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. 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; that the impact of forward guidance surprises on bank balance sheets increases as expectations de-anchor; and that adjusting the required reserve ratio can mute the effects of these shocks.

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

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

want to estimate:

$$X = F\Lambda + e$$

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.

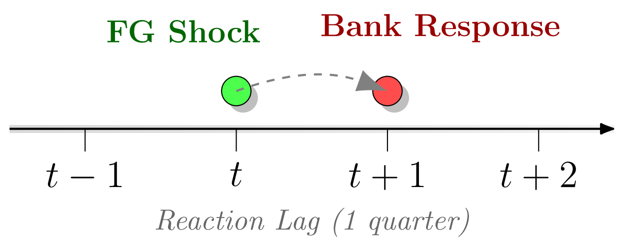
Following Bauer and Swanson (2023), I use six variables that are related to the Federal Reserve's monetary policy decisions: nonfarm payrolls surprise, employment growth, S&P 500, yield curve slope, commodity prices, and treasury skewness. The nonfarm payrolls surprise is calculated as the difference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

4 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:

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

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 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).

To address potential serial correlation and heteroskedasticity in the residuals, each regression is estimated with Newey-West standard errors. Following Barnichon and Brownlees (2019) I apply cubic smoothing splines with a smoothing parameter to the estimated impulse responses and their confidence intervals. This smoothing preserves the fundamental dynamic movements while also reducing excessive noise.

Figure 1 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.

I conduct a Wald test for each IRF in order to test the null hypothesis that the IRF responses across the 20 horizons are jointly zero. In all three categories tested here, the null hypothesis is strongly rejected, indicating statistically significant responses over time.

The figure illustrates a general trend in wake of a contractionary forward guidance shock, which is that, loan volume pulls back in general. However, it is clear that the drop-off over the near-term immediately following the shock is gradual, especially with regards to C&I

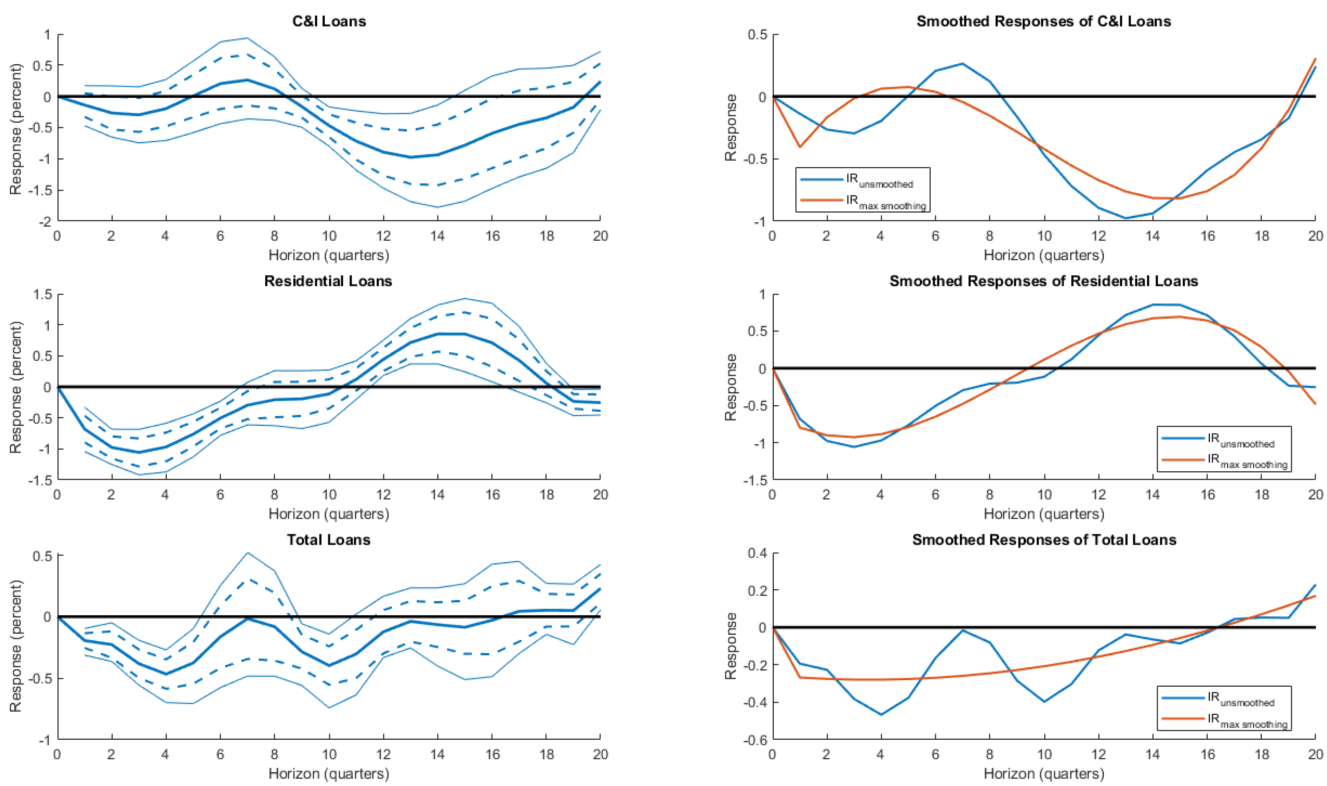


Figure 1: Loan Responses to a Contractionary Forward Guidance Shock

The figures are the impulse responses of various loan categories to the one standard deviation contractionary forward guidance shock. For the left hand figures, the inner dashed band corresponds to the 68% confidence band, while the outer solid band corresponds to the 90% confidence band. The right hand figures shows how the impulse response dynamics change as we go from a local projections IRF ($IR_{\text{unsmoothed}}$), to a smoothed local projections plot ($IR_{\text{max smoothing}}$).

Table 1: Joint Test Statistics for IRF Responses (Horizon 0 to 20)

Loan Category	**Chi-square Statistic**	**p-value**	**F-statistic**
Commercial and Industrial Loans	57.37	0.000	2.87
Residential Loans	141.12	0.000	7.06
Total Loans	72.21	0.000	3.61

loans, which hovers slightly below and then above zero until horizon nine, where it begins to fall more precipitously. The fact that the initial changes in C&I loans remain fairly gradual, and then begin to drop at later horizons is consitent with other findings in the literature, which offer up three possible explanations for this phenomenon.

The first factor in explaining the lagged response of banks in contracting C&I loans relates to supply-side contractual rigidities. 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, after the FOMC announcement, many loans are still being finalized at older rates, which also partly explains the delayed response in C&I loans overall.

The second factor involved 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). This contributes to the initial smooth response of aggregate C&I loans in that the volume of these kinds of loans only drops off after the effects of a tight-credit environment come to bear upon the macroeconomy; in the context of a forward guidance shock, it can be a considerable amount of time before the effects of the shock are felt. The 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).

Residential loan issuance gradually drops off immediately following a contractionary forward guidance shock, which is consistent with what we see elsewhere in the literature regarding the composition of loan supply in an environment of monetary policy tightening (Allen and Rogoff (2011), Jiménez et al. (2011)). As the central bank signals a future tightening to its policy rate, banks seek to limit their exposure to real estate markets that can be expected to depress in a tight credit environment.

An interesting feature of the IRFs is that the trough of the C&I loan response function occurs close to the same time that we see a peak in the response of residential loans. Many possible stories could be concocted to explain this. One story is that, on the demand side, by quarters 12 - 14 the uncertainty created by a forward guidance shock has largely been resolved and households that had delayed home purchases as a result of the initial shock are now reentering the housing market. Following the insights of Bernanke and Blinder (1992), the delayed response of C&I loans to contractionary shocks in general might be finally coming to fruition at this stage.

The rebound in residential lending being an artifact of the resolved uncertainty is further evidence by the impulse response of real GDP to a forward guidance shock over the same 20 quarter horizon. The impulse response of real GDP can be seen in the appendix under section 5.2. Around the same time that we see the rebound in residential lending, we also begin to see a sharp increase in real GDP following in wake of a muli-period loosening of the federal funds rate (figure in appendix 5.2). The delayed reaction of the federal funds rate to shocks is well documented in the literature. For instance, Gilchrist and Zakrajšek (2012) look at the macreconomic effects of a shock to credit spreads and show that, whereas variables like consumption, investment, and output respond almost immediately, there is a lag in the response of the federal funds rate.

