Forward Guidance and Bank Balance Sheets

Risk Reallocation, Leverage Dynamics, and Liquidity Preferences

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Abstract

In this paper, I examine how banks adjust their balance sheet to the central bank's forward guidance. I develop a model with a banking sector that enables us to explore this topic. When the central bank surprises markets with a policy tightening, banks contract credit and de-lever. Surprise tightenings trigger a sharp and persistent contraction in bank loans almost immediately. Surprise easings, by contrast, deliver a statistically detectable expansion in credit only after a multi-period lag, highlighting an asymmetric, front-loaded response to monetary tightening versus a delayed, back-loaded response to easing. I also find evidence in the data of countercyclical bank leverage in wake of forward guidance shocks, which I reproduce with my model. After reproducing key empirical results, I use the model to explore implications for macro-prudential policy, showing that forward guidance can stimulate bank lending during a liquidity trap, but to a limited extent.

Chapter 1: Forward Guidance and Bank Balance Sheets: Risk Reallocation, Leverage Dynamics, and Liquidity Preferences

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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.

[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 focus of this paper is on analyzing the effects of forward guidance on commercial bank balance sheets, specifically looking at how banks adjust their holdings of risky assets in response to a contractionary forward guidance shock. 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 risk-taking channel of monetary policy by illustrating how forward guidance uniquely shapes the timing and composition of bank balance-sheet adjustments.

In order to identify forward guidance shocks, I employ an established methodology in 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. Then, following GSS (2005) and by using the tools of PCA, I 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 contem-

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

poraneous 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, commercial banks reduce their leverage in wake of a contractionary forward guidance shock. However, over the medium-term they increase leverage as they substitute towards specific asset classes such as mortgage-backed securities (MBS), cash assets, as well as reserve and treasury holdings, while they substitute away from other assets such as commercial and industrial (C&I) loans and consumer loans. Over longer horizons, banks resume the process of delevering, creating a hump shape in the leverage response function. 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 contractionary forward guidance shock, the total loan volume issued by commercial banks steadily decreases over time.[4]

Interestingly, my results suggest that, despite the contractionary nature of the shock, banks exhibit behavior that reflects both precautionary and risk-taking motives. The shift away from C&I loans, which are generally considered less liquid and riskier in a tight credit environment, towards assets such as MBS aligns with a "search-for-yield" dynamic, as banks seek higher returns while navigating constrained credit conditions.

Taken together, the findings suggest banks exhibit a nuanced response to forward guidance shocks: banks engage in a dynamic portfolio reallocation process where they display

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

both precautionary and risk-taking behavior over various horizons. The findings also underscore the importance of the Federal Reserve's forward guidance policy in it's transmission to the financial sector, influencing not only credit supply, but leading banks to make important adjustments to their balance sheets.

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 Blinder (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 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, Evans, Fisher, and Justiniano (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

[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.

guidance on key asset prices such as treasuries and corporate bonds, along with commodity prices and the S&P 500, as in Gürkaynak, Sack an Swanson (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 the Bloomberg Terminal 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, I track changes in five key futures contracts: 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, I 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 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:

$$X = F\Lambda + e$$

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

After estimation, I find that two factors explain a large fraction of the variance in X, which is in agreement with 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.

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 (2022), Bauer and Swanson (2023), 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.

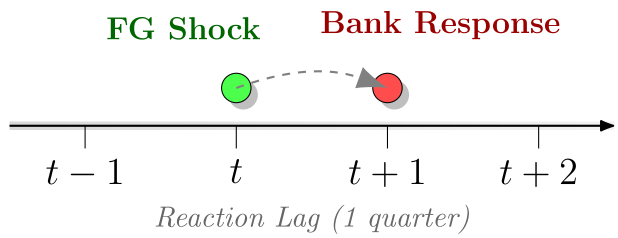
Following Bauer and Swanson (2023), I use six variables that are related to the Federal Reserve's monetary policy decisions: nonfarm payrolls surprise, employment growth, S&P 500, yield curve slope, commodity prices, and treasury skewness. The nonfarm payrolls surprise is calculated as the difference 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 (2023). 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:

$$FG_k = \alpha + \beta X_k + u_k$$

Where FG_k is one of the bi-quarterly forward guidance shocks at time k, and X_k 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:

$$\psi_t = \frac{\sum_{k \in t} u_k}{2}$$

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 (2022) 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. 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 1. 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) .

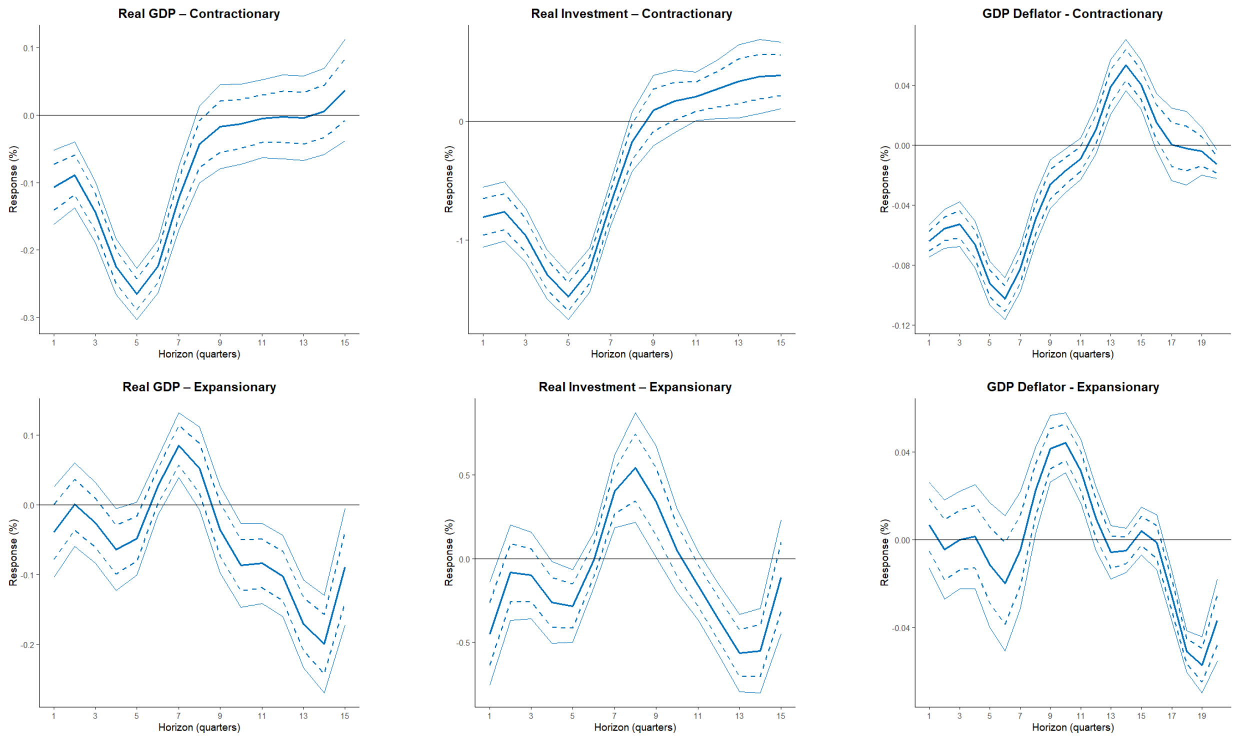


Figure 1: IRFs of Aggregates

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.

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 100 large and mid-sized U.S. commercial banks that I hand-picked for a 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

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:

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

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, $FG_{i,t}^{\text{con}}$ represents the expansionary forward guidance shock, and $FG_{i,t}^{\text{exp}}$ is its expansionary counterpart. They are constructed as follows:

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

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 2 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.

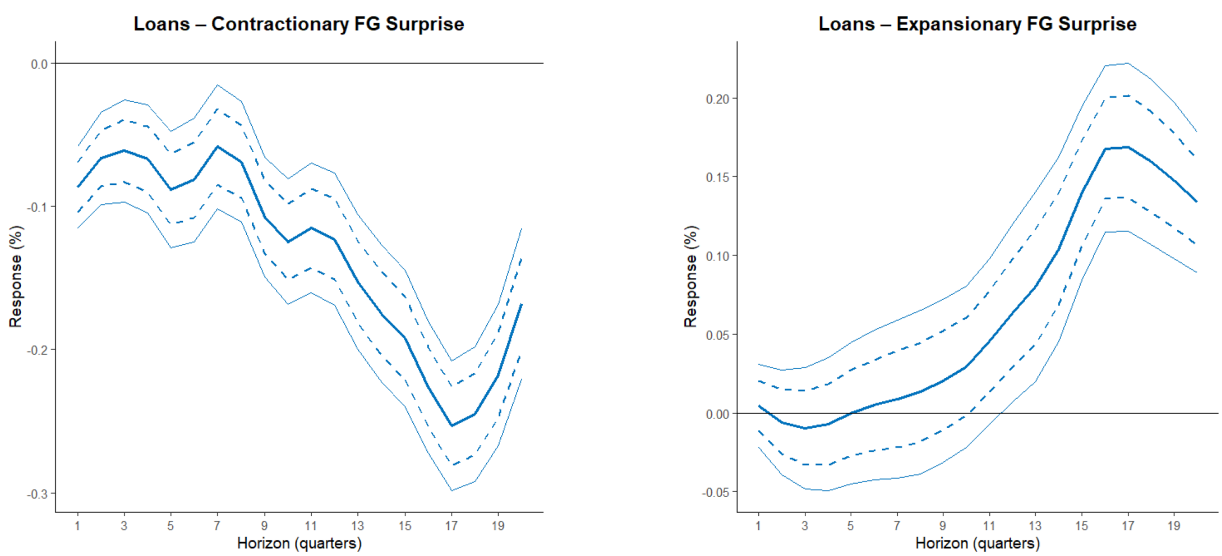


Figure 2: Loan Responses to Forward Guidance Shocks

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 dashed band corresponds to the 68%. confidence band, while the outer solid 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 2, 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 2 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.

