# Bank Credit Supply and the Unemployment Rate*

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**Abstract**

There is a strong negative relationship between US bank credit and the unemployment rate since the mid 1980s. In this paper I ask: *Is there a causal connection between changes in the supply of bank credit and the observed fluctuations of the unemployment rate?* If so, what are the transmission mechanisms governing such a relationship? To answer these questions, I proceed down two paths. First, I use a bank credit supply measure estimated by Bassett et al. (2014) to document the effect that bank credit supply shocks have on the unemployment rate in a VAR model. The results suggest that a one percent contraction in the supply of bank credit leads to a 0.3 percentage point increase in the unemployment rate. Moreover, bank credit supply shocks account for about 30% of the volatility in the unemployment rate. Second, I rationalize these results by incorporating a banking sector into an otherwise standard DSGE model with labour search frictions and nominal rigidities. Unlike standard banking models—which restrict banks to intermediaries of preaccumulated loanable funds—this paper allows banks to finance loans through deposit (i.e., money) creation as described in McLeay et al. (2014) and Bundesbank (2017). Matched firms must obtain a bank loan to purchase their inputs before production. When banks contract credit, there is less funds for firms to purchase their capital and labour inputs and the cost of borrowing rises. This lowers the firms' benefit of matching thereby lowering the benefits of posting a vacancy. As a result, less vacancies are posted and labour market tightness falls. In both empirical and model settings, a contraction in bank credit supply leads to a typical recession: GDP, investment and labour market tightness fall while the cost of external finance and the unemployment rate rise.
*JEL* codes: E32, E51, G21, J64, C11

**Keywords**: financing through money creation, deposit creation, search and matching frictions, unemployment, New Keynesian DSGE model

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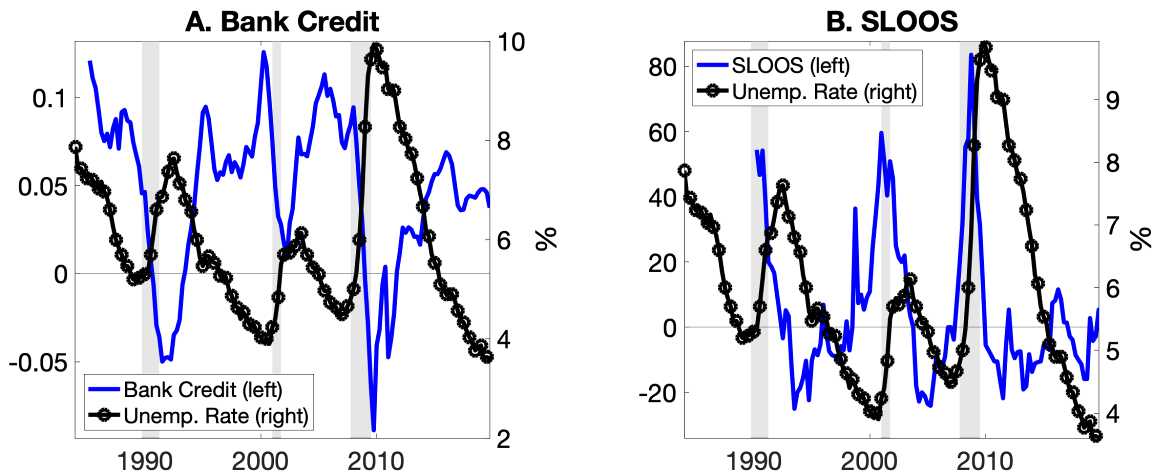


Figure 1: Bank Credit & Unemployment Rate

*Notes*: Shaded bars denote NBER recessions.
*Sources*: Bank for International Settlements; Bureau of Labor Statistics; Federal Reserve Board.

# 1 Introduction

There is a strong negative relationship between US bank credit growth and the unemployment rate.[1,2] Take Figure 1 panel A, for example. Each series exhibits a strong cyclical pattern as recessionary episodes (shaded areas) are associated with contracting credit and a rising unemployment rate. Of course, the cyclicality of bank credit can be driven by changes in either supply or demand—or both. Moreover, in a world with financial frictions—giving rise to an external finance premium—changes in economic uncertainty or risk have been shown to be important determinants of intermediated credit (Gilchrist and Zakrajšek, 2012; Christiano et al., 2014). Bank credit has long been understood to play an important role in the economy over the business cycle (see e.g., Mises (1912) and Fisher (1933)). Recent historical papers find that crises in financial markets can predict and amplify economic downturns (Schularick and Taylor, 2012; Jordà et al., 2013), while others have showed that disruptions to credit market during the Great Depression and Great Recession contributed to the loss of employment (Chodorow-Reich, 2014; Benmelech et al., 2019). When there is an impending recession and growing uncertainty, firms cut investment spending while banks tighten lending standards leading to a reduction in bank intermediated credit. Funds that would of have otherwise

[1] See Keen (2011) for a discussion regarding the relationship between the nominal/financial side and the real/goods side of the economy. Zanetti (2019) also discusses the relationship of firm debt and unemployment over the business cycles.

[2] I use the terms *bank credit* and *bank loans* interchangeably throughout the paper. Also, I use the term *bank* to refer to a deposit taking and loan granting financial institution that has been chartered by state or federal government and holds a reserve account with the Federal Reserve System.

been used to finance firm investment projects, for example, are not brought into circulation when bank lending is halted. This is captured by the senior loan officer opinion survey (SLOOS) in panel B (blue line). A net tightening of bank lending standards (positive value) is associated with recessionary periods and a subsequent rise in the unemployment rate.

