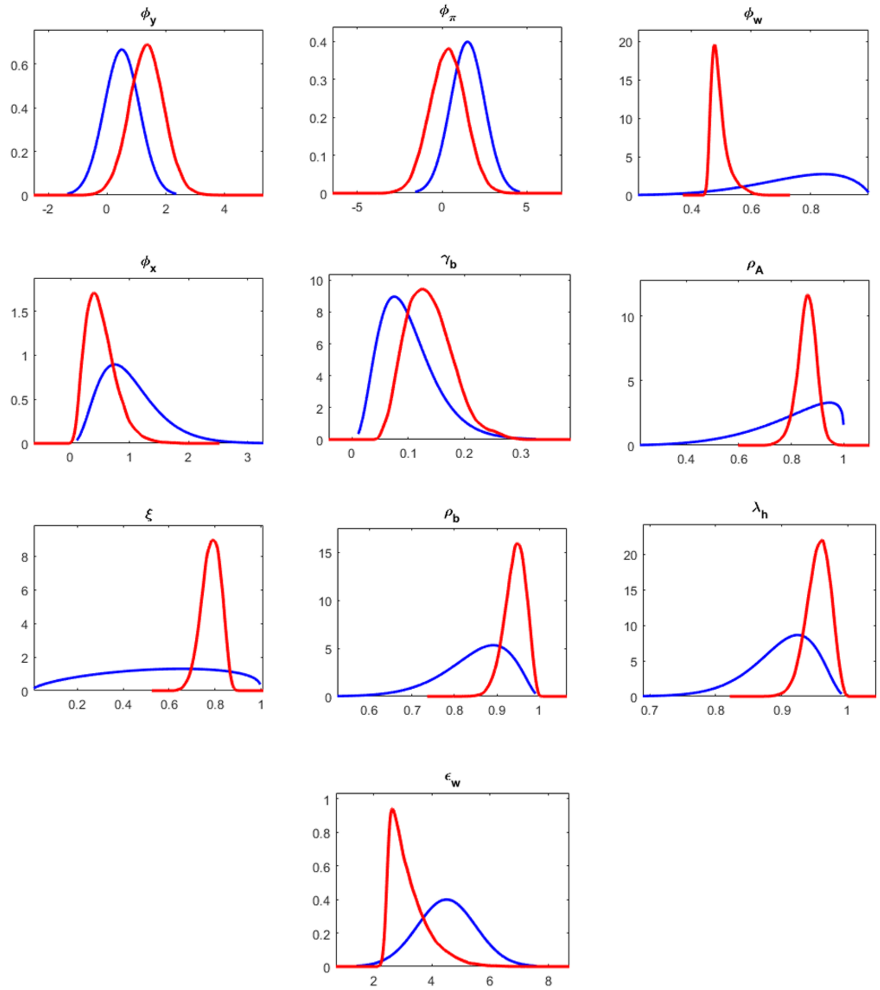


Figure 13: Prior and Posterior Marginal Distributions of Parameters

The posterior densities were generates from four chains with 250,000 draws each using the Metropolis algorithm. Red lines denote posterior distributions. Blue lines denote prior distributions