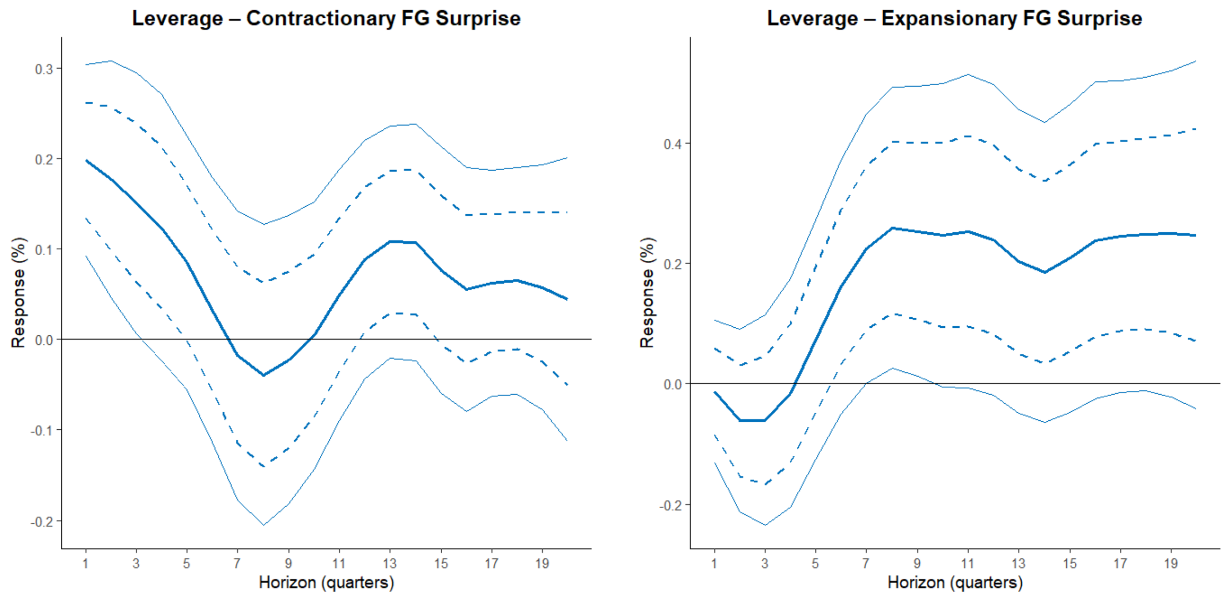


Figure 3: Leverage Responses to Forward Guidance Shocks

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 3, 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 1 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]

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).

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

6.1 Households

The representative household maximizes lifetime utility:

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

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 and Benigno. (2021) 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 yield it the interest rate i^R. The household holds deposits D with the bank, which the bank remunerates the houshold 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 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:

$$\phi_t = \sum_{i=0}^{20} w_{t+i} \hat{\psi}^i_{r,t+i} \tag{8}$$

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:

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

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

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	–
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	

Parameter	Prior distribution		Posterior distribution			
	Dist.	Mean / Std. dev.	Mean	5%	Median	95%
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	

Parameter	Prior distribution		Posterior distribution			
	Dist.	Mean / Std. dev.	Mean	5%	Median	95%
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

[8] From about 1993 until March 2020, the required reserve ratio, set by the Fed, was 10%. Since the onset

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

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

of the pandemic, the reserve ratio has been dropped to zero.

most of the point estimates of the LP IRF in panel d are statistically indistinguishable from zero.

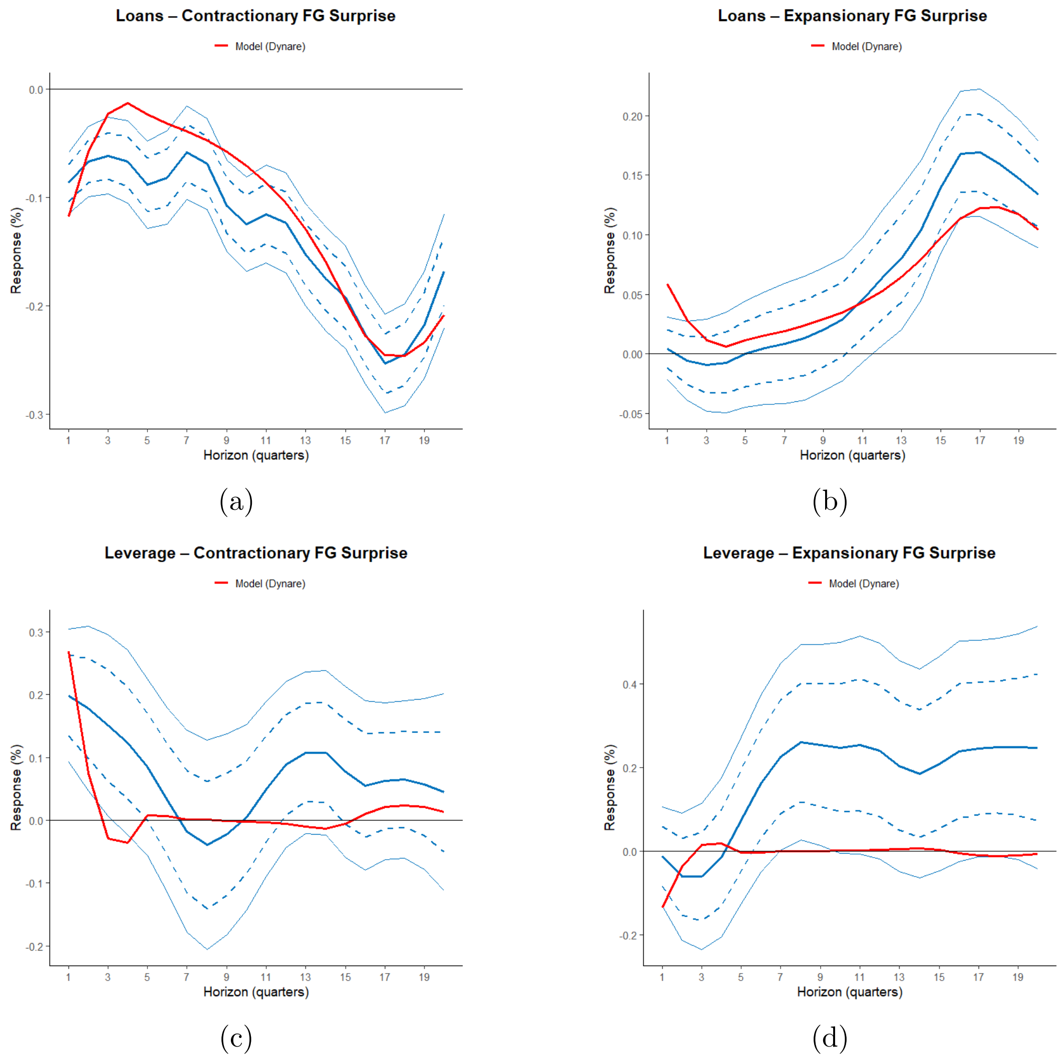


Figure 4: Empirical IRFs (blue) and model (red). Top: loans. Bottom: leverage. Left: contractionary. Right: expansionary.

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.

To test the effects of accommodative forward guidance on bank balance sheets during a zero lower bound (ZLB) period, I follow Guerrieri and Iacoviello (2017) in using an occasionally binding constraint on the policy rate. I separate the policy rate into two components, the actual rate that agents in the economy actually face, and the "shadow rate", which is what the policy rate *would be* if it were allowed to deviate below zero. So long as the policy rate is above zero, the actual rate and the shadow rate are identical. When the ZLB binds (policy rate equals 0), the shadow rate and the actual rate separate. Economically, a negative shadow rate does not imply observed negative policy rates; it indicates how much additional easing the rule would deliver without the bound, which agents interpret as staying at the ZLB for longer and a lower expected path of future short rates ("lower for longer"). Intuitively, the model uses the shadow path to determine when the constraint binds or releases. A very negative shadow rate keeps the economy in the constrained regime longer; and as it rises, agents anticipate a release from the constraint.

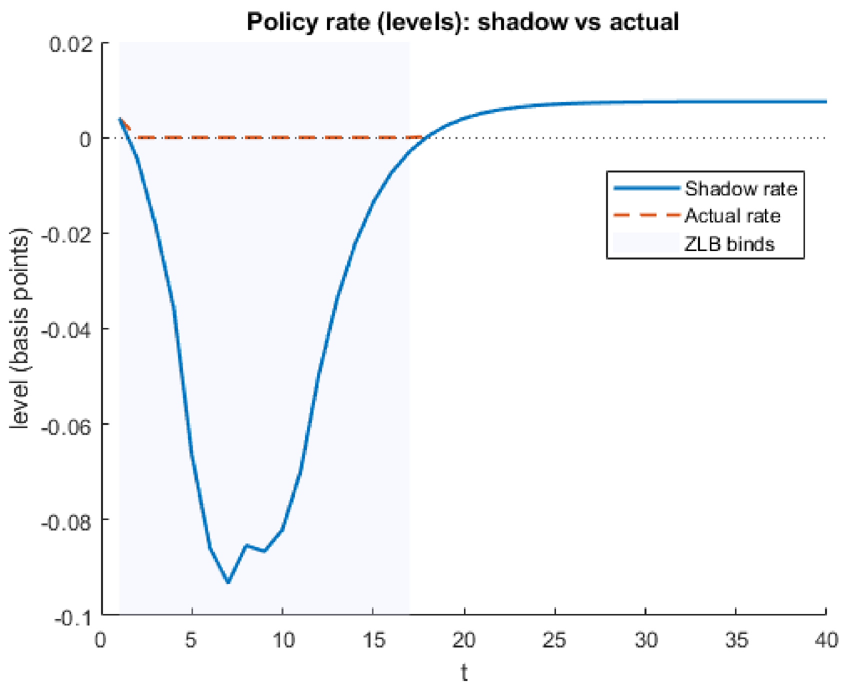
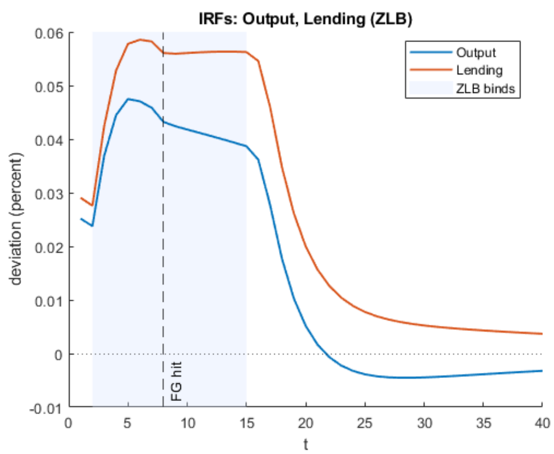


Figure 5: FG Shocks in the Context of a ZLB Episode

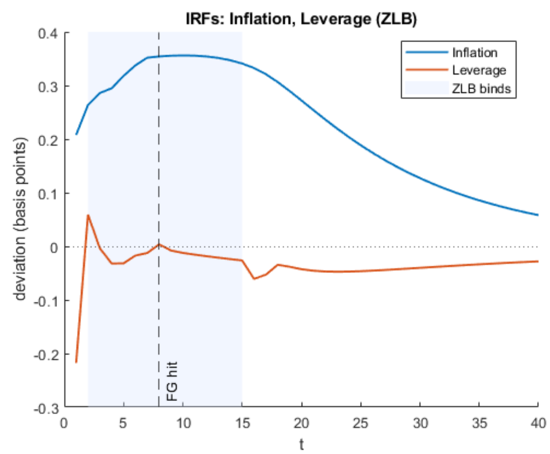
A comparison of the actual policy rate, which binds at the zero lower bound, and the shadow policy rate.