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 3. 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.

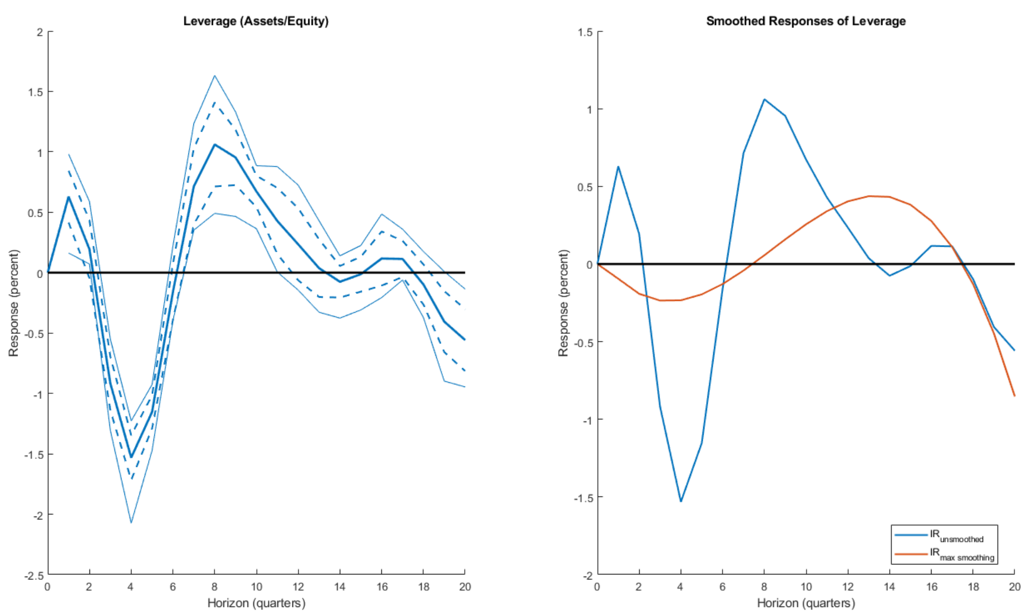


Figure 2: Response of Leverage to a Contractionary Forward Guidance Shock

The figures represent the impulse response of commercial bank leverage (assets/equity) to a one standard deviation contractionary forward guidance shock. A joint Wald test returns a chi-square statistic of 126.0845, a p-value of 0.0000, and an F statistic of 6.3042.

The figure for real GDP in the appendix (5.2) shows the response of real GDP to a contractionary forward guidance shock. One notable feature that becomes apparent when you compare the movements of the IRF of real GDP to that of bank leverage with minimal smoothing is that the slopes of the IRFs (i.e., whether a variable is trending up or down) often move in opposite directions, even when real GDP and leverage are both above or below their baselines. For example, on impact, leverage and real GDP move in opposite directions. Then, between quarters two and four, GDP begins to trend upward, indicating a phase of partial recovery. During roughly the same period, leverage becomes increasingly negative, 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. At medium intervals, around quarters 6–8, GDP falls again, while leverage surges upward, displaying another case of countercyclical movement (i.e., banks expand leverage while real activity weakens).

Figure 6 plots the slopes of the IRFs for leverage and real GDP with the background of the plot colored red whenever $\text{sign}(\Delta\text{IRF}_{\text{GDP},h}) \neq \text{sign}(\Delta\text{IRF}_{\text{Lev},h})$, and colored green whenever they are equal. I find that over 17 of the 20 horizons, the slopes of the IRFs are the opposite sign, underscoring countercyclical leverage dynamics.

The right-hand panels of the figures 2 and 3 show what happens to the IRFs as you apply a certain degree of smoothing. The orange line is generated by extreme smoothing.[7] This has the effect of averaging out the short-run fluctuations and gives the overall impression that leverage is procyclical. The takeaway is that at higher frequencies, which are more pertinent for understanding cyclical fluctuations, leverage appears countercyclical. If we were interested in lower frequencies (multiple years), then the smoothed result suggests that procyclicality might be inferred.

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

[7]Following the methodology of Barnichon and Brownlees (2019), I use an initial penalty value of 1e10.

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.[8]

5 Model with a Banking Sector

To analyze the empirical findings of the previous section, I put together a 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.

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

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).

5.1 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.

5.2 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:

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

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:

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

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.

5.3 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.

5.4 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:

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

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

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

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

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

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

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

$$\psi^{FG}_t = [s^0_t \;\; s^1_t \dots s^{20}_t]$$

The current policy rate is perfectly observed:

$$s^0_t = \psi^0_{r,t}$$

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

$$s^j_t = \psi^j_{r,t} + \nu_t, \qquad \nu_t \sim N(0, \sigma^2_\nu) \tag{10}$$

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

when a shock occurs to equation 10, either through ν_t or $\psi^j_{r,t}$, this feeds into equation 9, forcing the agent to update their beliefs about $\hat{\psi}^j_{r,t}$.The agent starts off period t with some belief about $\psi^j_{r,t}$. After observing the signal s^j_t, the agent compares it to their prior: $s^{20}_t - \hat{\psi}^{20}_{r,t-1}$. 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, $\hat{\psi}^{20}_{r,t}$.

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^R_t. 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.

5.5 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 will provide details on parameter calibration:

5.6 Model Calibration

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	-
ϕ_x	0.05	Adjustment Cost Parameter	Christiano, Motto, & Rostagno (2014)
α	0.01	Equity Issuance Cost Parameter	Corbae & D'Erasmo (2021)
ρ	0.1	Reserve Ratio	Benigno & Benigno (2021)
ϕ_π	1.8	Interest Rate Rule, Inflation	Campbell et al. (2019)
ϕ_Y	0.4	Interest Rate Rule, Output	Campbell et al. (2019)
κ	0.5	Kalman Gain	Coibion & Gorodnichenko (2015)
τ	0.3	Tax Rate	OECD Centre for Tax Policy & Administration

Table 2: Parameter Calibration

The calibration for the first five parameters listed in the table above are standard as these are very conventional modeling parameters. However, beginning with ϕ_x, we encounter less frequently used parameters. 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 0.05%, then using $f(\delta_t) = \frac{\alpha}{2}\delta_t^2$ and normalizing $\delta_t = 1$, we can set $\frac{\alpha}{2} \approx 0.005$, which yields $\alpha \approx 0.01$.

The reserve ratio is set at 10%. This is consistent with what the reserve ratio in the

U.S. banking system has been historically.[9] Benigno and Benigno (2021) experiment with varying levels of reserve requirements, with 10% being the lowest level they model with.

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

6 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 is the interest rate on reserve balances, specified by the Taylor Rule.

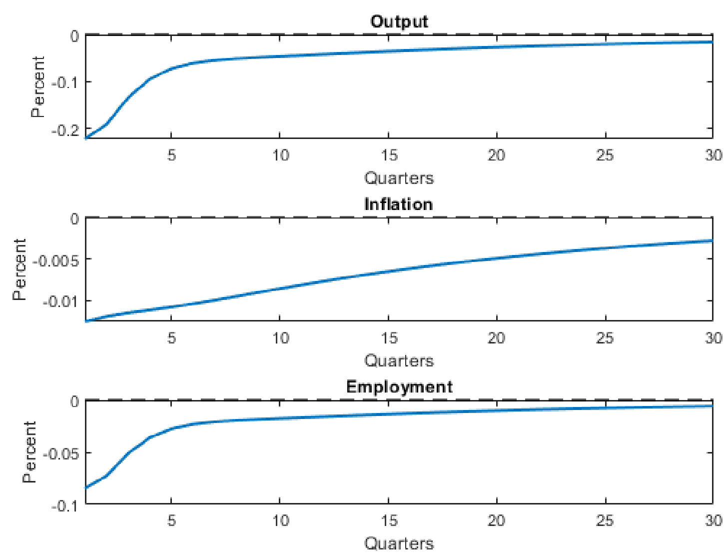


Figure 3: Macro Aggregates

The figure represents the impulse response of macro aggregates to a one standard deviation forward guidance contraction to the policy rate. The impulse responses themselves are expressed as percentage deviations from the steady state.