This leads me to the question addressed in this paper: *Is there a causal connection between changes in the supply of bank credit and the observed fluctuations of the unemployment rate*? If so, what are the transmission mechanisms governing such a relationship? To answer these questions, I proceed down two paths. First, I conduct an empirical analysis using a measure of US bank lending standards from Bassett et al. (2014) that is derived from bank-level senior loan officer opinion survey responses. The bank lending standards estimate is purged of factors which are known to influence loan demand making it a plausible instrument of exogenous shifts in the bank credit supply curve. This purged lending standards measure in then included in a monetary VAR model to quantify the importance that exogenous changes in the supply of bank credit have on the unemployment rate. Second, to shed light on the transmission mechanism I integrate a banking sector that is consistent with the *financing through money creation* (FMC) view of banks into an otherwise standard labour search-and-matching DSGE model with nominal frictions.[3] Unlike the standard banking models or lender/borrower relationships used in most papers (e.g., Petrosky-Nadeau (2014) and Monacelli et al. (2023)), the FMC view assumes that banks finance their lending activity—in part or in whole—with newly created nominal bank deposits. As a result, if a bank wants to issue a loan to a firm, for example, the bank does not have to wait until a saver deposits a preaccumulated amount of savings with the bank before the bank can issue the loan. Put differently, the bank can adjust its loans by creating additional deposits (i.e., money), thereby expanding the money supply.[4] Modelling banks in this way helps along two important dimensions. First, it allows the banking sector—under nominal rigidities—to be a potential source of economic fluctuations without relying on conventional borrowing or leverage constraints (e.g., Jermann and Quadrini (2012) and Gertler and Karadi (2011)). Second, it makes the banking sector in my model consistent with the description of banks found in central bank publications (e.g., McLeay et al. (2014) and Bundesbank (2017)).

The standard part of the model has labour search and nominal frictions which closely follows Leduc and Liu (2016). Each period there are unemployed workers searching for jobs with firms who have chosen to post a vacancy. A matching technology brings a worker and firm together to create an employment relation that lasts until an exogenous shock destroys the match. The novel part of the model is the banking sector.[5] The banking sector accumulates net worth, offers deposit

[3] I borrow the term *financing through money creation* from Jakab and Kumhof (2019).

[4] Of course, the bank also has the ability to curtail the amount of loans it offers, thereby contracting the amount of deposits (i.e., money) circulating in the economy when existing loans get repaid.

[5] As discussed below, there are two important differences between this model and Leduc and Liu (2016) besides the banking sector. Namely, I add money along with household liquidity preference and capital stock.

services to firms and households and issues loans to matched firms. All loans in the model are to the production sector.[6] In the model I require that intermediate-good firms who have successfully matched with a worker must obtain a bank loan to finance their wage and capital rental bills in advance of production. Each bank loan is financed using three sources of funds: (*i*) newly created bank demand deposits; (*ii*) preaccumulated household savings; and (*iii*) bank net worth. While bank net worth is a state variable and preaccumulated household savings are governed by the household's Euler equation, the main margin of adjustment for bank loans are demand deposits. As a result, I assume the bank is endowed with a proprietary FMC technology that allows it to adjust the level of FMC both endogenously and exogenously.[7] I refer to the exogenous adjustment of FMC as *FMC shocks* and are meant to represent a bank credit supply shifter. FMC shocks can be thought of as changes in the bank's lending preferences based on factors not associated with their liquidity availability. For example, exogenous changes in the bank's economic outlook, future uncertainty or industry competitiveness may be potential factors driving banks to either expand or contract their lending form one period to the next. In the benchmark model, the FMC shock process is treated as an unobservable and is, therefore, inferred by the macroeconomic data used in the Bayesian estimation procedure.

The empirical results suggest that exogenous shifts in bank credit supply account for about 30 percent of the volatility in the unemployment rate. Moreover, following a 1 percent contraction in the supply of bank credit leads to a 0.3 percentage point rise in the unemployment rate. In both the empirical VAR model estimated model, an unexpected contraction in the supply of bank credit leads to a typical recession: GDP, investment and labour market tightness fall while the external finance premium and the unemployment rate rise. According to the model, when the bank unexpectedly contracts the supply of loans, matched firms experience a (*i*) shortage of funds required to purchase their inputs, and (*ii*) a rising cost of external finance. As a result, both the quantity effect (*i*) and price effect (*ii*) reinforce one another resulting in a fall in demand for capital and labour inputs. The lower demand for factor inputs results in lower investment and GDP. Furthermore, firms who are able to attain financing following the credit contraction face higher borrowing costs which reduces the value of being matched with a worker. This leads to firms posting less vacancies and, thereby, reducing labour market tightness.

Since the FMC shock is treaded as an unobservable, there is a possibility the estimated FMC shock may be capturing other sources of variation. To test whether this is the case, I perform two

[6] While a nontrivial amount of US commercial bank lending is to households in the form of consumer loans and residential mortgages, I assume there are no loans in the household sector. In the context of this paper, I believe this assumption to be warranted since it has been shown empirically that investment and corporate debt play a particularly important role in the transmission of financial frictions and credit disruptions over the business cycle (Etoundi Atenga et al., 2021; Ivashina et al., 2024).

[7] The FMC technology used in this paper is a simplified version of that introduced in Langlais (2023a).

tests. First, I perform an out-of-sample test which compares the bank credit supply shock estimated in Bassett et al. (2014) with that estimated from the model. find that the model estimated FMC shock does a reasonably well job at capturing movements in the supply of bank credit especially in the period surrounding the 2007-09 financial crises. For the second test, I employ an alternative identification method to estimate the model implied FMC shock. Compared to the benchmark FMC shock estimate, the alternative estimate is measured directly from bank balance sheet data. The results suggest the FMC shock played a crucial role during the 2007-09 financial crises, but not during other periods.

The remainder of the paper is organized as follows. Section 2 provides a literature review. Section 3 describes the empirical bank credit supply shock used in the VAR model and analyzes the macroeconomic effects a bank credit supply shock has on the unemployment rate. Section 4 presents the DSGE model and performs equilibrium analyses. Section 5 describes the estimation procedure and presents the quantitative model results. Section 6 performs various out-of-sample tests. Section 7 concludes the paper.

# 2 Related Literature

This paper sits at the intersection of two large bodies of literature: macro-finance literature and the labour search-and-matching literature.