In terms of where this shows up in the model, the ϕ_t term in the Taylor rule governs expectations of the future interest rate path. At the ZLB, as the Fed becomes more accomodative and the shadow rate falls further below the actual rate, agents expect interest rates to stay at the ZLB for more periods. As the central bank begins to signal a future tightening, the expected window of time that the policy rate stays at the ZLB begins to close at nearer horizons, giving rise to a contraction in bank balance sheets and macro aggregates.

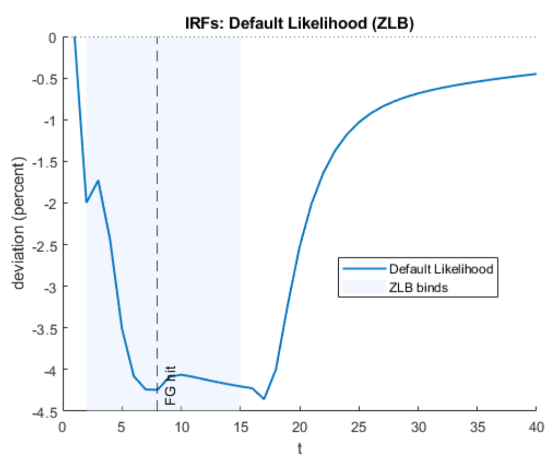
Once I introduce a contractionary shock, signaling a future tightening, the ZLB may still bind, but the shadow rate begins to rise, as illustrated in Figure 5, beginning at quarter 7, which will have an effect on agent's expectations of the future interest rate path. The monetary authority is announcing, in effect, "we're going to start being less accomodative in the future." The effects upon output, lending, and leverage are immediate: output and inflation begin to decrease, bank lending moderates, default risk rises toward steady state, and leverage dynamics adjust accordingly. In short, the shadow rate is a latent prescription that governs when the ZLB binds and for how long, and forward-guidance shocks operate by reshaping the expected path of the actual policy rate, even when today's rate is stuck at the lower bound.



(a) Output & Lending



(b) Inflation & Leverage



(c) Default Likelihood

Figure 6: ZLB forward-guidance experiment panels.

Response of aggregates and bank variables to monetary easing at zero lower bound, as measured in terms of deviation from the steady state.

Here is how the policy experiment goes: I introduce a sequence of expansionary forward-guidance announcements at $t = 1, 2, \ldots, 7$ each promising a lower policy rate four periods ahead (i.e., at horizons $h = 4$). These overlapping promises immediately depress the shadow policy rate and, by about $t \approx 2$ on Figure 5, push the actual rate against the ZLB, where it remains for many periods. At $t \approx 4$, I add a small positive forward guidance surprise (a partial reversal), which leave the net announcement that period still mildly expansionary. While the ZLB is binding, this signals that from $t \approx 8$ onward, the path will be less accommodative than previously expected. That tightening of expectations shows up around $t \approx 8$ (even though the actual rate is still at the bound), depressing output and inflation. As the effects of the earlier expansionary announcements wear out and the later tightening begins to dominate, the shadow rate rises, eventually crosses the bound, and the economy exits the ZLB around $t \approx 15$, at which point the actual and shadow rates realign.

In figure 6 we see the reaction of pertinent measures to an accommodative forward guidance shock at the zero lower bound. At $t = 1$, the Fed announces that starting at $t = 4$, they will begin to become more accommodative than previously anticipated. This surprise enters the policy rule contemporaneously through ϕ_t, with weight w_4, which rises as the promise moves its way down the pipeline. Upon arriving at the ZLB, output and and lending in panel (a) both make a steep upward climb until about period five, where they level off for a couple of periods, before we arrive at "FG hit", the vertical line denoting $t = 8$ where the trend of strong monetary easing reverses, altering agents beliefs about the future policy rate path. This leads to a slight decline in output, and virtually no change in lending until quarter 15, where we exit the ZLB. At that point lending and output drop off strongly. The same can be said for inflation in panel (b).

Moving in the opposite directions are bank leverage and default likelihood. As the Fed signals a more accomodative stance, firms' marginal costs fall, output increases, the future expected path of interest rates falls, all of which drive down the likelihood that firms default on their loans from the banks. Again, the countercyclical movement in leverage is attributable to the fact that equity moves faster than assets. Although both increase after the expansionary shock, equity adjusts faster than assets. Since equity is in the denominator, this causes leverage as a whole to jump downward, relaxing an important balance sheet constraint for banks.

Importantly, and this is a key finding, the absolute value of the response of each variable to the expansionary shock is significantly smaller than what is observed in response to a contractionary shock. The movement in the shadow rate in Figure 5 is calibrated to match the magnitude of the shock to the policy rate in the opposite direction during a contraction. When the economy experiences a one standard deviation contractionary shock to the policy rate, the absolute value of the response to output, lending, and leverage is larger than what is observed following an expansionary shock at the ZLB by about a factor of 10. This highlights the asymmetries we observe in the data: contractionary forward guidance shocks have a much more pronounced impact on economic activity, including bank activity, than expansionary forward guidance shocks. Here, this turns out to be especially true at the ZLB.

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 large commercial bank balance sheets. I've analyzed the effects of both expansionary and contractionary forward guidance shocks.

What I have found is that banks respond to contractions by reducing their exposure to risk. This manifests itself in banks reducing their loan supply, credit issuance in general, and leverage. Banks adjust their balance sheets in the opposite direction in wake of an expansion, with a few caveats. One, the data shows that banks' balance sheets are much more slow to respond to expansionary stimuli in the form of 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.

One of the principal interests that people have in forward guidance policy is its ability to stimulate the economy, even in the case of a liquidity trap, or zero lower bound period. 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.

Appendix

8.1 Banks in WRDS Data

Ticker	Bank Name	Ticker	Bank Name
BAC	Bank of America Corporation	JPM	JPMorgan Chase & Co.
WFC	Wells Fargo & Company	C	Citigroup Inc.
PNC	The PNC Financial Services Group, Inc.	USB	U.S. Bancorp
GS	The Goldman Sachs Group, Inc.	TFC	Truist Financial Corporation
COF	Capital One Financial Corporation	SCHW	The Charles Schwab Corporation
STT	State Street Corporation	FITB	Fifth Third Bancorp
CTZN	Citizens Financial Group, Inc.	KEY	KeyCorp
FRCB	First Republic Bank (Acquired by JPM)	HBAN	Huntington Bancshares Inc.
SIVBQ	SVB Financial Group (Filed for bankruptcy)	MTB	M&T Bank Corporation
RF	Regions Financial Corporation	NTRS	Northern Trust Corporation
FCNCA	First Citizens BancShares, Inc.	SAN	Banco Santander, S.A.
CMA	Comerica Incorporated	ZION	Zions Bancorporation, N.A.
SNV	Synovus Financial Corp.	FHN	First Horizon Corporation
VNBCQ	Vintage Bank	WBS	Webster Financial Corporation
PNFP	Pinnacle Financial Partners, Inc.	SSB	SouthState Corporation
AUB	Atlantic Union Bankshares Corporation	PB	Prosperity Bancshares, Inc.
WTFC	Wintrust Financial Corporation	UMBF	UMB Financial Corporation
OZK	Bank OZK	EWBC	East West Bancorp, Inc.
CFR	Cullen/Frost Bankers, Inc.	ONB	Old National Bancorp
ASB	Associated Banc-Corp	BOKF	BOK Financial Corporation
FIBK	First Interstate BancSystem, Inc.	PPBI	Pacific Premier Bancorp, Inc.
WAL	Western Alliance Bancorporation	IBTX	Independent Bank Group, Inc.
CBSH	Commerce Bancshares, Inc.	BK	The Bank of New York Mellon Corporation
VLY	Valley National Bancorp	BKU	BankUnited, Inc.
CUBI	Customers Bancorp, Inc.	COLB	Columbia Banking System, Inc.
WSFS	WSFS Financial Corporation	HOMB	Home BancShares, Inc.
UBSI	United Bankshares, Inc.	GBCI	Glacier Bancorp, Inc.
CBU	Community Bank System, Inc.	FFBC	First Financial Bancorp
TCBI	Texas Capital Bancshares, Inc.	FFIN	First Financial Bankshares, Inc.
HWC	Hancock Whitney Corporation	CHCO	City Holding Company
TCBK	TriCo Bancshares	ABCB	Ameris Bancorp
BOH	Bank of Hawaii Corporation	FHB	First Hawaiian, Inc.
LKFN	Lakeland Financial Corporation	NBHC	National Bank Holdings Corporation
FRME	First Merchants Corporation	DCOM	Dime Community Bancshares, Inc.
SASR	Sandy Spring Bancorp, Inc.	BKSC	Bank of South Carolina Corporation
CATY	Cathay General Bancorp	HOPE	Hope Bancorp, Inc.
HAFC	Hanmi Financial Corporation	CVBF	CVB Financial Corp.
BUSE	First Busey Corporation	MSBI	Midland States Bancorp, Inc.
PRK	Park National Corporation	EGBN	Eagle Bancorp, Inc.
TMP	Tompkins Financial Corporation	SRCE	1st Source Corporation
NWBI	Northwest Bancshares, Inc.	NBTB	NBT Bancorp Inc.
SMMF	Summit Financial Group, Inc.	PEBO	Peoples Bancorp Inc.
CTBI	Community Trust Bancorp, Inc.	BMRC	Bank of Marin Bancorp
HFWA	Heritage Financial Corporation	TOWN	TowneBank
GSBC	Great Southern Bancorp, Inc.	BANR	Banner Corporation
WAFD	Washington Federal, Inc.	BHLB	Berkshire Hills Bancorp, Inc.
HTLF	Heartland Financial USA, Inc.	HBNC	Horizon Bancorp, Inc.
OSBC	Old Second Bancorp, Inc.	CPF	Central Pacific Financial Corp.
AMTB	Amerant Bancorp Inc.	VBTX	Veritex Holdings, Inc.

Table 4: List of Banks and Their Tickers

The list of banks in my 100 bank sample used to construct a broad measure of bank leverage from 1995Q3 to 20204Q3.

8.2 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 preceeding 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 us 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 Gürkaynak, Sack, and Swanson (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 we use 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 I restrict 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, I ensure 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 we can identify Υ.