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

Figure 3 provides us with the responses of important macroeconomic variables like output, inflation, and employment. In a contractionary monetary policy environment, each response accords with economic intuition. An unexpected tightening in the form of an announcement that signals tighter policy in the near future will lead all three aggregates to fall on impact, which gradually recover to baseline. Next we turn to the response of the main variables of interest in this paper: bank balance sheet variables.

The response of bank balance sheet variables to a contractionary forward guidance shock are found in figure 4. Across the board, you see banks attempting to systematically reduce their risk exposure. In the immediate aftermath of the shock, several things happen that drive this response. For one, the probability of intermediate goods producers defaulting on bank loans spikes above trend. We also see that bank leverage jumps above trend.

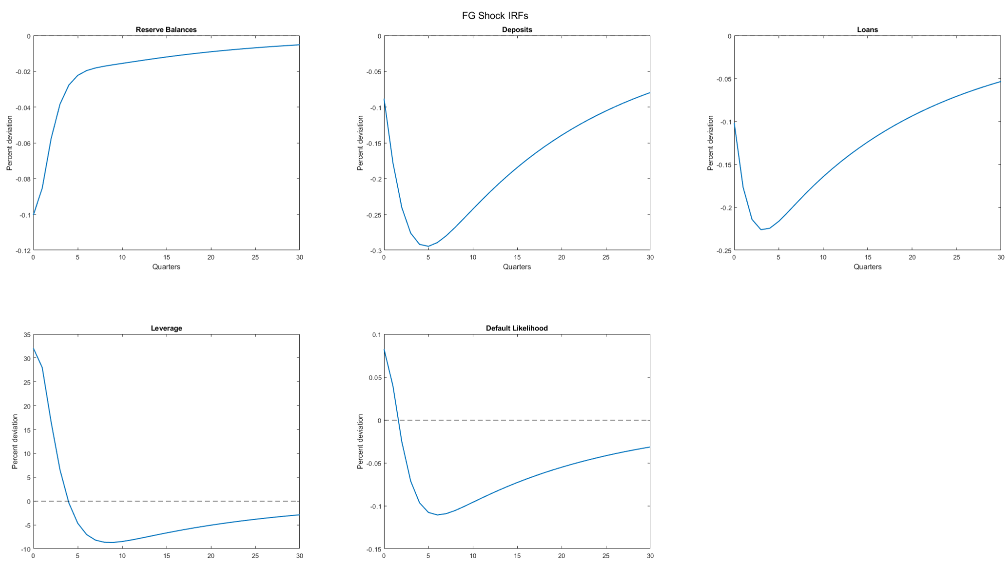


Figure 4: Bank Balance Sheet Items

The figure represents the impulse response of bank balance sheet variables to a one standard deviation forward guidance shock to the policy rate. The impulse responses themselves are expressed as percentage deviations from the steady state.

These two factors, the spike in leverage and the increase in default, 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.

The final set of results pertains to what happens in interest rates and interest rate spreads in wake of the monetary policy contraction. Figure 5 provides us with an illustration of the response of interest rates to a contractionary forward guidance shock.

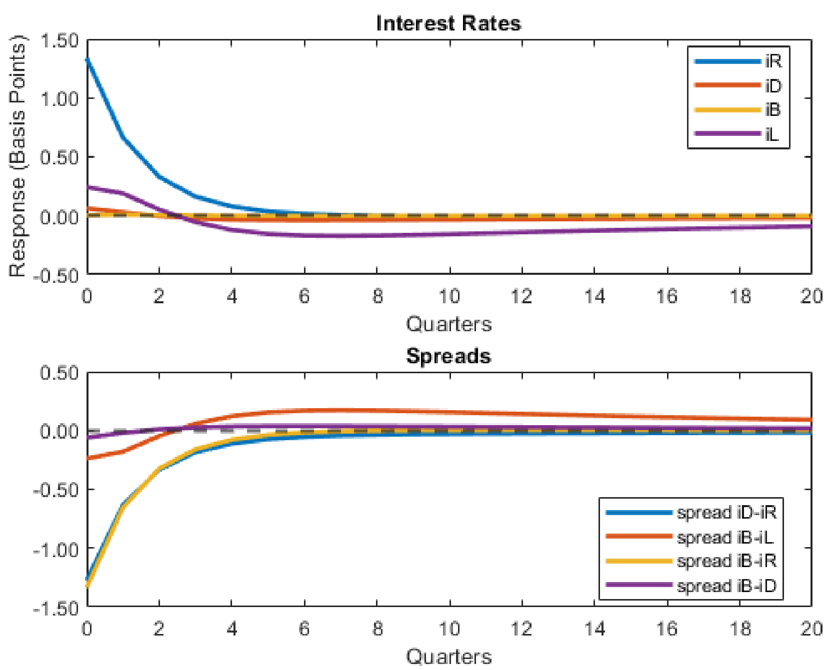


Figure 5: Interest Rates and Spreads

The legend is labelled as follows: iR represents the policy rate (interest on reserves), iD is the interest rate on deposits; iB is the interest on short term risk free private debt; and iL is the interest rate on loans.

All interest rates rise in the immediate wake of a signal of future credit tightening.

The policy rates jumps the most, followed by the interest rate of loans, then deposits, then short-term risk free private debt. Interestingly, the interest rate on loans, although it increases on impact, after it begins to fall, instead of recovering to the zero trend line, it falls below the trend line for some time, before slowly recovering. This is an artifact of the sluggishness of loan supply given the adjustment cost on loans incorporated into the model, but is nonetheless a sensible outcome since, given the slow recovery of lending after the shock, a substantial adjustments in loan rates might be necessary over an extended horizon in order to get lending back to trend.

One discovery in the literature that is relevant to the present study is that economic variables display a fairly muted response to forward guidance surprises relative to surprises in the current federal funds rate target (Del Negro et al. (2023), McKay et al. (2016)). This makes sense a priori, as the effects of an immediate federal funds rate adjustment is far more binding than the effects of an announcement about the future charted course for the federal funds rate. Additionally, forward guidance leaves room for uncertainty and ambiguity regarding what will happen to interest rates over the near to medium term, however shocks to the current target leave no room for ambiguity or misapprehension. Hence, we should see a much more muted response in our variables of interest in response to a forward guidance shock, relative to their response in wake of a federal funds rate shock.

This is precisely what is borne out by both the data and my model. Figure 6 compares the effects of a contractionary federal funds rate shock to the effects of a contractionary forward guidance shock in the left and right panels, respectively. Although the direction of the response of loans is similar in both cases, the magnitudes are strikingly different. There is a much larger effect on commercial bank lending in wake of a contractionary federal funds rate shock.

Figure 6 illustrates the significance of the differences in magnitudes. The gold IRF respresents the response of bank balance sheet items to a contractionary federal funds rate shock, whereas the blue line is the response of loans to a forward guidance shock. The effect on all balance sheet items is much more muted in wake of a forward guidance shock than it is upon a federal funds rate shock.

This is in line with the literature that forward guidance should have effects upon economic variables that are much smaller in magnitude than adjustments to the current policy rate, thereby avoiding the forward guidance puzzle. When an announcement is made that signals a surprise tightening two quarters ahead, as in figure 6, uncertainty about this signal mutes the magnitude of the changes, in contrast to the response of these variables when an actual policy change goes into effect immediately.