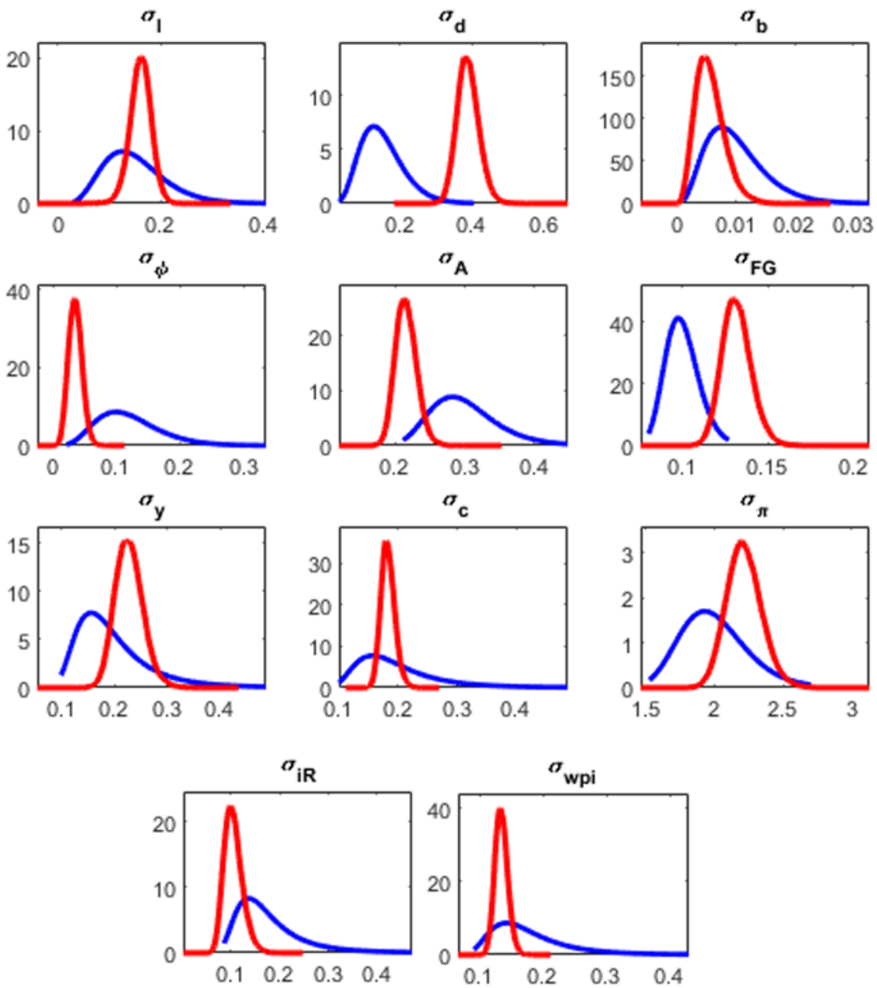
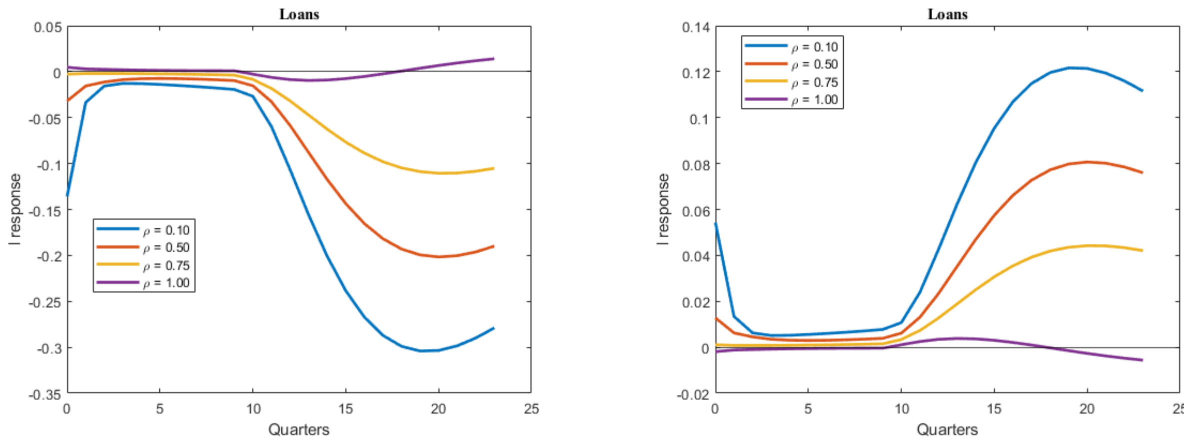


Figure 14: Prior and Posterior Marginal Distributions of Shocks

The posterior densities were generates from four chains with 250,000 draws each using the Metropolis algorithm. Red lines denote posterior distributions. Blue lines denote prior distributions



(a) Contractionary FG Surprise

(b) Expansionary FG Surprise

Figure 15: Responses of loans under different reserve ratios
ρ denotes the reserve requirement. When $\rho = 0.10$, banks must hold 10% of deposits in reserves; when $\rho = 1$, deposits must be fully backed.

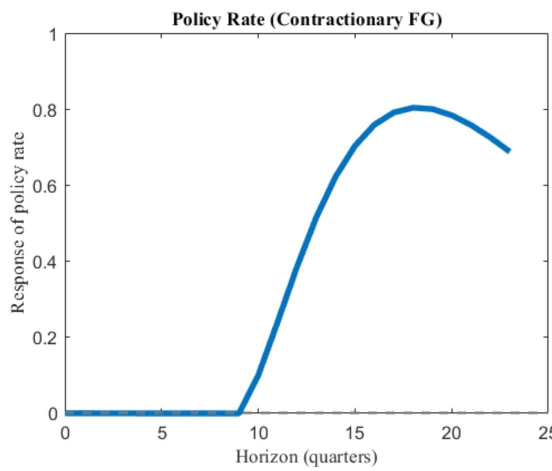


Figure 16: 10 Quarter Ahead Policy Rate Tightening
Here we see that the policy rate does not lift off until horizon 10 after a contractionary forward guidance shock, even though the effects of this affect the rest of the economy today in the model.