The macro-finance literature can be traced back to Carlstrom and Fuerst (1997) and Bernanke et al. (1999) which focused on information asymmetries in the lender-borrower relationship. Like my paper, these papers give rise to a financial friction embedded in the cost of external finance. There are, however, three key distinctions between my paper and traditional macro-finance literature. First, in my paper the financial frictions are not a result of agency costs between the lenders and borrowers: there are no information asymmetries between lenders and borrowers in my model as all loans are risk-less intraperiod working capital loans. Second, my paper does not rely on collateral or leverage constraints—as in Kiyotaki and Moore (1997), Gertler and Karadi (2011) and Jermann and Quadrini (2012)—in order for the financial sector to contribute to aggregate fluctuations in real variables. Instead, the financial frictions in my model endogenously arise from the bank's optimality condition and lending technology. Third, unlike the early macro-finance literature which focus on the propagation and amplification mechanisms of shocks originating outside the financial sector—such as monetary policy or various productivity shocks—the financial sector in my paper is also a potential source of volatility—via the FMC shock.

This is not the first paper in which shocks originating in the lender/borrower relationship can play a role in generating economic fluctuations.[8] For example, Jermann and Quadrini (2012) incorporate

[8] I refrain form using the term *financial sector* when describing the lender/borrower relationships in these papers

a Kiyotaki and Moore (1997)-style collateral constraint subject to shocks on firm debt finance. They call these financial shocks. Like my paper, they find that financial shocks are not only important at explaining financial flows but also real variables, especially employment.[9] Extending the Bernanke et al. (1999) financial accelerator framework with nominal frictions, Christiano et al. (2003) and Nolan and Thoenissen (2009) estimate various structural shocks and find that shocks to a borrower's net worth are an important source of volatility in the US economy. Goodfriend and McCallum (2007) and Jakab and Kumhof (2019) each develop a banking sector which is a potential source of volatility. Goodfriend and McCallum (2007), however, focus on monetary policy transmission in the presence of an optimizing bank with various interest rates. Moreover, the banking sector developed in their paper differs from that presented in this paper in four important ways. First, the bank's deposit creation technologies are fundamentally different. Their bank produces loans based on labour effort and collateral values whereas the bank's FMC technology in my paper depends on the bank's liquidity holdings and an exogenous supply shifter. Second, the type of bank loans offered are different. Their bank loans are for consumption expenditures, while the bank loans in this paper are working capital loans on the production side of the economy. Third, there bank does not accumulate new worth. And fourth, my paper estimates bank loan supply shocks. Jakab and Kumhof (2019), like this paper, focus on the macroeconomic effects of FMC shocks. They find that FMC shocks can have a sizeable effect on the economy. Unlike this paper, however, Jakab and Kumhof (2019) do not explicitly model the unemployment rate or various other labour market variables. Additionally, their FMC technology is black-boxed and their model is not estimated.

The macroeconomic labour search-and-matching literature goes back to Pissarides (1987) and Mortensen and Pissarides (1994). These papers attempt to explain the observed cyclical variation of labour market variables. For example, Leduc and Liu (2020) introduce time varying search and recruiting intensities to improves the model fit, while Tsasa (2022) introduces nonlinear production function with capital and finds that it reduces the model's ability to match labour market volatility. Taking a different approach, Petrosky-Nadeau (2014) assumed that unmatched vacant firms must obtain external finance to fund their cost of posting a vacancy. As in Bernanke et al. (1999), Petrosky-Nadeau (2014) assume agency costs between lenders and borrowers giving rise to financial frictions in credit markets. These financial frictions allow for higher persistence in labour marker variables leading to a better empirical fit relative to the standard search-and-matching model of unemployment. Using a New Keynesian framework with labour search-and-matching frictions,

since many of them omit banks or intermediaries entirely and focus on direct finance between savers and borrowers. Moreover, most of the literature also omit money and therefore commercial banks. Since a crucial role of banks is the production of money—i.e., deposits—when issuing loans.

[9] It is worth mentioning, however, Pfeifer (2016) reestimates Jermann and Quadrini (2012)'s model correcting capital stock timing—among other modelling issues—and finds that shocks to the marginal efficiency of investment displace financial shocks as the dominant source of volatility among real variables.

Gertler et al. (2008) and Christiano et al. (2016) introduce a novel wage setting condition showing that it can also improve the model's fit of business cycle dynamics.

My paper is closely related to Mumtaz and Zanetti (2016), Zanetti (2019) and Monacelli et al. (2023) who also study financial disruptions in a model with labour search frictions. Adding a labour search and matching block to the model proposed in Jermann and Quadrini (2012), Zanetti (2019) find that financial shocks have sizeable effects on financial variables and wages, and that job destruction shocks play an important role in describing unemployment rate fluctuations. On the other hand, Monacelli et al. (2023) impose an endogenous borrowing constraint on firms and study the implications of the wage bargaining channel on employment. Like my paper, these papers also allow for disturbances within the financial sector to potentially affect real variables such as employment. However, my paper differs from theirs in an important way. My paper explicitly model's the banking sector that is consistent with McLeay et al. (2014) and Bundesbank (2017) descriptions of banks leading to a financial friction originating from the bank's proprietary FMC technology. In this way, the mechanism linking bank credit supply to the external finance premium is similar to that in Langlais (2023a). As a result, nominal bank deposits and the loan interest rate play a critical role in the transmission mechanism between the disturbances in the banking sector and the real economy.

My paper is also related to Wasmer and Weil (2004) and Petrosky-Nadeau and Wasmer (2013). These papers impose search frictions on both labour and credit markets leading to a financial accelerator mechanism capable of amplifying shocks much like the standards financial accelerator models of Carlstrom and Fuerst (1997) and Bernanke et al. (1999). Unlike my paper, however, the focus of these papers is on improving the fit of search-and-matching models when financial frictions are added.

Empirical papers who have studied the role of bank credit and labour market outcomes is vast. For example, studying the effects of credit contractions on 20 OECD countries, Borsi (2018) finds that periods of credit contractions are associated with a 1 percentage point rise in the general unemployment rate while the effect on youth unemployment rate is 2.4 percentage points. From the perspective of credit expansions, Acosta and Cortés (2022), using Mexican firm-bank level data, find that a one standard deviation in the issuance of bank loans to firms leads to a 2.6% increase in firm's employment. Similarly, Jeong (2023) studies the role of government programs aimed at improving access to credit for small business owners in disadvantaged communities, and finds that better access to credit increases firm employment. Chodorow-Reich (2014) finds that the credit supply channel explains one-third to one-half of the employment decline in small and medium sized firms during the Great Recession. Using bank-firm Spanish data, Alfaro et al. (2021) find that bank credit supply shocks have sizeable propagation effects, especially during the financial crises, on employment, investment, and output.