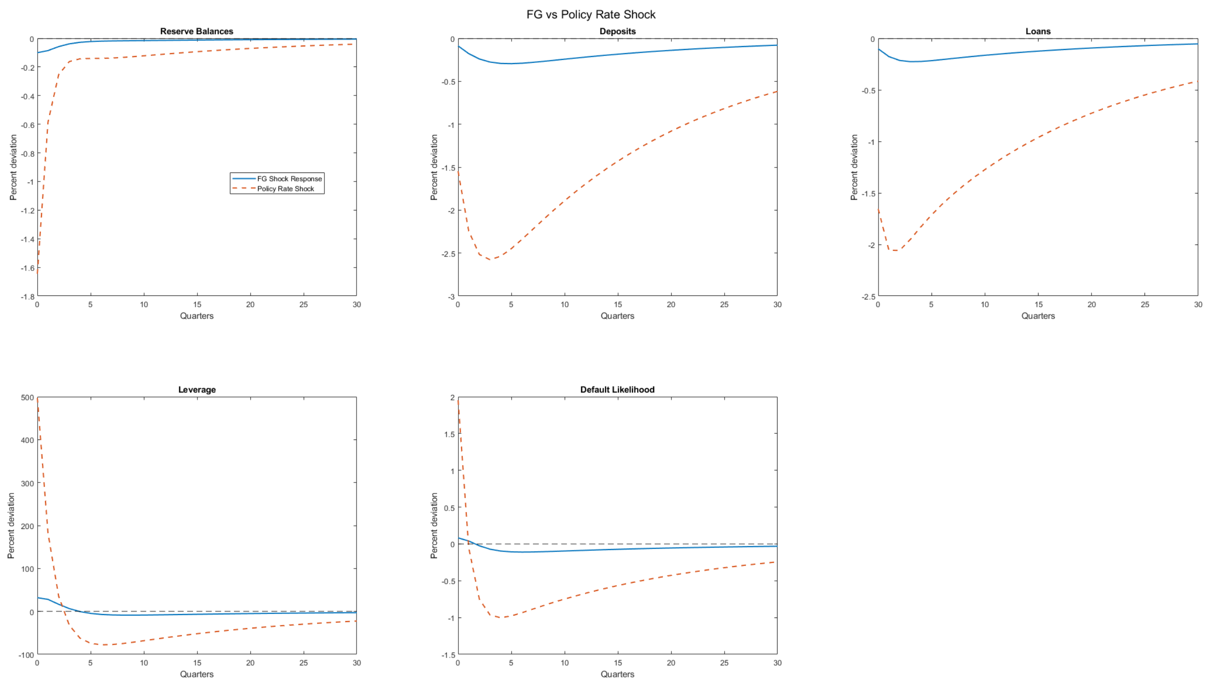


Figure 6: FFR vs FG Shock in the Model

An overlay of the impulse responses of commercial bank loans in wake of a one standard deviation contractionary forward guidance shock (blue line) versus a forward federal funds rate shock (orange line). This plot is generated by the structural model laid out in section 5.

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. 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 7 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.

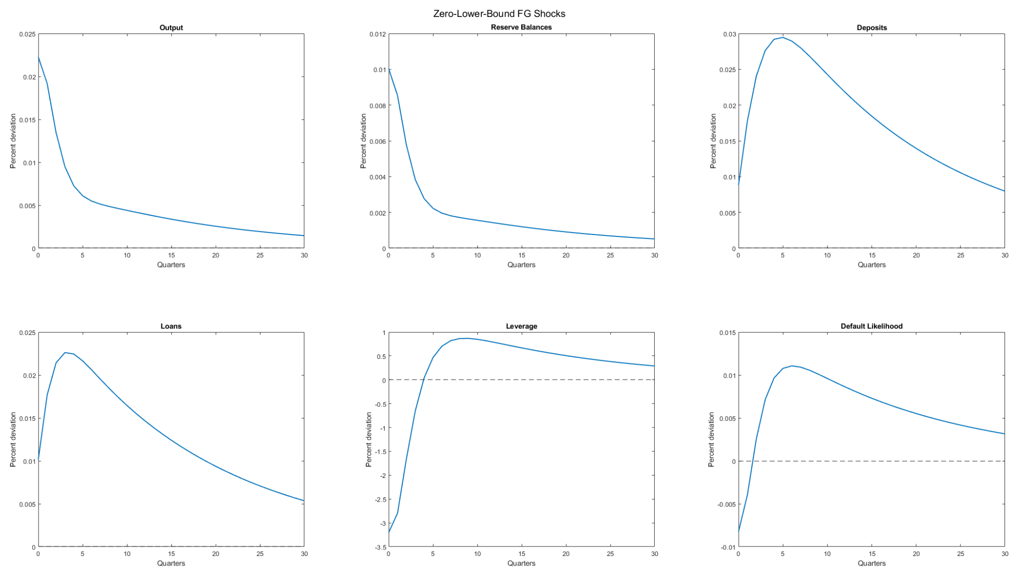


Figure 7: FG Shocks in the Context of a ZLB Episode

The impulse responses of commercial bank balance sheets to an accomodative forward guidance shock (one standard deviation shock)

Figure 7 suggests that banking activity can be stimulated by an accommodative stance by the central bank, even when the policy rate is already at the ZLB. Lending, reserve balances held at the Fed, and deposits increase on impact. Additionally, leverage falls on impact due to inverse of the reasons it rises in wake of a contractionary shock: equity rises faster than asset holdings, which causes leverage to fall immediately after the forward guidance shock.

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 8 shows the effects of a contractionary forward guidance shock on bank balance sheet items in the case of anchored versus de-anchored beliefs.

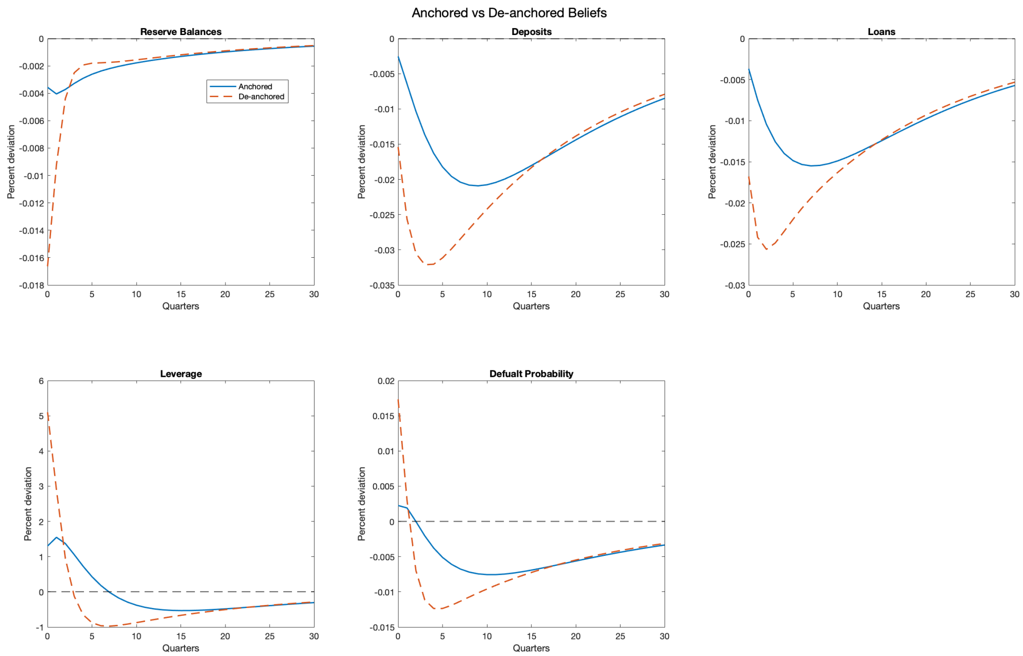


Figure 8: FG Shocks when Expectations are Anchored vs De-Anchored

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.

7 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. In all cases, I've analyzed the effects of a contractionary forward guidance shock. A contractionary forward guidance shock is represented by a signal or communication from the central bank which indicates that the future path of interest rates will be higher than what the public had anticipated before the announcement.

What I have found is that banks respond to these kinds of contractions by reducing their exposure to risk. This manifests itself in the banks reducing their loan supply, credit issuance in general, and leverage. However, as I discover in my model, and as is consistent with the broader literature, the effects of forward guidance shocks are more muted than shocks to the current policy rate target. Nonetheless, forward guidance does display real, non-negligible effects on bank balance sheets, even during relatively normal times, which leads us to a topic that is an avenue for further inquiry.

One of the main interests people have with forward guidance policy and its effects is what it can potentially do to the economy in the case of a liquidity trap. In that case, we'd be interested in what expansionary forward guidance could do. I've provided cursory intuition in my model about how an accommodative signal by the central during a ZLB episode can stimulate bank balance sheets by increasing loan supply, and deposits while lowering their leverage and default likelihood.