8.3 Additional IRFs

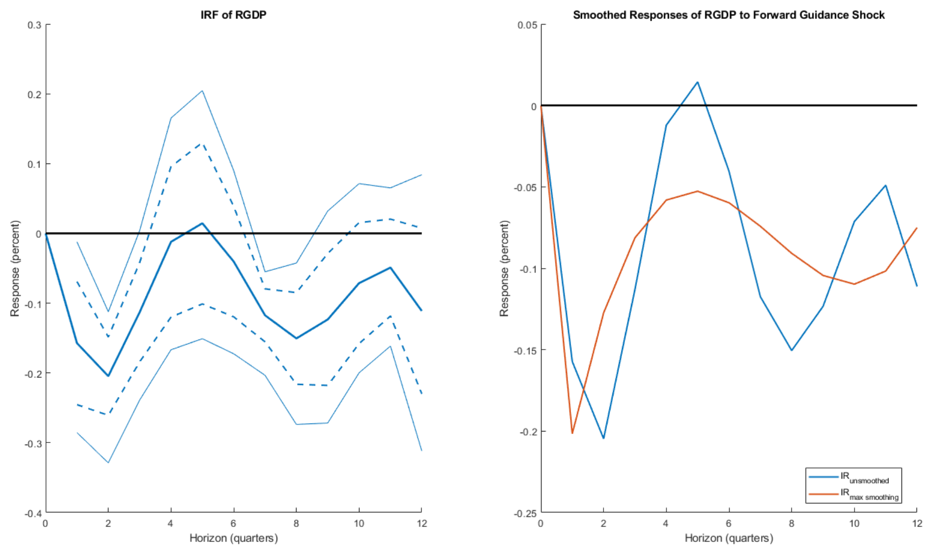


Figure 7: Real GDP Response to a Contractionary Forward Guidance Shock

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 ($IR_{slp,maxpen}$).

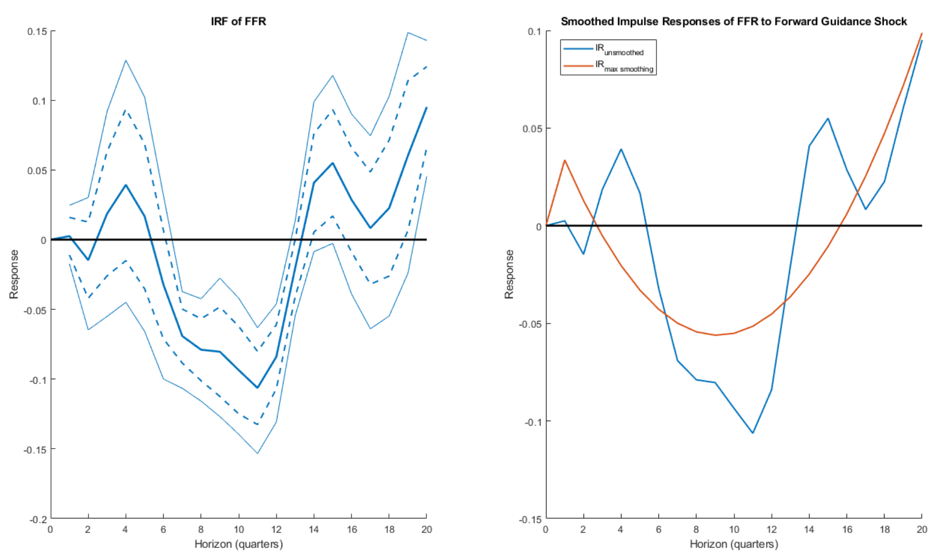


Figure 8: Federal Funds Rate Response to a Contractionary Forward Guidance Shock

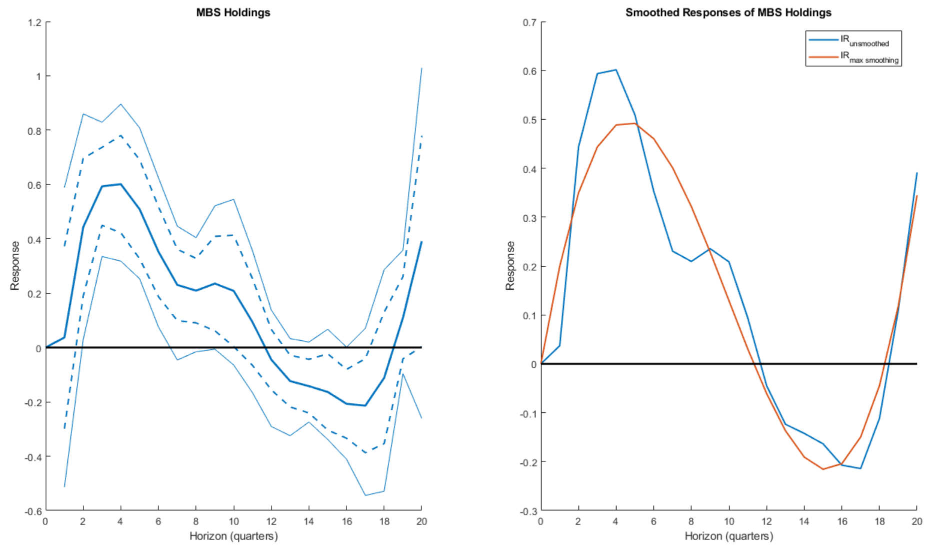


Figure 9: MBS Holdings Response to a Contractionary Forward Guidance Shock

The figures represent the impulse response of the value of mortage-backed securities held by commercial banks to a one standard deviation contractionary forward guidance shock. A joint Wald test returns a chi-square statistic of 64.45, a p-value of 0.0000, and an F statistic of 3.2226.

In contrast to the immediate responses of loans to a signal of monetary contraction, the response of the value of mortgage-backed securities (MBS) held by commercial banks increases, as seen in figure 4. The explanation of this is likely a valuation effect, as opposed to some kind of portfolio shift by commercial banks, or "flight to safety." When interest rates fall, mortgage-borrowers can refinance, leading to a surge in prepayments, which strips MBS holders of their above-market coupons, leaving them only the option to invest at lower rates.

Conversely, if the FOMC signals a rate hike, the present value of existing MBS rise as prepayments are expected to become increasingly infrequent. Data that separates the value of commercial bank MBS holdings and the quantity of MBS holdings does not exist publicly, so we cannot be certain about whether this IRF reflects a valuation channel or a portfolio shift, but in light of the explanation above and given the overall picture that all of our IRFs paint together, the valuation channel appears more likely.

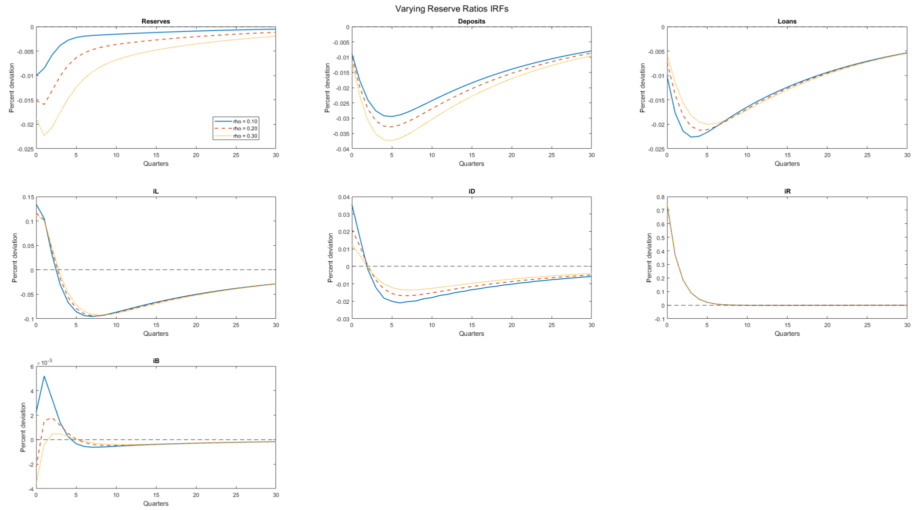


Figure 10: Comparison of GDP and Leverage IRF Slopes

These IRFs show the responses of bank balance sheet items to a forward guidance shock where banks are required to hold varying levels of reserves. The blue line represents a reserve requirement of 10%, the orange line 20%, and the yellow line 30%.

Figure 11 shows how bank balance sheets adjust depending upon the required reserve ratio, examing the effect for a 10, 20, and 30% reserve ratio.

Model

Household's Problem

The representative household maximizes lifetime utility:

$$\max_{\{C_t, N_t, B_{t+1}, D_t\}} E_0 \sum_{t=0}^{\infty} \beta^t \left(\frac{C_t^{1-\sigma}}{1-\sigma} - \theta \frac{N_t^{1+\eta}}{1+\eta} + \phi \ln \left(\frac{D_t + B_t^T}{P_t} \right) \right) \tag{13}$$

subject to the budget constraint:

$$P_tC_t + B_{t+1} + D_t + B_t^T \leq W_tN_t + \Psi_t + \Phi_t + (1+i_{t-1}^B)B_t + (1+i_{t-1}^D)(D_{t-1} + B_{t-1}^T) - P_tT_t \tag{14}$$

Lagrangian Formulation

Define the Lagrangian:

$$\mathcal{L} = E_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{C_t^{1-\sigma}}{1-\sigma} - \theta \frac{N_t^{1+\eta}}{1+\eta} + \phi \ln\left(\frac{D_t + B_t^T}{P_t}\right) + \lambda_t \left(W_tN_t + \Psi_t + \Phi_t + (1+i_{t-1}^B)B_t + (1+i_{t-1}^D)(D_{t-1} + B_{t-1}^T) - P_tT_t - P_tC_t - B_{t+1} - D_t - B_t^T \right) \right] \tag{15}$$

First-Order Conditions

FOC for Consumption C_t

$$C_t^{-\sigma} = \lambda_t P_t \tag{16}$$

FOC for Labor Supply N_t

$$\theta N_t^{\eta} = \lambda_t W_t \tag{17}$$

FOC for Bonds B_{t+1}

$$\lambda_t = \beta E_t[\lambda_{t+1}(1 + i_t^B)] \tag{18}$$

FOC for Deposits D_t

$$\frac{\phi}{D_t + B_t^T} = \lambda_t - \beta E_t[\lambda_{t+1}(1 + i_t^D)] \tag{19}$$

Labor Supply Condition

$$N_t = \left(\frac{w_t}{\theta} C_t^{-\sigma}\right)^{\frac{1}{\eta}} \tag{20}$$

Euler Equation for Bonds

$$1 = \beta E_t \left[\frac{C_{t+1}^{-\sigma}}{C_t^{-\sigma}} \frac{P_t}{P_{t+1}} (1 + i_t^B)\right] \tag{21}$$