# 3 Empirical Evidence

## 3.1 Bank Credit Supply Shock

Obtaining an exogenous bank credit supply shifter requires finding a source—or sources—of variation that banks respond to when deciding to issue loans, and that this source of variation does not simultaneously influence loan demand. As a consequence, estimating a bank credit supply shock can be challenging. Fortunately, there exists a bank credit supply measure for the US economy. Bassett et al. (2014) (BCDZ henceforth) derived a measure of bank credit supply from US commercial bank Senior Loan Officer Opinion Survey (SLOOS) data. Banks who participate in the SLOOS are asked to report if they have changed their lending standards—such as collateral requirements, risk tolerance etc.—of various types of loans from the previous period. Importantly, the SLOOS asks about the direction of changes in lending standards—e.g., BCDZ group responses in one of three groups: eased, tightened or remained unchanged—and not the magnitude of change. The result is a *qualitative* measure of bank credit supply as opposed to a *quantitative* measure. Additionally, the SLOOS also asks banks about any change in demand for various types of their loans. BCDZ construct their bank credit supply shock by purging the bank-level lending officer survey responses of macroeconomic, projection/outlook, and banking sector factors believed to influence loan demand. An asset-weighted aggregated measure of their series is publicly available on the Federal Reserve's website.[10] I refer to this bank credit supply shock series as the *BCDZ shock*.

Figure 2 panel A plots the BCDZ shock spanning the period 1991:Q4–2012:Q3. By construction, a positive (negative) value denotes a tightening (easing) of lending standards indicative of a contraction (expansion) in bank credit supply. Generally speaking, the raw series exhibits very little autocorrelation; notwithstanding, just prior to the 2001 and 2007-09 recessionary episodes the BCDZ series predicts three and six periods, respectively, of sustained tightening of lending standards. This cyclical pattern is further revealed when the cumulative sum of the raw BCDZ shock is plotted against the unemployment rate (panel B). A strong positive relationship reveals itself suggesting exogenous shifts in the bank credit supply curve may potentially contain information regarding employment dynamics. This is particularly true surrounding the 2007-09 financial crises. The boom period between 2003 through 2006 was characterized by easing credit conditions and a falling unemployment rate. By 2007, however, the boom quickly reversed when banks began to contract credit by tightening lending standards leading to a rise in the unemployment rate shortly

[10] For further information regarding the BCDZ shock series, see https://doi.org/10.1016/j.jmoneco.2013.12.005; whereas the data files can be found here: https://www.federalreserve.gov/econres/feds/changes-in-bank-lending-standards-and-the-macroeconomy.htm. For further information regarding the SLOOS, see https://www.federalreserve.gov/data/sloos.htm.

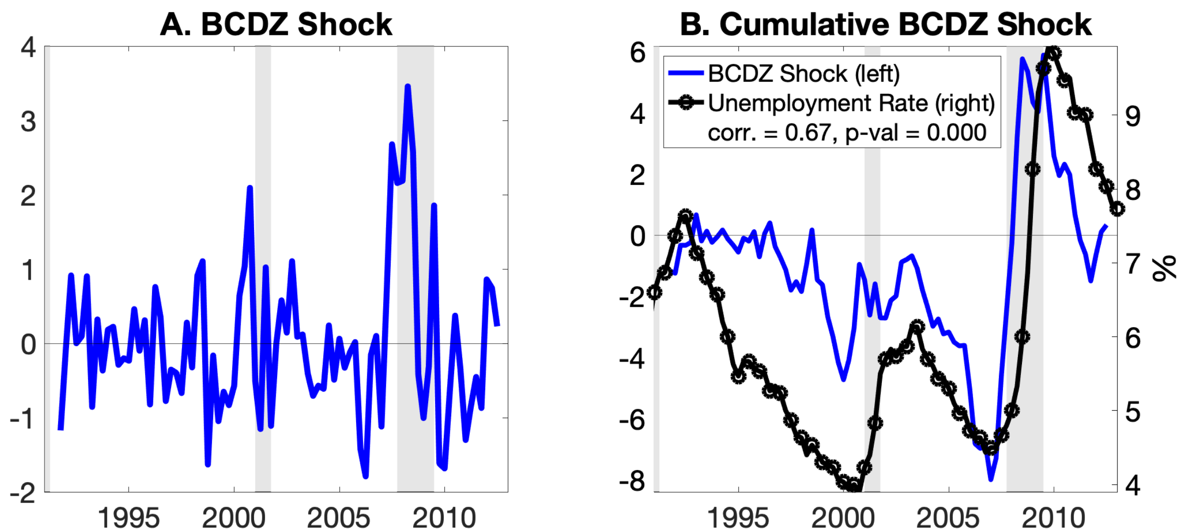


Figure 2: BCDZ Bank Credit Supply Shock

*Notes*: Shaded bars denote NBER recessions.
*Source*: Bassett et al. (2014); Bureau of Labor Statistics; authors calculation.

thereafter.

Next, I use a monetary VAR model to explore the empirical significance of the relationship between the unemployment rate and bank credit supply.

## 3.2 VAR Model

In this subsection I estimate the empirical significance that bank credit supply shocks have on the unemployment rate using a monetary VAR model. The VAR model consists of six endogenous variables and the BCDZ shock. The endogenous variables (in order) are log real GDP, unemployment rate, log bank credit capacity, log GDP deflator, credit spread and the federal funds rate. Bank credit capacity is the sum of total bank loans and unused credit commitments. The measure of credit spread used is the 'GZ' spread.[11] I include the 'GZ' spread to capture potential financial shocks originating outside of the banking system while the federal funds rate controls for the stance of monetary policy. As discussed in Bassett et al. (2014), since the BCDZ shock has been purged of macroeconomic and loan demand side factors, the endogenous variables should not have any influence on the BCDZ shock through loan demand. As a result, I order the BCDZ shock first in the VAR model. Under this identification scheme the bank credit supply shock can potentially influence the remaining six variables within one quarter.