Appendix

7.1 Commercial 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 3: List of Banks and Their Tickers

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

7.2 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[10]:

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

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[11]:

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

[10] All of the following mathematical details can be found in Gürkaynak, Sack, and Swanson (2005) and are derived from there.

[11] 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.

7.3 Additional IRFs

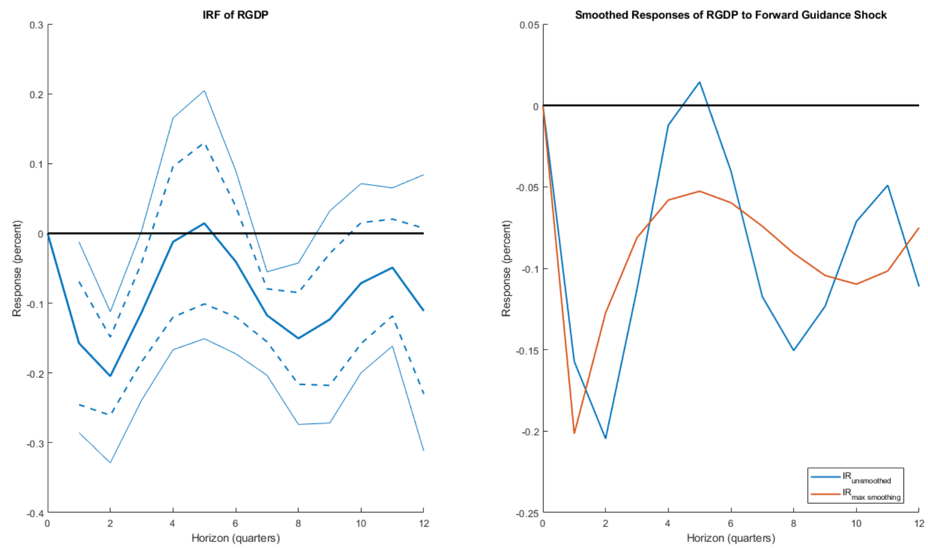


Figure 9: Real GDP Response to a Contractionary Forward Guidance Shock

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 ($IR_{slp,maxpen}$).

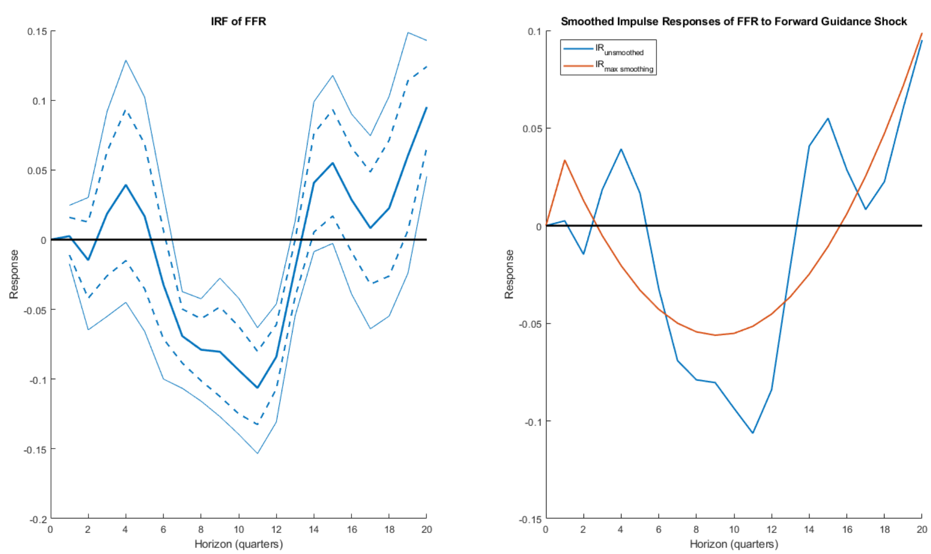


Figure 10: Federal Funds Rate Response to a Contractionary Forward Guidance Shock

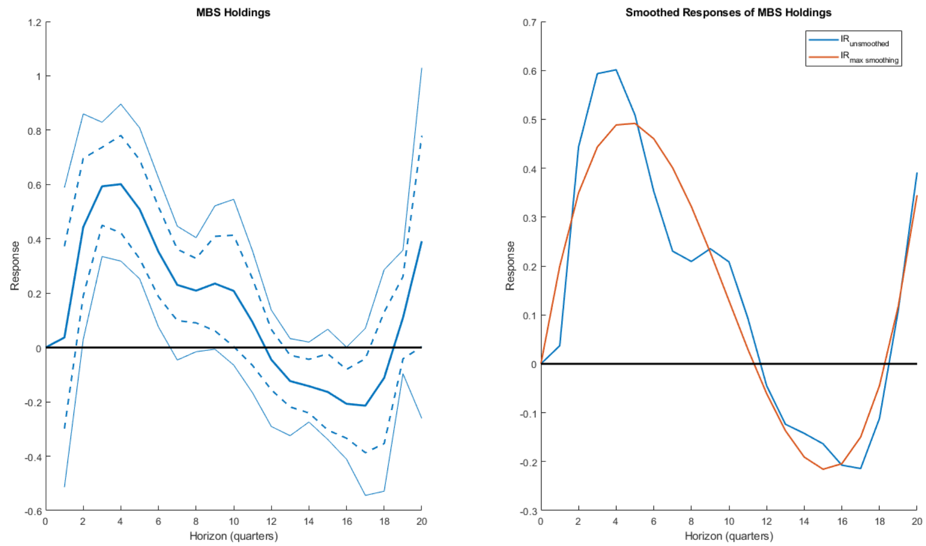


Figure 11: MBS Holdings Response to a Contractionary Forward Guidance Shock

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.

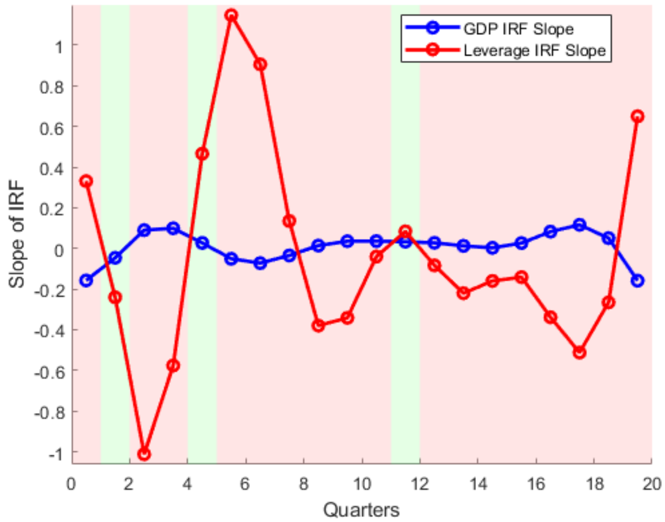


Figure 12: Comparison of GDP and Leverage IRF Slopes

Here I stack two line plots, one for the slope of real GDP and one for leverage. The background is color coded based on whether the signs of the slopes are different. Green represents a horizons where the slopes are the same sign, while red represents horizons where the slopes are different signs. Out of 20 horizons, 17 are coded red, indicating that over the majority of horizons the signs for leverage and GDP are opposite.