Which can be simplified to:

$$\frac{1}{1 + i_t^B} = E_t\{\Lambda_{t+1}\} \tag{22}$$

Implicit Demand for Real Balances

Combining equations 6 and 7 we get

$$\frac{\phi}{D_t + B_t^T} = \beta E_t[\lambda_{t+1}(1 + i_t^B)] - \beta E_t[\lambda_{t+1}(1 + i_t^D)] \tag{23}$$

which simplifies to

$$\frac{\phi}{D_t + B_t^T} = \beta E_t \lambda_{t+1}(i_t^B - i_t^D) \tag{24}$$

using equation 6 again, we can get:

$$\frac{\phi}{D_t + B_t^T} = \frac{\lambda_t}{(1 + i_t^B)}(i_t^B - i_t^D) \tag{25}$$

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

$$\frac{\phi}{D_t + B_t^T} = \frac{C_t^{-\sigma}}{P_t(1+i_t^B)}(i_t^B - i_t^D) \tag{26}$$

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

$$d_t = \phi C_t^{\sigma} \frac{(1+i_t^B)}{(i_t^B - i_t^D)} - b_t^T \tag{27}$$

Stochastic Discount Factors

We define the one-period stochastic discount factor as:

$$\Lambda_{t+1} = \beta \left(\frac{C_{t+1}}{C_t}\right)^{-\sigma} \frac{P_t}{P_{t+1}}. \tag{28}$$

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

$$\Lambda_{t+j} = \beta^j \left(\frac{\lambda_{t+j}}{\lambda_t}\right). \tag{29}$$

Final Goods Sector

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

$$Y_t = \left(\int_0^1 Y_t(j)^{\frac{\epsilon-1}{\epsilon}} dj\right)^{\frac{\epsilon}{\epsilon-1}}, \quad \epsilon > 1 \tag{30}$$

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:

$$\max_{\{Y_t(j)\}} P_t \left(\int_0^1 Y_t(j)^{\frac{\epsilon-1}{\epsilon}} dj \right)^{\frac{\epsilon}{\epsilon-1}} - \int_0^1 P_t(j) Y_t(j) dj \tag{31}$$

Aggregate Price Level

The aggregate price level P_t is given by:

$$P_t = \left(\int_0^1 P_t(j)^{1-\epsilon} dj \right)^{\frac{1}{1-\epsilon}} \tag{32}$$

Intermediate Goods Firm's Problem

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

$$Y_t(j) = A_t N_t(j), \tag{33}$$

where A_t is the aggregate productivity shock.

The firm's profit function is given by:

$$\Psi_t(j) = P_t(j) Y_t(j) - (1 + i_t^L)(1 - \phi_{d,t+1}) W_t N_t(j). \tag{34}$$

Where firms finance their inputs via loans from the bank:

$$W_t N_t(j) = L_t(j) \tag{35}$$

So, we get:

$$\Psi_t(j) = P_t(j) Y_t(j) - (1 + i_t^L(j))(1 - \phi_{d,t+1}(j)) L_t(j). \tag{36}$$

which allows us to endogenize default:

$$\phi_{d,t+1} = \max\left(1 - \frac{Y_t(j)P_t(j)}{(1+i_t^L(j))L_t(j)}, 0\right) \tag{37}$$

which in aggregated terms is:

$$\phi_{d,t+1} = \max\left(1 - \frac{Y_t}{(1+i_t^L)\ell_t}, 0\right) \tag{38}$$

Substituting for $N_t(j)$

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

$$\Psi_t(j) = P_t(j)Y_t(j) - (1+i_t^L)(1+\phi_{t+1})\frac{W_t}{A_t}Y_t(j). \tag{39}$$

Demand Constraint

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

$$Y_t(j) = \left(\frac{P_t(j)}{P_t}\right)^{-\epsilon} Y_t. \tag{40}$$

Profit Function with Demand Substituted

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

$$\Psi_t(j) = P_t(j)\left(\frac{P_t(j)}{P_t}\right)^{-\epsilon} Y_t - (1+i_t^L)(1+\phi_{t+1})\frac{W_t}{A_t}\left(\frac{P_t(j)}{P_t}\right)^{-\epsilon} Y_t. \tag{41}$$

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

$$\Psi_t(j) = \left(\frac{P_t(j)}{P_t}\right)^{-\epsilon} Y_t \left[P_t(j) - (1+i_t^L)(1+\phi_{t+1})\frac{W_t}{A_t}\right]. \tag{42}$$

Profit Maximization Problem

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

$$\max_{P_t(j)} \quad \left(\frac{P_t(j)}{P_t}\right)^{-\epsilon} Y_t \left[P_t(j) - (1+i_t^L)(1+\phi_{t+1})\frac{W_t}{A_t}\right]. \tag{43}$$

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:

$$\max_{P_t(j)} X_t \sum_{s=0}^{\infty} \xi^s \Lambda_{t,t+s} \left[\frac{P_t(j)}{P_{t+s}}\left(\frac{P_t(j)}{P_{t+s}}\right)^{-\epsilon} Y_{t+s} - (1+i_t^L)(1+\phi_{t+1})\frac{w_{t+s}}{A_{t+s}}\left(\frac{P_t(j)}{P_{t+s}}\right)^{-\epsilon} Y_{t+s}\right]. \tag{44}$$

subject to the demand function:

$$Y_{t+s}(j) = \left(\frac{P_t(j)}{P_{t+s}}\right)^{-\epsilon} Y_{t+s}. \tag{45}$$

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:

$$P_t(j) = \frac{\epsilon}{\epsilon-1}\frac{X_t \sum_{s=0}^{\infty} \xi^s \Lambda_{t,t+s} mc_{t+s} P_{t+s}^{\epsilon} Y_{t+s}}{X_t \sum_{s=0}^{\infty} \xi^s \Lambda_{t,t+s} P_{t+s}^{\epsilon-1} Y_{t+s}}. \tag{46}$$

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:

$$P_t^{\#} = \frac{\epsilon}{\epsilon - 1}\frac{X_{1,t}}{X_{2,t}}, \tag{47}$$

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

$$X_{1,t} = mc_t P_t^{\epsilon} Y_t + \xi X_t \Lambda_{t,t+1} X_{1,t+1}, \tag{48}$$

$$X_{2,t} = P_t^{\epsilon-1} Y_t + \xi X_t \Lambda_{t,t+1} X_{2,t+1}. \tag{49}$$

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:

$$mc_t = (1 + i_t^L)(1 - \phi_{t+1})\frac{w_t}{A_t}. \tag{50}$$

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:

$$N_{d,t} = \left[\int_0^1 N_t(i)^{\frac{\epsilon_w - 1}{\epsilon_w}} di\right]^{\frac{\epsilon_w}{\epsilon_w - 1}} \tag{51}$$

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

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

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:

$$u_t^{\#} = \frac{\epsilon_w}{\epsilon_w - 1} \frac{f_{1,t}}{f_{2,t}} \tag{52}$$

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

$$f_{1,t} = w_t u_t^{\epsilon_w} N_{d,t} + \phi_w E_t \Lambda_{t,t+1} \Pi_{t+1}^{\epsilon_w} f_{1,t+1} \tag{53}$$

$$f_{2,t} = u_t^{\epsilon_w} N_{d,t} + \phi_w E_t \Lambda_{t,t+1} \Pi_{t+1}^{\epsilon_w - 1} f_{2,t+1} \tag{54}$$

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

$$u_t^{1-\epsilon_w} = (1-\phi_w)(u_t^{\#})^{1-\epsilon_w} + \phi_w \Pi_t^{\epsilon_w - 1} u_{t-1}^{1-\epsilon_w} \tag{55}$$

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:

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

9 Bank's Problem

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

$$\Phi_t = E_t\Big\{\Lambda_{t+1}\Big[(1+i_t^L)(1-\phi_d)L_t + (1+i_t^B)B_t + (1+i_t^R)R_t - (1+i_t^D)D_t\Big]\Big\} - X_t - \frac{\phi_x}{2}(L_t - L_{t-1})^2 \tag{56}$$

subject to:

$$L_t + B_t + R_t = D_t + (1 - f(\delta_t))X_t, \quad \text{where} \quad \delta_t = \frac{L_t}{X_t}, \tag{57}$$

$$f(\delta_t) = \frac{\alpha}{2}\delta_t^2, \tag{58}$$

$$R_t \geq \rho D_t, \quad 0 \leq \rho < 1. \tag{59}$$

10 Lagrangian Formulation

Defining multipliers:

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

The Lagrangian is:

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

11 First-Order Conditions (FOCs)

11.1 FOC with respect to B_t

$$E_t[\Lambda_{t+1}(1+i_t^B)] - \mu_t = 0. \tag{60}$$

11.2 FOC with respect to R_t

$$E_t[\Lambda_{t+1}(1+i_t^R)] - \mu_t - \alpha_t = 0. \tag{61}$$

11.3 FOC with respect to D_t

$$-E_t[\Lambda_{t+1}(1+i_t^D)] + \mu_t + \rho\alpha_t = 0. \tag{62}$$

11.4 FOC with respect to L_t

$$E_t[\Lambda_{t+1}(1+i_t^L)(1-\phi_d)] - \phi_x(L_t - L_{t-1}) - \mu_t(1+\alpha\delta_t) = 0. \tag{63}$$

11.5 FOC with respect to X_t

Using the chain rule for the balance-sheet constraint:

$$-1 + \mu_t(1 - \frac{\alpha}{2}\delta_t^2) = 0 \tag{64}$$

Solving for μ_t:

$$\mu_t = \frac{1}{(1 - \frac{\alpha}{2}\delta_t^2)}. \tag{65}$$

12 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:

$$\Lambda_{t+1}(1+i_t^L)(1-\phi_d) - \phi_x\big(L_t - L_{t-1}\big) - \Lambda_{t+1}(1+i_t^B)\Big[1 + \alpha\,\delta_t\Big] = 0. \tag{66}$$

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

$$(1+i_t^L)(1-\phi_d) = (1+i_t^B)(1+\alpha\,\delta_t) + \frac{\phi_x}{\Lambda_{t+1}}\big(L_t - L_{t-1}\big). \tag{67}$$

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

$$\frac{1+i_t^L}{1+i_t^B}(1-\phi_d) = 1 + \alpha\,\delta_t + \frac{\phi_x}{\Lambda_{t+1}(1+i_t^B)}\big(L_t - L_{t-1}\big). \tag{68}$$

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

$$\frac{1+i_t^L}{1+i_t^B} = \frac{1+\alpha\,\delta_t}{1-\phi_d} + \frac{\phi_x}{\Lambda_{t+1}(1+i_t^B)(1-\phi_d)}\big(L_t - L_{t-1}\big). \tag{69}$$

Final Result

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

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

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.