The VAR model is estimated using standard OLS techniques with four lags and a quadratic

[11] See Table 8 of the Appendix for a complete description of the data and sources.

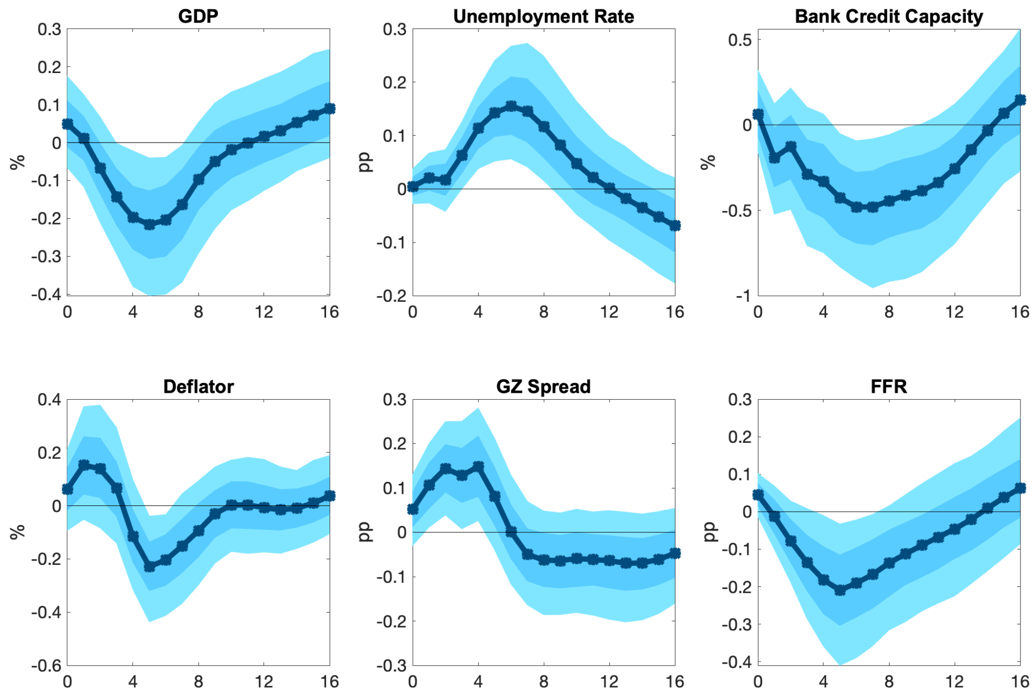


Figure 3: Impulse Responses to Contractionary BCDZ Shock

*Notes*: Light shaded and dark shaded areas denote 95% and 68% confidence intervals, respectively. Confidence intervals are computed using 1000 bootstrap draws. See text for further details.

time trend.[12] Sample data is quarterly and spans the period 1991:Q4–2012:Q3. Figure 3 display the impulse responses of the endogenous variables due to a one standard deviation increase in the BCDZ shock. Following the bank credit supply shock—corresponding to an unexpected contraction in the supply of bank credit—the economy experiences an economic contraction consistent with the recession phase of the business cycle. Notwithstanding, the economy responds very little upon impact. Only after about one-year following the shock does the economy begin contracting. By the two-year mark the capacity of bank credit (panel C) contracts by 0.5% and the unemployment rate (left column) rises about 0.15 percentage points. The delayed response to the tightening of bank lending standards has been documented in previous literature. For example, Gilchrist and Zakrajšek (2012) find that precommitted lines of credit, which are held off-balance sheet, play an important role in credit markets over the business cycle. When banks begin tightening lending standards, credit constrained firms and households begin to draw down credit lines which may lead to a temporary stagnation—or potential rise—in bank credit before beginning to contract.[13]

While Figure 3 suggests bank credit supply shocks can affect the unemployment rate in the

[12] Lag length was selected based on AIC criteria.

[13] This is apparent when comparing bank credit growth (blue line) in Figure 1 panel A and the SLOOS (blue line) in Figure 1 panel B. Bank credit growth begins to contract only after banks begin tightening lending standards.

Table 1: VAR Variance Decompositions

| horizon | GDP | Unemp. Rate | Bank Credit Capacity | Deflator | GZ Spread | Federal Funds Rate |
|---|---|---|---|---|---|---|
| $h = 4$ | 12 | 10 | 10 | 11 | 21 | 12 |
| | [2–32] | [1–32] | [1–30] | [1–32] | [5–43] | [2–33] |
| $h = 8$ | 24 | 33 | 22 | 20 | 22 | 24 |
| | [4–52] | [7–60] | [4–46] | [5–41] | [7–43] | [3–52] |
| $h = 16$ | 22 | 28 | 24 | 18 | 21 | 21 |
| | [5–49] | [6–57] | [5–49] | [6–38] | [6–43] | [4–47] |
| $h = 32$ | 22 | 26 | 22 | 18 | 20 | 22 |
| | [5–48] | [6–54] | [6–47] | [6–36] | [6–42] | [4–47] |

*Notes*: Each cell entry denotes the percentage contribution attributed to the bank credit supply shock in explaining the volatility of the column variable at horizon $h$. Entries in square brackets denote the 95% confidence interval based on 1000 bootstrap draws.

predicted manner, it does not quantify the bank credit supply shock's relative importance of generating the observed volatility of the unemployment rate. Table 1 shows the variance decomposition performed on the same VAR model. Each cell entry denotes the percent contribution of the BCDZ shock at generating the variation of the endogenous variables. Numbers in square brackets denotes 95 percent confidence intervals. Consistent with the impulse response results, at short horizon (four quarters) the BCDZ shock plays a limited role in generating economic volatility; however, around the two-year horizon, the BCDZ shock accounts for 33 and 24 percent of the volatility in the unemployment rate and GDP, respectively. Moreover, the BCDZ shock can explain at least 20 percent of the volatility of the remaining endogenous variables at the same horizon.