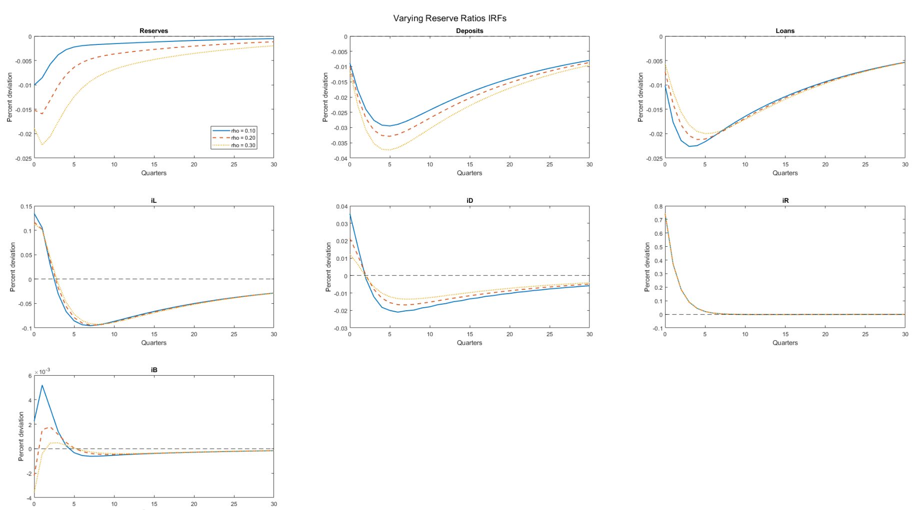


Figure 13: Comparison of GDP and Leverage IRF Slopes

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:

$$P_t C_t + B_{t+1} + D_t + B_t^T \leq W_t N_t + \Psi_t + \Phi_t + (1 + i_{t-1}^B) B_t + (1 + i_{t-1}^D)(D_{t-1} + B_{t-1}^T) - P_t T_t \tag{14}$$

Lagrangian Formulation

Define the Lagrangian:

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

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}

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

FOC for Deposits D_t

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

Labor Supply Condition

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

Euler Equation for Bonds

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

Which can be simplified to:

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

Implicit Demand for Real Balances

Combining equations 6 and 7 we get

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

which simplifies to

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

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:

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

which allows us to endogenize default:

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

which in aggregated terms is:

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

To ensure that $\phi_{d,t+1}$ takes on values between 0 and 1, I transform the endogenous default rate using a logistic function. We end up with:

$$\phi_{d,t+1} = \frac{1}{1 + \exp\left(-\left(1 - \frac{Y_t}{(1+i_t^L)l_t}\right)\right)} \tag{39}$$

When a contractionary shock hits the economy, due to the sluggishness of loans, the fall in output will exceed the decline in the interest-rate-adjusted value of loans. When the economy is underperforming relative to its debt obligations, the likelihood of default rises.

Substituting for $N_t(j)$

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

$$\Psi_t(j) = P_t(j)Y_t(j) - (1 + i_t^L)(1 + \phi_{t+1})\frac{W_t}{A_t}Y_t(j). \tag{40}$$

Demand Constraint

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

$$Y_t(j) = \left(\frac{P_t(j)}{P_t}\right)^{-\epsilon} Y_t. \tag{41}$$

Profit Function with Demand Substituted

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

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

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

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

Profit Maximization Problem

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

$$\max_{P_t(j)} \quad \left(\frac{P_t(j)}{P_t}\right)^{-\epsilon} Y_t \left[P_t(j) - (1 + i_t^L)(1 + \phi_{t+1})\frac{W_t}{A_t}\right]. \tag{44}$$

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:

$$\max_{P_t(j)} X_t \sum_{s=0}^{\infty} \xi^s \Lambda_{t,t+s} \left[\frac{P_t(j)}{P_{t+s}} \left(\frac{P_t(j)}{P_{t+s}} \right)^{-\epsilon} Y_{t+s} - (1+i_t^L)(1+\phi_{t+1}) \frac{w_{t+s}}{A_{t+s}} \left(\frac{P_t(j)}{P_{t+s}} \right)^{-\epsilon} Y_{t+s} \right]. \tag{45}$$

subject to the demand function:

$$Y_{t+s}(j) = \left(\frac{P_t(j)}{P_{t+s}} \right)^{-\epsilon} Y_{t+s}. \tag{46}$$

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:

$$P_t(j) = \frac{\epsilon}{\epsilon - 1} \frac{X_t \sum_{s=0}^{\infty} \xi^s \Lambda_{t,t+s} mc_{t+s} P_{t+s}^{\epsilon} Y_{t+s}}{X_t \sum_{s=0}^{\infty} \xi^s \Lambda_{t,t+s} P_{t+s}^{\epsilon-1} Y_{t+s}}. \tag{47}$$

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:

$$P_t^{\#} = \frac{\epsilon}{\epsilon - 1} \frac{X_{1,t}}{X_{2,t}}, \tag{48}$$

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

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

$$X_{2,t} = P_t^{\epsilon-1} Y_t + \xi X_t \Lambda_{t,t+1} X_{2,t+1}. \tag{50}$$

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:

$$mc_t = (1 + i_t^L)(1 - \phi_{t+1})\frac{w_t}{A_t}. \tag{51}$$

8 Bank's Problem

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

$$\Phi_t = E_t \Big\{ \Lambda_{t+1} \Big[(1+i_t^L)(1-\phi_d)L_t + (1+i_t^B)B_t + (1+i_t^R)R_t - (1+i_t^D)D_t \Big] \Big\} - X_t - \frac{\phi_x}{2}(L_t - L_{t-1})^2 \tag{52}$$

subject to:

$$L_t + B_t + R_t = D_t + (1 - f(\delta_t))X_t, \quad \text{where} \quad \delta_t = \frac{L_t}{X_t}, \tag{53}$$

$$f(\delta_t) = \frac{\alpha}{2}\delta_t^2, \tag{54}$$

$$R_t \geq \rho D_t, \quad 0 \leq \rho < 1. \tag{55}$$

9 Lagrangian Formulation

Defining multipliers:

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

The Lagrangian is:

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

10 First-Order Conditions (FOCs)

10.1 FOC with respect to B_t

$$E_t[\Lambda_{t+1}(1+i_t^B)] - \mu_t = 0. \tag{56}$$

10.2 FOC with respect to R_t

$$E_t[\Lambda_{t+1}(1+i_t^R)] - \mu_t - \alpha_t = 0. \tag{57}$$

10.3 FOC with respect to D_t

$$-E_t[\Lambda_{t+1}(1+i_t^D)] + \mu_t + \rho\alpha_t = 0. \tag{58}$$

10.4 FOC with respect to L_t

$$E_t[\Lambda_{t+1}(1+i_t^L)(1-\phi_d)] - \phi_x(L_t - L_{t-1}) - \mu_t(1+\alpha\delta_t) = 0. \tag{59}$$

10.5 FOC with respect to X_t

Using the chain rule for the balance-sheet constraint:

$$-1 + \mu_t(1 - \frac{\alpha}{2}\delta_t^2) = 0 \tag{60}$$

Solving for μ_t:

$$\mu_t = \frac{1}{(1-\frac{\alpha}{2}\delta_t^2)}. \tag{61}$$

11 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:

$$\Lambda_{t+1}(1+i_t^L)(1-\phi_d) - \phi_x\big(L_t - L_{t-1}\big) - \Lambda_{t+1}(1+i_t^B)\Big[1+\alpha\,\delta_t\Big] = 0. \tag{62}$$

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

$$(1+i_t^L)(1-\phi_d) = (1+i_t^B)(1+\alpha\,\delta_t) + \frac{\phi_x}{\Lambda_{t+1}}\big(L_t - L_{t-1}\big). \tag{63}$$

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

$$\frac{1+i_t^L}{1+i_t^B}(1-\phi_d) = 1 + \alpha\,\delta_t + \frac{\phi_x}{\Lambda_{t+1}(1+i_t^B)}\big(L_t - L_{t-1}\big). \tag{64}$$

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

$$\frac{1+i_t^L}{1+i_t^B} = \frac{1+\alpha\,\delta_t}{1-\phi_d} + \frac{\phi_x}{\Lambda_{t+1}(1+i_t^B)(1-\phi_d)}\big(L_t - L_{t-1}\big). \tag{65}$$

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.