13 Deriving the Relationship Between L_t and B_t

From the budget constraint, we isolate loans and bonds:

$$L_t + B_t = D_t + (1 - f(\delta_t))X_t - R_t. \tag{70}$$

Substituting the reserve requirement $R_t = \rho D_t$:

$$L_t + B_t = (1-\rho)D_t + (1 - f(\delta_t))X_t. \tag{71}$$

Define the allocation ratio:

$$L_t = \gamma_t(L_t + B_t), \quad B_t = (1-\gamma_t)(L_t + B_t). \tag{72}$$

This says that the bank allocates a fraction γ_t of total funds available to be invested to loans and a fraction $1-\gamma_t$ to bonds.

Substituting the budget constraint:

$$L_t = \gamma_t \left[(1-\rho)D_t + (1-f(\delta_t))X_t\right], \tag{73}$$

$$B_t = (1-\gamma_t) \left[(1-\rho)D_t + (1-f(\delta_t))X_t\right]. \tag{74}$$

To express γ_t in terms of the interest rate spread, we assume:

$$\gamma_t = g\left(\frac{1+i_t^L}{1+i_t^B}\right). \tag{75}$$

This means that the fraction of loans in a bank's investment portfolio allocated to loans is an increasing function interest rate spread between loans and bonds.

Thus, the final expressions for L_t and B_t are:

$$L_t = g\left(\frac{1+i_t^L}{1+i_t^B}\right) \left[(1-\rho)D_t + (1-f(\delta_t))X_t\right], \tag{76}$$

$$B_t = \left(1 - g\left(\frac{1+i_t^L}{1+i_t^B}\right)\right) \left[(1-\rho)D_t + (1-f(\delta_t))X_t\right]. \tag{77}$$

14 Final Relationship Between L_t and B_t

Dividing the two equations:

$$\frac{L_t}{B_t} = \frac{g\left(\frac{1+i_t^L}{1+i_t^B}\right)}{1 - g\left(\frac{1+i_t^L}{1+i_t^B}\right)} \tag{78}$$

We define the loan allocation function $g(x)$ as:

$$g(x) = \frac{x}{1+x}, \tag{79}$$

where the loan-bond interest rate spread is given by:

$$x = \frac{1 + i_t^L}{1 + i_t^B} \tag{80}$$

thus, we have:

$$\gamma_t = g\left(\frac{1 + i_t^L}{1 + i_t^B}\right) = \frac{\frac{1+i_t^L}{1+i_t^B}}{1 + \frac{1+i_t^L}{1+i_t^B}} \tag{81}$$

15 Final Expressions for Loan and Short-Term Debt Allocation

Substituting $g(x)$ into equation 66, we obtain the following:

$$\frac{L_t}{B_t} = \frac{\frac{(1+i_t^L/1+i_t^B)}{1+(1+i_t^L/1+i_t^B)}}{\frac{1}{1+(1+i_t^L/1+i_t^B)}} = \frac{(1 + i_t^L)}{(1 + i_t^B)}. \tag{82}$$

Which gives us:

$$L_t = B_t \left[\frac{(1 + i_t^L)}{(1 + i_t^B)}\right] \tag{83}$$

Recall from from equation 23 we get $L_t = W_t N_t$. Using this and equations 41, 42, and 71, we get:

$$W_t N_t \frac{(1 + i_t^B)}{(1 + i_t^L)} + W_t N_t + \left(1 - \frac{1}{\rho}\right) R_t = (1 - \frac{\alpha}{2}\delta_t^2) X_t \tag{84}$$

which simplifies to:

$$\boxed{R_t = \frac{1}{1 - \frac{1}{\rho}} \left[\left(1 - \frac{\alpha}{2}\delta_t^2\right) X_t - \left(\frac{(1 + i_t^L) + (1 + i_t^B)}{(1 + i_t^L)}\right) W_t N_t\right]} \tag{85}$$

16 Deriving the Loan Equation

Recall our FOC wrt. L from the Bank's Lagrangian:

$$E_t[\Lambda_{t+1}(1+i_t^L)(1-\phi_d)] - \phi_x(L_t - L_{t-1}) - \mu_t(1+\alpha\delta_t) = 0 \tag{86}$$

Note that if adjustment were costless ($\phi_x = 0$), then the bank would choose the optimal level of loans L_t^*, and we'd have:

$$E_t[\Lambda_{t+1}(1+i_t^L)(1-\phi_d)] - \mu_t(1+\alpha\frac{L_t^*}{X_t}) = 0 \tag{87}$$

Which implies that the right hand side is proportional to the gap between current L and the optimal L^*:

$$E_t[\Lambda_{t+1}(1+i_t^L)(1-\phi_d)] - \mu_t\left(1+\alpha\frac{L_t^*}{X_t}\right) \approx \kappa(L_t^* - L_t), \quad \text{with} \quad \kappa > 0. \tag{88}$$

Therefore:

$$\phi_x(L_t - L_{t-1}) \approx \kappa(L_t^* - L_t) \tag{89}$$

Therefore, after some rearranging we get:

$$L_t = \frac{\kappa}{\phi_x+\kappa}L_t^* + \frac{\phi_x}{\phi_x+\kappa}L_{t-1} \tag{90}$$

Define:

$$\rho_L = \frac{\phi_x}{\phi_x+\kappa}; \quad (1-\rho_L) = \frac{\kappa}{\phi_x+\kappa} \tag{91}$$

Without adjustment costs, using the bank's balance sheet, the optimal level of loans would be:

$$L_t^* = \left(\frac{1}{\rho} - 1\right)R_t + \left(1 - \frac{\alpha}{2}\delta_t^2\right)X_t - B_t \tag{92}$$

Which, finally, gives us our final loan equation:

$$\boxed{L_t = \rho_L L_{t-1} + (1-\rho_L)\left(\left(\frac{1}{\rho}-1\right)R_t + (1-\frac{\alpha}{2}\delta_t^2)X_t - B_t\right)} \tag{93}$$

17 Equity

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

$$x_t = \left[1 - \frac{(1+i_t^L)}{(1+i_t^B)}(1-\phi_{d,t+1})\right]\ell_t + \frac{i_t^D - i_t^B}{1+i_t^B}d_t + \frac{i_t^B - i_t^R}{1+i_t^B}r_t \tag{94}$$

18 Treasury Bond Issuance and Tax Rule

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

$$B_t^T = (1+i_t^D)B_{t-1}^T - T_t \tag{95}$$

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

$$T_t = \tau Y_t, \qquad 0 < \tau < 1 \tag{96}$$

19 Taylor Rule (Monetary Policy)

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

$$1 + i_t^R = (1 + i^R)^\rho \left(\frac{\Pi_t}{\Pi^*}\right)^{\phi_\pi} \left(\frac{Y_t}{Y^*}\right)^{\phi_Y} e^{\phi_t}. \tag{97}$$

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:

$$\phi_t = \sum_{i=0}^{20} w_{t+i} \hat{\psi}_{r,t+i}^i \tag{98}$$

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:

$$\hat{\psi}_{r,t}^j = \hat{\psi}_{r,t-1}^j + \kappa_j (s_t^j - \hat{\psi}_{r,t-1}^j), \quad j = 1, ..., 20. \tag{99}$$

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 $j \geq 1$

$$s_t^j = \psi_{r,t}^j + \nu_t, \qquad \nu_t \sim N(0, \sigma_\nu^2) \tag{100}$$

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.

20 Equilibrium Conditions

$$E_t\{\Lambda_{t+1}(1 + i_t^B)\} = 1 \tag{101}$$

$$\theta N_t^\eta = w_t C_t^{-\sigma} \tag{102}$$

$$d_t = \varphi C_t^\sigma \frac{1 + i_t^B}{i_t^B - i_t^D} - b_t^T \tag{103}$$

$$\Lambda_t = \beta \left(\frac{C_t}{C_{t-1}} \right)^{-\sigma} \Pi_t^{-1} \tag{104}$$

$$1 = (1 - \xi)(p_t^\#)^{1-\epsilon} + \xi \Pi_t^{\epsilon - 1} \tag{105}$$

$$u_t^{1-\epsilon_w} = (1 - \phi_w)(u_t^\#)^{1-\epsilon_w} + \phi_w \Pi_t^{\epsilon_w - 1} u_{t-1}^{1-\epsilon_w} \tag{106}$$

$$p_t^\# = \frac{\epsilon}{\epsilon - 1} \frac{\hat{X}_{1,t}}{\hat{X}_{2,t}} \tag{107}$$

$$u_t^\# = \frac{\epsilon_w}{\epsilon_w - 1} \frac{f_{1,t}}{f_{2,t}} \tag{108}$$

$$\hat{X}_{1,t} = mc_t Y_t + \xi E_t \Lambda_{t+1} \Pi_{t+1}^\epsilon \hat{X}_{1,t+1} \tag{109}$$

$$\hat{X}_{2,t} = Y_t + \xi E_t \Lambda_{t+1} \Pi_{t+1}^{\epsilon-1} \hat{X}_{2,t+1} \tag{110}$$

$$f_{1,t} = w_t u_t^{\epsilon_w} N_{d,t} + \phi_w E_t \Lambda_{t+1} \Pi_{t+1}^{\epsilon_w} f_{1,t+1} \tag{111}$$

$$f_{2,t} = u_t^{\epsilon_w} N_{d,t} + \phi_w E_t \Lambda_{t+1} \Pi_{t+1}^{\epsilon_w - 1} f_{2,t+1} \tag{112}$$

$$u_t = mc_t A_t \tag{113}$$

$$mc_t = (1 + i_t^L)(1 - \phi_{d,t+1}) \frac{w_t}{A_t} \tag{114}$$

$$Y_t = C_t + \frac{\alpha}{2} \delta_t^2 X_t + \frac{\varphi_x}{2} (L_t - L_{t-1})^2 \tag{115}$$

$$b_t^T = (1+i_t^D)b_{t-1}^T - T_t \tag{116}$$

$$T_t = \tau Y_t \tag{117}$$

$$A_t N_t = Y_t \nu_t^P \tag{118}$$

$$N_t = N_{d,t}\nu_t^w \tag{119}$$

$$\nu_t^P = (1-\xi)(p_t^{\#})^{-\epsilon} + \xi \Pi_t^{\epsilon}\nu_{t-1}^P \tag{120}$$

$$\nu_t^w = (1-\phi_w)\left(\frac{u_t^{\#}}{u_t}\right)^{-\epsilon_w} + \phi_w \Pi_t^{\epsilon_w}\left(\frac{u_t}{u_{t-1}}\right)^{\epsilon_w}\nu_{t-1}^w \tag{121}$$

$$\ln A_t = \rho_A \ln A_{t-1} + s_A \epsilon_{A,t} \tag{122}$$

$$1+i_t^R = (1+i^R)^{\rho_r}\left(\frac{\Pi_t}{\Pi^*}\right)^{\phi_\pi}\left(\frac{Y_t}{Y^*}\right)^{\phi_Y} e^{\epsilon_t^{FG}} \tag{123}$$