How do bank credit supply shocks affect the historical unemployment rate over the business cycle? Consider the historical decomposition results shown in Figure 4. The solid black line represents the deviation of the unemployment rate from its trend. The blue shaded area denotes the deviations of the unemployment driven by the BCDZ shock only. Not only does the BCDZ shock play an important role at generating the cyclical pattern observed in the data—i.e., the blue area and black line are positively correlated—the BCDZ shock played a particularly important role during the 2001 and 2007-09 recessionary episodes.

**Robustness Test:** To test whether the BCDZ shock accurately captures exogenous variation in the bank credit supply curve, I estimate an alternative bank credit supply shock using a Bayesian VAR model with sigh restrictions. The details of the estimation procedure are available in the online Appendix. After performing identical analysis with the alternative bank credit supply measure, I find that the results are remarkably similar to those presented above—especially during the period around the financial crises.

Overall, these results suggest that bank credit supply shocks are an important determinant of

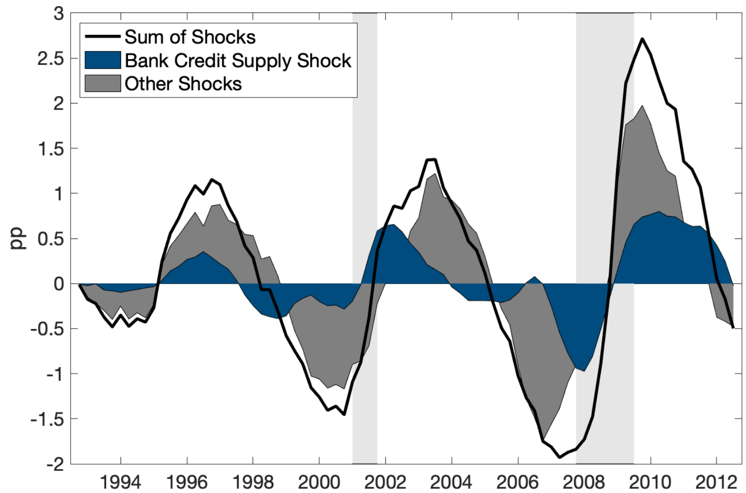


Figure 4: Historical Decomposition of the Unemployment Rate

*Notes*: Shaded bars denote NBER recessions. See text for further details.

the unemployment rate and, more broadly, a driver of economic volatility in the recent past. Next I build a model to rationalize these empirical results.

# 4 Model

In this section I derive a discrete time infinite horizon DSGE model economy which rationalizes the empirical findings outlined above: that a bank credit supply shocks play an important role in describing the observed comovement between outstanding bank credit and the unemployment rate. Three critical ingredients in the model are (*i*) labour market search frictions, (*ii*) nominal rigidities in the form of sticky prices, and (*iii*) that the banking sector is consistent with the FMC view. Since the money supply and bank credit in the model are treated as nominal variables, these assumptions allow bank credit supply shocks to potentially contribute to the short-term volatility of the unemployment rate over the business cycle.

The model closely follows Leduc and Liu (2016). Different than Leduc and Liu (2016), however, this paper includes capital accumulation, money, and a banking sector. There are five main sectors of the economy: household, a production, banking, a government, and a monetary authority. The household sector consists of a continuum of infinitely lived and identical households with unit measure. The representative household consists of a continuum of worker members who, at any moment, are either employed or unemployed. The household accumulates the currency and capital stock, and owns each firm and the representative bank. The production sector consists of three types of firms: a continuum of intermediate-good firms, a continuum of monopolistically competitive retail firms, and a representative final-goods firm. Each intermediate-good firm uses one worker and some capital to produce a homogenous intermediate good. Each retail sector firm then uses intermediate goods to produce a differentiated output good which it sells to the final-goods firm. The final-goods firm combines all the differentiated goods into a final good that can be consumed, invested in the capital stock, used up for capital utilization or used up when posting a vacancy.

In each period, the share of workers who are unemployed must search for jobs with the intermediate-good firms who have posted a vacancy. Moreover, each time an intermediate-good firms posts a vacancy they incur a fixed cost. Successful matches are produced with a matching technology that transforms searching workers and vacancies into an employment relation. Following a successful match, the intermediate-good firm then rent some capital from the household. Wages are determined by Nash bargaining between a searching worker and a hiring firm, while the capital rental rate is determined in a competitive capital market.

## 4.1 Bank & Money Supply

The banking sector in this paper is a modified version of that developed in Langlais (2023a) and is composed of a representative bank that is risk neutral and accumulates net worth. At the beginning of period $t$ the bank has net worth ($NetWorth_t$) in money units. The bank offers two types of deposit services to agents in the economy—demand deposits and savings deposits—and extends loans to intermediate-good firms. The bank is situated in a fractional reserve system and is licensed by the monetary authority to operate a proprietary *financing through money creation* (FMC) technology. The FMC license allows the bank's short-term liabilities—i.e., demand deposits—to trade on par with the government issued currency. In other words, the FMC technology gives the bank the ability to create part of the economy's money supply through the bank's issuance of new demand deposits. As a result, the economy's agents view demand deposits as money and use it—along with currency in circulation—for transaction purposes and settlement of any outstanding debt. The savings deposits, however, are non-transaction deposits. Thus, the supply of money is comprised of currency in circulation, $M_t$, and total bank demand deposits.

At the beginning of each period the household deposits a share of their currency holdings with the bank. In return for the currency, the bank issues the household savings deposit, $D_t^s$. Of which, the bank is required by the monetary authority to hold fraction $\rho^s \in [0,1]$ of these savings deposits as reserves.[14] As a result, total currency in circulation just before the period $t$ production cycle is

$$M_t = M_t^{\text{base}} - D_t^s, \tag{1}$$

[14] Since I do not explicitly model the monetary authority's balance sheet, the bank does not have deposit—i.e., reserve accounts—with the monetary authority. As a consequence, all *reserves* consist of money base held by the bank—i.e., currency not in circulation.

where $M_t^{\text{base}}$ is the total currency base held by the household entering period $t$. Towards the end of the production cycle, however, the monetary authority injects or removes $X_t \in [-M_t^{\text{base}}, \infty)$ units of currency from the economy. As a result, towards the end of the period total currency in circulation is $M_t + X_t$, and total currency entering period $t+1$ is $M_{t+1}^{\text{base}} = M_t^{\text{base}} + X_t$.