12 Deriving the Relationship Between L_t and B_t

From the budget constraint, we isolate loans and bonds:

$$L_t + B_t = D_t + (1 - f(\delta_t))X_t - R_t. \tag{66}$$

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

$$L_t + B_t = (1-\rho)D_t + (1 - f(\delta_t))X_t. \tag{67}$$

Define the allocation ratio:

$$L_t = \gamma_t(L_t + B_t), \quad B_t = (1 - \gamma_t)(L_t + B_t). \tag{68}$$

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:

$$L_t = \gamma_t \left[(1 - \rho)D_t + (1 - f(\delta_t))X_t\right], \tag{69}$$

$$B_t = (1 - \gamma_t) \left[(1 - \rho)D_t + (1 - f(\delta_t))X_t\right]. \tag{70}$$

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

$$\gamma_t = g\left(\frac{1 + i_t^L}{1 + i_t^B}\right). \tag{71}$$

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:

$$L_t = g\left(\frac{1 + i_t^L}{1 + i_t^B}\right) \left[(1 - \rho)D_t + (1 - f(\delta_t))X_t\right], \tag{72}$$

$$B_t = \left(1 - g\left(\frac{1 + i_t^L}{1 + i_t^B}\right)\right) \left[(1 - \rho)D_t + (1 - f(\delta_t))X_t\right]. \tag{73}$$

13 Final Relationship Between L_t and B_t

Dividing the two equations:

$$\frac{L_t}{B_t} = \frac{g\left(\frac{1+i_t^L}{1+i_t^B}\right)}{1 - g\left(\frac{1+i_t^L}{1+i_t^B}\right)} \tag{74}$$

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

$$g(x) = \frac{x}{1+x}, \tag{75}$$

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

$$x = \frac{1+i_t^L}{1+i_t^B} \tag{76}$$

thus, we have:

$$\gamma_t = g\left(\frac{1+i_t^L}{1+i_t^B}\right) = \frac{\frac{1+i_t^L}{1+i_t^B}}{1+\frac{1+i_t^L}{1+i_t^B}} \tag{77}$$

14 Final Expressions for Loan and Short-Term Debt Allocation

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

$$\frac{L_t}{B_t} = \frac{\frac{(1+i_t^L/1+i_t^B)}{1+(1+i_t^L/1+i_t^B)}}{\frac{1}{1+(1+i_t^L/1+i_t^B)}} = \frac{(1+i_t^L)}{(1+i_t^B)}. \tag{78}$$

Which gives us:

$$L_t = B_t\left[\frac{(1+i_t^L)}{(1+i_t^B)}\right] \tag{79}$$

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

$$W_t N_t \frac{(1+i_t^B)}{(1+i_t^L)} + W_t N_t + \left(1 - \frac{1}{\rho}\right) R_t = (1 - \frac{\alpha}{2}\delta_t^2) X_t \tag{80}$$

which simplifies to:

$$\boxed{R_t = \frac{1}{1-\frac{1}{\rho}}\left[\left(1 - \frac{\alpha}{2}\delta_t^2\right) X_t - \left(\frac{(1+i_t^L) + (1+i_t^B)}{(1+i_t^L)}\right) W_t N_t\right]} \tag{81}$$

15 Deriving the Loan Equation

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

$$E_t[\Lambda_{t+1}(1+i_t^L)(1-\phi_d)] - \phi_x(L_t - L_{t-1}) - \mu_t(1+\alpha\delta_t) = 0 \tag{82}$$

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:

$$E_t[\Lambda_{t+1}(1+i_t^L)(1-\phi_d)] - \mu_t(1+\alpha\frac{L_t^*}{X_t}) = 0 \tag{83}$$

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

$$E_t[\Lambda_{t+1}(1+i_t^L)(1-\phi_d)] - \mu_t\left(1+\alpha\frac{L_t^*}{X_t}\right) \approx \kappa(L_t^* - L_t), \quad \text{with} \quad \kappa > 0. \tag{84}$$

Therefore:

$$\phi_x(L_t - L_{t-1}) \approx \kappa(L_t^* - L_t) \tag{85}$$

Therefore, after some rearranging we get:

$$L_t = \frac{\kappa}{\phi_x + \kappa}L_t^* + \frac{\phi_x}{\phi_x + \kappa}L_{t-1} \tag{86}$$

Define:

$$\rho_L = \frac{\phi_x}{\phi_x + \kappa}; \quad (1-\rho_L) = \frac{\kappa}{\phi_x + \kappa} \tag{87}$$

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

$$L_t^* = \left(\frac{1}{\rho} - 1\right)R_t + \left(1 - \frac{\alpha}{2}\delta_t^2\right)X_t - B_t \tag{88}$$

Which, finally, gives us our final loan equation:

$$\boxed{L_t = \rho_L L_{t-1} + (1-\rho_L)\left(\left(\frac{1}{\rho} - 1\right) R_t + (1 - \frac{\alpha}{2}\delta_t^2)X_t - B_t\right)} \tag{89}$$

16 Equity

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

$$x_t = \left[1 - \frac{(1+i_t^L)}{(1+i_t^B)}(1-\phi_{d,t+1})\right]\ell_t + \frac{i_t^D - i_t^B}{1+i_t^B}d_t + \frac{i_t^B - i_t^R}{1+i_t^B}r_t \tag{90}$$

17 Treasury Bond Issuance and Tax Rule

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

$$B_t^T = (1+i_t^D)B_{t-1}^T - T_t \tag{91}$$

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

$$T_t = \tau Y_t, \qquad 0 < \tau < 1 \tag{92}$$

18 Taylor Rule (Monetary Policy)

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

$$1 + i_t^R = (1 + i^R)^\rho \left(\frac{\Pi_t}{\Pi^*}\right)^{\phi_\pi} \left(\frac{Y_t}{Y^*}\right)^{\phi_Y} e^{\phi_t}. \tag{93}$$

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:

$$\phi_t = \sum_{i=0}^{20} w_{t+i} \hat{\psi}^i_{r,t+i} \tag{94}$$

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:

$$\hat{\psi}^j_{r,t} = \hat{\psi}^j_{r,t-1} + \kappa_j (s_t^j - \hat{\psi}^j_{r,t-1}), \quad j = 1, ..., 20. \tag{95}$$

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:

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

The current policy rate is perfectly observed:

$$s_t^0 = \psi^0_{r,t}$$

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

$$s_t^j = \psi_{r,t}^j + \nu_t, \qquad \nu_t \sim N(0, \sigma_\nu^2) \tag{96}$$

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.

19 Equilibrium Conditions

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

$$\theta N_t^\eta = w_t C_t^{-\sigma} \tag{2}$$

$$d_t = \phi C_t^\sigma \frac{1 + i_t^B}{i_t^B - i_t^D} - b_t^T \tag{3}$$

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

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

$$p_t^\# = \frac{\epsilon}{\epsilon - 1} \frac{\hat{X}_{1,t}}{\hat{X}_{2,t}} \tag{6}$$

$$\hat{X}_{1,t} = mc_t Y_t + \xi X_t \Lambda_{t,t+1} \Pi_{t+1}^\epsilon \hat{X}_{1,t+1} \tag{7}$$

$$\hat{X}_{2,t} = Y_t + \xi X_t \Lambda_{t,t+1} \Pi_{t+1}^{\epsilon-1} \hat{X}_{2,t+1} \tag{8}$$

$$mc_t = (1 + i_t^L)(1 - \phi_{d,t+1}) \frac{w_t}{A_t} \tag{9}$$

$$Y_t = C_t \tag{10}$$

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

$$T_t = \tau Y_t \tag{12}$$

$$g_t^d = (1 - \rho) g^d + \rho g_{t-1}^d + s_d X_t^{FG} \tag{13}$$

$$g_t^d = \ln d_t - \ln d_{t-1} + \ln \Pi_t \tag{14}$$

$$A_t N_t = Y_t \nu_t^P \tag{15}$$

$$\nu_t^P = (1-\xi)(p_t^{\#})^{-\epsilon} + \xi \Pi_t^{\epsilon} \nu_{t-1}^P \tag{16}$$

$$lnA_t = \rho_A lnA_{t-1} + s_A \epsilon_{A,t} \tag{17}$$

$$1 + i_t^R = (1+i^R)^{\rho_r} \left(\frac{\Pi_t}{\Pi^*}\right)^{\phi_\pi} \left(\frac{Y_t}{Y^*}\right)^{\phi_Y} e^{\epsilon_t^{FG}} \tag{18}$$

$$\phi_{d,t+1} = \frac{1}{1 + \exp\left(-\left(1 - \frac{Y_t}{(1+i_t^L)l_t}\right)\right)} \tag{19}$$