$$\phi_{d,t+1} = 1 - \frac{Y_t}{(1+i_t^L)\ell_t} \tag{124}$$

$$\frac{(1+i_t^L)}{(1+i_t^B)} = \frac{1+\alpha\delta_t}{1-\phi_{d,t+1}} + \frac{\phi_x}{\Lambda_{t+1}(1+i_t^B)(1-\phi_{d,t+1})}(\ell_t - \ell_{t-1}) \tag{125}$$

$$\ell_t = \rho_\ell \ell_{t-1} + (1-\rho_\ell)\left(\left(\frac{1}{\rho}-1\right)r_t + \left(1-\frac{\alpha}{2}\delta_t^2\right)x_t - b_t\right) \tag{126}$$

$$r_t = \frac{1}{1-\rho}\left[\left(1-\frac{\alpha}{2}\delta_t^2\right)x_t - \left(\frac{(1+i_t^L)+(1+i_t^B)}{(1+i_t^L)}\right)w_t N_t\right] \tag{127}$$

$$\ell_t + b_t + r_t = d_t + \left(1-\frac{\alpha}{2}\delta_t^2\right)x_t \tag{128}$$

$$x_t = \left[1 - \frac{(1+i_t^L)}{(1+i_t^B)}(1-\phi_{d,t+1})\right]\ell_t + \frac{i_t^D - i_t^B}{1+i_t^B}d_t + \frac{i_t^B - i_t^R}{1+i_t^B}r_t \tag{129}$$

$$\delta_t = \frac{\ell_t}{x_t} \tag{130}$$

Steady State

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

$$Y = 1$$

$$C = 1$$

$$N = 1$$

$$\Pi = 1$$

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:

$$\theta = w \tag{131}$$

$$\nu^P = 1 \tag{132}$$

$$mc = (1 + i_L)(1 - \phi_d)\frac{w}{A} \tag{133}$$

$$\phi_d = 1 - \frac{Y}{(1 + i_L)\ell} \tag{134}$$

$$i_D = \frac{\tau}{b_T} \tag{135}$$

$$d = \varphi\frac{1 + i_B}{i_B - i_D} - b_T \tag{136}$$

$$\ell + b + r = d + \left(1 - \frac{\alpha}{2}\delta^2\right) x \tag{137}$$

$$x = \left[1 - \frac{(1 + i_L)}{(1 + i_B)}(1 - \phi_d)\right] \ell + \frac{i_D - i_B}{1 + i_B}d + \frac{i_B - i_R}{1 + i_B}r \tag{138}$$

$$A = 1 \tag{139}$$

$$f1 = \frac{w}{1 - \phi_w\beta} \tag{140}$$

$$f2 = \frac{1}{1 - \phi_w\beta} \tag{141}$$

$$u^{\#} = 1 \tag{142}$$

$$\delta = \frac{l}{x} \tag{143}$$

Log Linearized Conditions

$$E_t\tilde{\Lambda}_{t+1} + \tilde{i}_{B,t} = 0 \tag{144}$$

$$\eta\tilde{n}_t - \tilde{w}_t + \sigma\tilde{c}_t = 0 \tag{145}$$

$$\tilde{d}_t = \frac{\varphi C^{*\sigma}\sigma}{d^*}\frac{1 + i^{B*}}{i^{B*} - i^{D*}}\tilde{C}_t - \frac{\varphi C^{*\sigma}}{d^*}\frac{(1 + i^{D*})}{(i^{B*} - i^{D*})^2}\tilde{i}_t^B + \frac{\varphi C^{*\sigma}}{d^*}\frac{1 + i^{B*}}{(i^{B*} - i^{D*})^2}\tilde{i}_t^D - \frac{b^{T*}}{d^*}\tilde{b}_t^T \tag{146}$$

$$\tilde{\Lambda}_t = -\sigma(\tilde{C}_t - \tilde{C}_{t-1}) - \tilde{\Pi}_t \tag{147}$$

$$0 = (1-\xi)(1-\epsilon)(p^{\#*})^{1-\epsilon}\tilde{p}_t^{\#} + \xi(\epsilon-1)(\Pi^*)^{\epsilon-1}\tilde{\Pi}_t \tag{148}$$

$$\tilde{u}_t = \frac{(1-\phi_w))u^{\#1-\epsilon_w *}}{u^{*1-\epsilon_w}}\tilde{u}_t^{\#} + \phi_w(\epsilon_w - 1)\Pi^{*\epsilon_w - 1}(\tilde{\Pi}_t - \tilde{u}_{t-1}) \tag{149}$$

$$\tilde{p}_t^{\#} = \tilde{X}_{1,t} - \tilde{X}_{2,t} \tag{150}$$

$$\tilde{u}_t^{\#} = \tilde{f}_{1,t} - \tilde{f}_{2,t} \tag{151}$$

$$\tilde{X}_{1,t} = \frac{mc^* Y^*}{X_1^*}(\tilde{mc}_t + \tilde{Y}_t) + \xi\Lambda^*(\Pi^*)^{\epsilon}E_t(\tilde{\Lambda}_{t+1} + \epsilon\tilde{\Pi}_{t+1} + \tilde{X}_{1,t+1}) \tag{152}$$

$$\tilde{X}_{2,t} = \frac{Y^*}{X_2^*}\tilde{Y}_t + \xi\Lambda^*(\Pi^*)^{-1}E_t(\tilde{\Lambda}_{t+1} - \tilde{\Pi}_{t+1} + \tilde{X}_{2,t+1}) \tag{153}$$

$$\tilde{f}_{1,t} = \frac{w^* u^{\epsilon_w *} N_d^*}{f_1^*}(\tilde{w}_t + \epsilon_w\tilde{u}_t + \tilde{N}_{d,t}) + \phi_w\Lambda^*\Pi^{\epsilon_w *}(\tilde{\Lambda}_{t+1} + \epsilon_w\tilde{\Pi}_{t+1} + \tilde{f}_{1,t+1}) \tag{154}$$

$$\tilde{f}_{2,t} = \frac{u^{\epsilon_w *} N_d^*}{f_2^*}(\tilde{u}_t + \tilde{N}_{d,t}) + \phi_w\Lambda^*\Pi^{\epsilon_w - 1*}(\tilde{\Lambda}_{t+1} + (\epsilon_w - 1)\tilde{\Pi}_{t+1} + \tilde{f}_{2,t+1}) \tag{155}$$

$$\tilde{u}_t = \tilde{mc}_t + \tilde{A}_t \tag{156}$$

$$\tilde{mc}_t = \tilde{i}_t^L - \frac{1}{1-\phi_d^*}\tilde{\phi}_{d,t+1} + \tilde{w}_t - \tilde{A}_t \tag{157}$$

$$\tilde{Y}_t = \frac{C^*}{Y^*}\tilde{C}_t + \frac{\alpha(\delta^*)^2 X^*}{Y^*}(\tilde{X}_t + \tilde{\delta}_t) \tag{158}$$

$$\tilde{b}_t^T = (1+i^{D*})\tilde{b}_{t-1}^T + \tilde{i}_t^D - \frac{T^*}{b^{T*}}\tilde{T}_t \tag{159}$$

$$\tilde{T}_t = \tau\tilde{Y}_t \tag{160}$$

$$\tilde{A}_t + \tilde{N}_t = \tilde{Y}_t + \tilde{\nu}_t^P \tag{161}$$

$$\tilde{N}_t = \tilde{N}_{t,t} + \tilde{\nu}_t^w \tag{162}$$

$$\tilde{\nu}_t^P = \xi(\Pi^*)^{\epsilon}(\epsilon\tilde{\Pi}_t + \tilde{\nu}_{t-1}^P) - \frac{\epsilon(1-\xi)(p^{\#*})^{-\epsilon}}{\nu^{P*}}\tilde{p}_t^{\#} \tag{163}$$

$$\tilde{\nu}_t^w = \frac{(1-\phi_w)\epsilon_w\left(\frac{u^{\#*}}{u^*}\right)^{-\epsilon_w}}{\nu^{w*}}(\tilde{u} - \tilde{u}_t^{\#}) + \phi_w\Pi^{\epsilon_w}(\epsilon_w\tilde{\Pi}_t + \epsilon_w(\tilde{u}_t - \tilde{u}_{t-1}) + \tilde{\nu}_{t-1}^w) \tag{164}$$

$$\tilde{A}_t = \rho_A\tilde{A}_{t-1} + \gamma_A\varepsilon_{A,t} \tag{165}$$

$$\tilde{i}_t^R = (1+i^{R*})^{\rho_r}(\phi_\pi\tilde{\Pi}_t + \phi_Y\tilde{Y}_t + \tilde{\varepsilon}_t^{FG}) \tag{166}$$

$$\tilde{\phi}_{d,t+1} = \frac{1-\phi_d^*}{\phi_d^*}(\tilde{i}_t^L + \tilde{\ell}_t - \tilde{Y}_t) \tag{167}$$

$$\frac{1}{1+i^{B*}}\tilde{i}_t^L - \frac{1+i^{L*}}{(1+i^{B*})^2}\tilde{i}_t^B = \frac{\alpha\delta^*}{1-\phi_d^*}\tilde{\delta}_t + \frac{(1+\alpha\delta^*)\phi_d^*}{(1-\phi_d^*)^2}\tilde{\phi}_{d,t+1} + \frac{\phi_x l^*}{\Lambda^*(1+i^{B*})(1-\phi_d^*)}(\tilde{l}_t - \tilde{l}_{t-1}) \tag{168}$$

$$\tilde{\ell}_t = \rho_\ell \tilde{\ell}_{t-1} + \frac{(1-\rho_\ell)}{\ell^*}\left[\left(\frac{1}{\rho}-1\right)r^*\tilde{r}_t + \left(1-\frac{\alpha}{2}(\delta^*)^2\right)x^*\tilde{x}_t - \alpha\delta^*(x^*)^2\tilde{\delta}_t - b^*\tilde{b}_t\right] \tag{169}$$

$$\ell^*\tilde{\ell}_t + b^*\tilde{b}_t + r^*\tilde{r}_t = d^*\tilde{d}_t + \left(1-\frac{\alpha}{2}(\delta^*)^2\right)x^*\tilde{x}_t - \alpha\delta^* x^*\tilde{\delta}_t \tag{170}$$

$$\tilde{r}_t = \frac{1}{r^*}\left[\left(1-\frac{\alpha}{2}\delta^{*2}\right)x^*\tilde{x}_t - \alpha\delta^{*2}x^*\tilde{\delta}_t - \frac{w^*N^*}{1+i_L^*}\tilde{i}_t^B + \frac{1+i_B^*}{(1+i_L^*)^2}w^*N^*\tilde{i}_t^L - \left(1+\frac{1+i_B^*}{1+i_L^*}\right)w^*N^*(\tilde{w}_t + \tilde{N}_t)\right] \tag{171}$$