Each intermediate-good firm $i$ who has successfully matched with a worker is required to pay their labour and capital rental bills in advance of production.[15] As a result, each operating firm must obtain a loan from the bank that is financed by three different sources of funds: newly created demand deposits, preaccumulated household savings, and bank net worth. While the bank does not directly lend out currency from its reserves—and there is no incentive for agents to withdraw their demand deposits as currency—part of the demand deposits are backed by the household's currency deposits. As a result, the portion of firm $i$'s bank loan financed by demand deposits is denoted $D_{it}^d$ and in aggregate is determined by the bank's FMC technology. Namely, total demand deposits used to finance loans to matched firms are

$$\int_{i \in \mathscr{M}_t} D_{it}^d \mathrm{d}i = \underbrace{\zeta_{bt} \times E_t}_{\text{FMC}} + \underbrace{E_t}_{\text{backed by currency deposits}}, \tag{2}$$

where $\zeta_{bt}$ denotes the FMC shock which follows a stationary AR(1) process and $E_t$ denotes the bank's excess reserves holdings. The term $\mathscr{M}_t$ denotes the set of matched firms during the period $t$ production cycle. Moreover, like the savings deposits, the monetary authority requires the bank to hold a minimum amount of reserves equal to fraction $\rho^d \in [0,1]$ total demand deposits. Unlike savings deposits, however, the FMC technology allows the bank to choose its desired demand deposit reserve ratio, denoted $\tilde{\rho}_t^d$, so long as $\tilde{\rho}_t^d \geq \rho^d$. The term $\zeta_{bt}$ in equation 2 represents an exogenous bank credit supply shifter meant to capture shifts driven by factors not related to liquidity—i.e., excess reserve—position.

The bank's balance sheet immediately following the issuing of loans, and before the end of the period $t$ production cycle, is shown in Table 2.

Table 2: Bank Balance Sheet Prior to Production

| Assets | Liabilities |
|---|---|
| loans: $\int_{i \in \mathscr{M}} D_{it}^d \mathrm{d}i + NetWorth_t$ | deposits: $D_t^s + \int_{i \in \mathscr{M}} D_{it}^d \mathrm{d}i$ |
| reserves: $\rho^s D_t^s + \tilde{\rho}_t^d \int_{i \in \mathscr{M}} D_{it}^d \mathrm{d}i$ | $NetWorth_t$ |

Using the balance sheet identity, it is straight forward to show that total reserves are equal to total savings deposits, $D_t^s$, and given the bank can choose its desired demand deposit reserve

[15] Unlike Christiano et al. (2010), I assume, that each firm must finance 100% of their variable costs with a bank loan instead of 75%—in the US case—or 92%—in the EU case—proposed by Christiano et al. (2010).

ratio—insofar as it chooses a ratio above the minimum required—it holds an amount of excess reserves, $E_t \geq 0$. Formally,

$$\underbrace{D_t^s}_{\text{total reserves}} = \underbrace{\rho^s D_t^s + \rho^d \int_{i\in\mathcal{M}_t} D_{it}^d \mathrm{d}i}_{\text{required reserves}} + \underbrace{E_t}_{\text{excess reserves}},$$

where excess reserves can be written as

$$E_t = (1-\rho^s)D_t^s - \rho^d \int_{i\in\mathcal{M}_t} D_{it}^d \mathrm{d}i, \tag{3}$$

where the first term on the right-hand-side denotes total savings deposits available to be lent and the second term denotes the (minus) total required reserves of the deposits created by the bank's FMC technology.

Proposition 4.1 shows that the bank's time varying desired reserve ratio is inversely related to the FMC shock.

**Proposition 4.1** *The bank's desired demand deposit reserve ratio, $\tilde{\rho}_t^d$, can be written as*

$$\tilde{\rho}_t^d = \frac{1}{1+\zeta_{bt}} + \rho^d. \tag{4}$$

This result shows the link within the banking sector between FMC and its desired amount of liquidity holdings. As banks curtail lending, less deposits are created to finance loans implying a higher desired reserve ratio. Not only does this mechanism determine the quantity of deposits available to finance loans to firms, as shown below, this mechanism is crucial for understanding the dynamics of credit spreads—i.e., the cost of external finance. The bank's *money multiplier* is shown in Corollary 4.1.1.

**Corollary 4.1.1** *The bank's money multiplier—i.e., the ratio of total demand deposits to savings deposits—is found as*

$$\frac{1-\rho^s}{\tilde{\rho}_t^d}. \tag{5}$$

I leave the proofs in the Appendix.

Following the period $t$ production cycle settlement of all contracts occurs. The bank's balance sheet a moment after the production cycle, but just before the end of the period, is displayed in Table 3.

Table 3: Bank Balance Sheet Following Production

| Assets | Liabilities |
|---|---|
| loans: $(1+R_t^l)\left[\int_{i\in\mathscr{M}} D_{it}^d \mathrm{d}i + NetWorth_t\right]$ | deposits: $(1+R_t^s)D_t^s + (1+R_t^d)\int_{i\in\mathscr{M}} D_{it}^d \mathrm{d}i$ |
| reserves: $\rho^s D_t^s + \tilde{\rho}_t^d \int_{i\in\mathscr{M}} D_{it}^d \mathrm{d}i$ | $NetWorth_t + \Pi_t^b$ |

Interest rates $R_t^l$, $R_t^s$, and $R_t^d$ denote the net nominal interest rate on loans, savings deposits and demand deposits, respectively. The variable $\Pi_t^b$ denotes the bank's net profits:

$$\Pi_t^b = (1+R_t^l)\left[\int\limits_{i\in\mathscr{M}_t} D_{it}^d \mathrm{d}i + NetWorth_t\right] + \rho^s D_t^s + \rho_t^d \int\limits_{i\in\mathscr{M}_t} D_{it}^d \mathrm{d}i$$
$$- (1+R_t^s)D_t^s - (1+R_t^d)\int\limits_{i\in\mathscr{M}_t} D_{it}^d \mathrm{d}i - NetWorth_t. \quad (6)$$