$$\frac{(1+i_t^L)}{(1+i_t^B)} = \frac{1+\alpha\delta_t}{1-\phi_{d,t+1}} + \frac{\phi_x}{\Lambda_{t+1}(1+i_t^B)(1-\phi_{d,t+1})}(l_t - l_{t-1}) \tag{20}$$

$$r_t = \frac{1}{1-\frac{1}{\rho}}\left[\left(1 - \frac{\alpha}{2}\delta_t^2\right)x_t - \left(\frac{(1+i_t^L)+(1+i_t^B)}{(1+i_t^L)}\right)w_t N_t\right] \tag{21}$$

$$\ell_t = \rho_\ell \ell_{t-1} + (1-\rho_\ell)\left(\left(\frac{1}{\rho} - 1\right)r_t + \left(1 - \frac{\alpha}{2}\delta_t^2\right)x_t - b_t\right) \tag{22}$$

$$\ell_t + b_t + r_t = d_t + \left(1 - \frac{\alpha}{2}\delta_t^2\right)x_t \tag{23}$$

$$b_{t+1} - b = (1+b^g)(b_t - b) \tag{24}$$

$$\delta = \frac{\ell_t}{x_t} \tag{25}$$

$$x_t = \left[1 - \frac{(1+i_t^L)}{(1+i_t^B)}(1-\phi_{d,t+1})\right]\ell_t + \frac{i_t^D - i_t^B}{1+i_t^B}d_t + \frac{i_t^B - i_t^R}{1+i_t^B}r_t \tag{26}$$

References

Adrian, T. and N. Boyarchenko (2012). Intermediary leverage cycles and financial stability. *Becker Friedman Institute for Research in Economics Working Paper* (2012-010).

Adrian, T., E. Etula, and T. Muir (2014). Financial intermediaries and the cross-section of asset returns. *The journal of Finance 69*(6), 2557–2596.

Adrian, T., E. Moench, and H. S. Shin (2013). Leverage asset pricing. Technical report, Staff report.

Adrian, T. and H. S. Shin (2010). Liquidity and leverage. *Journal of financial intermediation 19*(3), 418–437.

Allen, F. and K. Rogoff (2011). Asset prices, financial stability and monetary policy. Technical report.

Barnichon, R. and C. Brownlees (2019). Impulse response estimation by smooth local projections. *Review of Economics and Statistics 101*(3), 522–530.

Bauer, M. D. and E. T. Swanson (2023). A reassessment of monetary policy surprises and high-frequency identification. *NBER Macroeconomics Annual 37*(1), 87–155.

Benigno, G. and P. Benigno (2021). Interest, reserves, and prices. *FRB of New York Staff Report* (971).

Berlin, M. and L. J. Mester (1999). Deposits and relationship lending. *The Review of Financial Studies 12*(3), 579–607.

Bernanke, B. S. and M. Gertler (1989). Agency costs, net worth, and busines fluctuations.

Bernanke, B. S. and M. Gertler (1995). Inside the black box: the credit channel of monetary policy transmission. *Journal of Economic perspectives 9*(4), 27–48.

Brunnermeier, M. K. and L. H. Pedersen (2009). Market liquidity and funding liquidity. *The review of financial studies 22*(6), 2201–2238.

Brunnermeier, M. K. and Y. Sannikov (2014). A macroeconomic model with a financial sector. *American Economic Review 104*(2), 379–421.

Bruno, V. and H. S. Shin (2015). Capital flows and the risk-taking channel of monetary policy. *Journal of monetary economics 71*, 119–132.

Bundick, B. and A. L. Smith (2020). The dynamic effects of forward guidance shocks. *Review of Economics and Statistics 102*(5), 946–965.

Campbell, J. R., C. L. Evans, J. D. Fisher, A. Justiniano, C. W. Calomiris, and M. Woodford (2012). Macroeconomic effects of federal reserve forward guidance [with comments and discussion]. *Brookings papers on economic activity*, 1–80.

Christiano, L. J., R. Motto, and M. Rostagno (2014). Risk shocks. *American Economic Review 104*(1), 27–65.

Cieslak, A. (2018). Short-rate expectations and unexpected returns in treasury bonds. *The Review of Financial Studies 31*(9), 3265–3306.

Cochrane, J. H. and M. Piazzesi (2002). The fed and interest rates—a high-frequency identification. *American economic review 92*(2), 90–95.

Coibion, O. and Y. Gorodnichenko (2015). Information rigidity and the expectations formation process: A simple framework and new facts. *American Economic Review 105*(8), 2644–2678.

Corbae, D. and P. D'Erasmo (2019). Capital requirements in a quantitative model of banking industry dynamics.

Del Negro, M., M. P. Giannoni, and C. Patterson (2023). The forward guidance puzzle. *Journal of Political Economy Macroeconomics 1*(1), 43–79.

Di Tella, S. (2017). Uncertainty shocks and balance sheet recessions. *Journal of Political Economy 125*(6), 2038–2081.

Galí, J. and M. Gertler (1999). Inflation dynamics: A structural econometric analysis. *Journal of monetary Economics 44*(2), 195–222.

Gambacorta, L. and H. S. Shin (2018). Why bank capital matters for monetary policy. *Journal of Financial Intermediation 35*, 17–29.

Gertler, M. and S. Gilchrist (1994). Monetary policy, business cycles, and the behavior of small manufacturing firms. *The quarterly journal of economics 109*(2), 309–340.

Gilchrist, S. and E. Zakrajšek (2012). Credit spreads and business cycle fluctuations. *American economic review 102*(4), 1692–1720.

Gurkaynak, R. S. (2005). Using federal funds futures contracts for monetary policy analysis.

Gurkaynak, R. S., B. Sack, and E. T. Swanson (2005). Do actions speak louder than words? the response of asset prices to monetary policy actions and statements.

He, Z., B. Kelly, and A. Manela (2017). Intermediary asset pricing: New evidence from many asset classes. *Journal of Financial Economics 126*(1), 1–35.

He, Z. and A. Krishnamurthy (2013). Intermediary asset pricing. *American Economic Review 103*(2), 732–770.

Holmstrom, B. and J. Tirole (1997). Financial intermediation, loanable funds, and the real sector. *the Quarterly Journal of economics 112*(3), 663–691.

Jiménez, G., S. Ongena, J. Peydró, and J. Saurina (2011). The impact of economic and monetary conditions on loan supply: Identifying firm and bank balance-sheet channels. *Banco de España*.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American economic review 95*(1), 161–182.

Kashyap, A. K. and J. C. Stein (2000). What do a million observations on banks say about the transmission of monetary policy? *American Economic Review 90*(3), 407–428.

Kashyap, A. K., J. C. Stein, and D. W. Wilcox (1996). Monetary policy and credit conditions: Evidence from the composition of external finance: Reply. *The American Economic Review 86*(1), 310–314.

Kroner, N. (2021). Firm-level uncertainty and the transmission of forward guidance to investment. *Available at SSRN: https://ssrn.com/abstract=3931591 or http://dx.doi.org/10.2139/ssrn.3931591*.

Kuttner, K. N. (2001). Monetary policy surprises and interest rates: Evidence from the fed funds futures market. *Journal of monetary economics 47*(3), 523–544.

McKay, A., E. Nakamura, and J. Steinsson (2016). The power of forward guidance revisited. *American Economic Review 106*(10), 3133–3158.

Nakamura, E. and J. Steinsson (2018). High-frequency identification of monetary non-neutrality: the information effect. *The Quarterly Journal of Economics 133*(3), 1283–1330.

Orphanides, A. and J. C. Williams (2006). Monetary policy with imperfect knowledge. *Journal of the European Economic Association 4*(2-3), 366–375.

Swanson, E. and V. Jayawickrema (2023). Speeches by the fed chair are more important than fomc announcements: An improved high-frequency measure of us monetary policy shocks. *Unpublished Manuscript*.

Swanson, E. T. (2021). Measuring the effects of federal reserve forward guidance and asset purchases on financial markets. *Journal of Monetary Economics 118*, 32–53.

Van den Heuvel, S. J. et al. (2002). The bank capital channel of monetary policy. *The Wharton School, University of Pennsylvania, mimeo*, 2013–14.