$$\begin{gathered}\tilde{x}_t = \left[1-\frac{1+i_L^*}{1+i_B^*}(1-\phi_d^*)\right]\frac{l^*}{x^*}\tilde{l}_t + \frac{i_D^*-i_B^*}{1+i_B^*}\frac{d^*}{x^*}\tilde{d}_t + \frac{i_B^*-i_R^*}{1+i_B^*}\frac{r^*}{x^*}\tilde{r}_t + \\ \frac{l^*}{x^*}\left[-\frac{(1-\phi_d^*)}{(1+i_B^*)}\tilde{i}_t^L + \frac{(1+i_L^*)(1-\phi_d^*)}{(1+i_B^*)^2}\tilde{i}_t^B + \frac{(1+i_L^*)}{(1+i_B^*)}\tilde{\phi}_{d,t+1}\right] + \frac{d^*}{x^*}\left[\frac{1}{1+i_B^*}\tilde{i}_t^D - \frac{1+i_D^*-i_B^*}{(1+i_B^*)^2}\tilde{i}_t^B\right] + \\ \frac{r^*}{x^*}\left[\frac{1+i_R^*-i_B^*}{(1+i_B^*)^2}\tilde{i}_t^B - \frac{1}{1+i_B^*}\tilde{i}_t^R\right]\end{gathered} \tag{172}$$

$$\tilde{\delta}_t = \tilde{\ell}_t - \tilde{x}_t \tag{173}$$

Table 5: 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

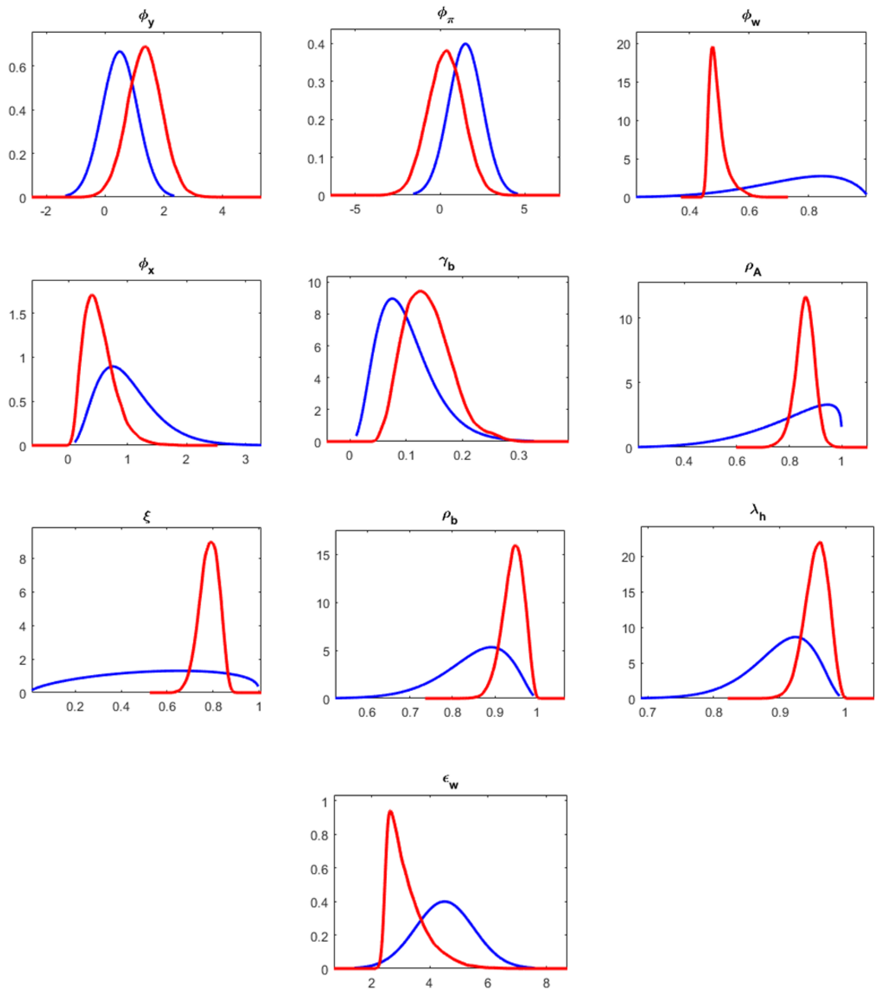


Figure 11: Prior and Posterior Marginal Distributions of Parameters

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

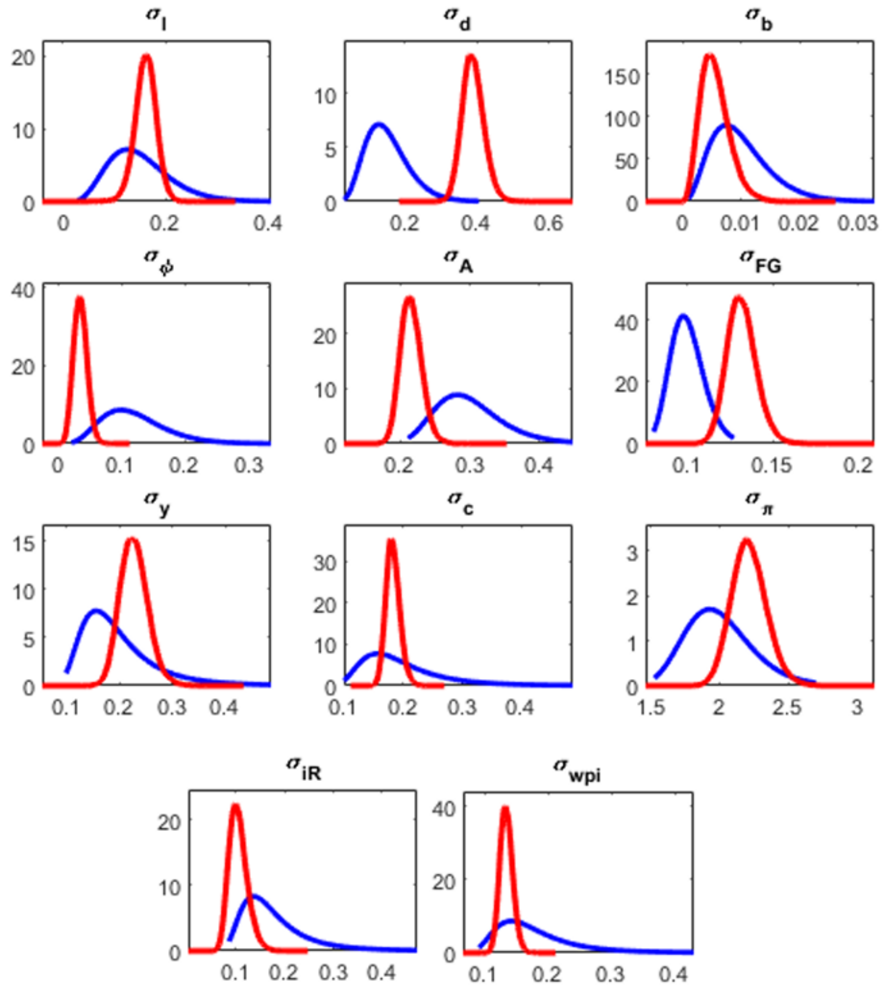


Figure 12: Prior and Posterior Marginal Distributions of Shocks

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

One additional experiment that we can run with in this context is to look at how banks adjust their balance sheets when their expectations "de-anchor." Orphanides and Williams (2006) show that as agents become less credulous regarding the central bank's planned future policy path, they react more strongly to new information, increasing volatility of the economic aggregates. This phenomenon is known as expectation de-anchoring. Figure 15 shows the effects of a contractionary forward guidance shock on bank balance sheet items in the case of anchored versus de-anchored beliefs.

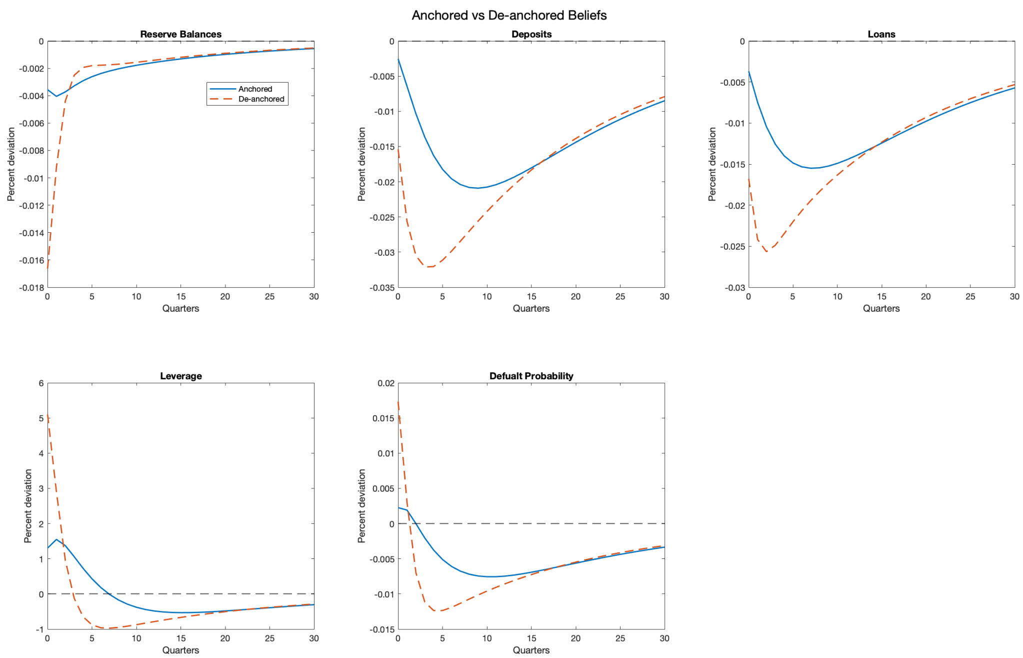


Figure 13: FG Shocks when Expectations are Anchored vs De-Anchored

The impulse responses of commercial bank balance sheets a forward guidance shock when expectations are anchored (blue line) versus de-anchored (orange line). This is achieved by setting kappa = 0.2 for anchored beliefs and 0.8 for de-anchored beliefs.

The way this is achieved is by setting the Kalman filter parameter $\kappa = 0.2$ for anchored beliefs and $\kappa = 0.8$ for beliefs that have become de-anchored. By de-anchoring beliefs, agents attribute much more weight, through the Kalman filter, to new information, which increases their responsiveness to news.

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