Optimal behaviour of the bank requires choosing $\{\{D_{it}\}_{i\in\mathscr{M}_t}, E_t, D_t^s\}$ to maximize profits (6) subject to the FMC technology (2) and excess reserves (3). When the bank is behaving optimally, the credit spread—denoted $R_t^l - R_t^d$—is shown in proposition 4.2

**Proposition 4.2** *The bank's optimality conditions yield the interest rate spread between the loan rate, $R_t^l$, and demand deposit rate, $R_t^d$:*

$$R_t^l - R_t^d = \frac{\tilde{\rho}_t^d}{1-\rho^s} R_t^s.$$

I leave its proof in the Appendix. Proposition 4.2 shows the crucial pricing link between the bank's desired reserve ratio, $\tilde{\rho}_t^d$, and the firms' cost of borrowing, $R_t^l$. As discussed below, this is a key transmission mechanism in the model linking the dynamics between the (nominal) banking sector and the firms' demand for capital and labour, and therefore, the economy's unemployment rate. Since the demand deposit rate is governed by the monetary authority and the savings deposit rate governs the household's intertemporal consumption-savings choice (see below), when the bank contracts loans and increases it desired reserve ratio, the main margin of adjustment is the loan interest rate.

After the production cycle and towards the end of the period, the bank pays a share $\tau \in (0,1)$ of gross profits as a dividend payment to the household. After which, the bank then receives lump-sum banking fees, $P_t\phi^b$, from the household where $P_t$ denotes the money price of the final good and $\phi^b > 0$ denotes an amount of final goods. As a result, the bank's net worth evolves according to

$$NetWorth_{t+1} = (1-\tau)\left\{\Pi_t^b + NetWorth_t\right\} + P_t\phi^b,$$

where the first term denotes the remaining share of gross profits—apart from fees—retained by the bank.

## 4.2 Households

The representative household owns and accumulates the economy's aggregate raw capital stock, $K_t$, and aggregate currency, $M_t^{\text{base}}$. After observing period $t$ state, the household chooses the capital utilization rate, $\varkappa_t$, which turns $K_t$ units of raw capital into $\varkappa_t K_t$ units of capital services. Capital services are rented to intermediate-good firms in a competitive market. The household receives utility from consumption of the final output good, $C_t$, but receives disutility proportional to the share of members who work, $n_t$. As a result, share $1-n_t$ of members are unemployed. To motivate public holdings of money, additional utility is gained by holding real currency value, $M_t/P_t$, during period $t$ production cycle. The representative household's preferences are as follows:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left\{ \log(C_t - hC_{t-1}) - \psi_L n_t + \overbrace{\mathscr{V}\left(\frac{M_t}{P_t}\right)}^{\text{real currency holding preference}} \right\}, \tag{7}$$

where $\beta \in (0,1)$ denotes the household's subjective discount factor, $h \in (0,1)$ measures consumption habit persistence, and $\psi_L > 0$ denotes the disutility weight on employment. The function $\mathscr{V}(\cdot)$ is increasing in its argument and governs the preference of liquidity holdings of currency.

The household receives income from labour services, $W_t n_t$, and capital rental services, $P_t r_t^k \varkappa_t K_t$, where $W_t$ and $r_t^k$ denote the nominal wage rate and real capital rental rate, respectively. Additionally, the household receives unemployment benefit income, $P_t \mathscr{B}(1-n_t)$, deposit income on previous period's savings deposits, $(1+R_{t-1}^s)D_{t-1}^s$, as well as currency injection from the monetary authority, $X_t$. The term $\mathscr{B} > 0$ denotes an amount of final goods.

Following Christiano et al. (2010), I assume the currency injection is received by the household after period $t$ deposit decisions are made. Different than the literature, however, I assume the that income generated by savings deposits are only available for use in the next period.[16] The household uses income and currency holdings to purchase consumption goods, $P_t C_t$, investment goods, $P_t I_t$, pay for capital utilization cost $P_t a(\varkappa_t)$, and to accumulate next period's currency, $M_{t+1}^{\text{base}}$. As a result, the household's asset accumulation equation looks like,

$$\begin{aligned} M_{t+1}^{\text{base}} \leq\ & W_t n_t + [\varkappa_t r_t^k - a(\varkappa_t)] P_t K_t + P_t \mathscr{B}(1-n_t) \\ & + (1+R_{t-1}^s) D_{t-1}^s + M_t + X_t + \text{Lump}_t - P_t C_t - P_t I_t, \end{aligned} \tag{8}$$

[16]This distinguishes savings deposits from demand deposits which is important for the bank's FMC abilities, and, importantly, is a technical assumption needed to ensure a model solution given the values of calibrated parameters discussed below.

where $\text{Lump}_t$ denotes lump-sum transfers which is composed of bank profits and firm profits, as well as taxes/subsidies. The function $a(\varkappa_t)$ captures the convex capital utilization cost in terms of final goods. The aggregate capital stock evolves according to

$$K_{t+1} = (1-\Delta)K_t + \left[1 - S(\frac{I_t}{I_{t-1}})\right] I_t, \tag{9}$$

where $\Delta \in (0,1)$ denotes the depreciation rate of capital and $S(\cdot)$ is a convex function representing capital installation costs in real terms.

Each period the household chooses a bundle $\{C_t, M_{t+1}^{\text{base}}, D_t^s, K_{t+1}, I_t, M_t, \varkappa_t\}$ that maximizes lifetime utility (7) subject to the currency constraint (1), asset accumulation (8) and law of motion of capital (9). The household's formal optimization problem is in the Appendix.

Next I describe the production sector of the economy.

## 4.3 Aggregation Sector

At each time $t$ a composite final good, $Y_t$, is produced by a perfectly competitive representative firm. The firm produces the composite good by combining a continuum of retail goods, indexed by $j \in (0,1)$, using technology

$$Y_t = \left[\int_0^1 Y_{jt}^{\frac{1}{\lambda_f}} \mathrm{d}j\right]^{\lambda_f}, \quad 1 \leq \lambda_f < \infty, \tag{10}$$

where $Y_{jt}$ denotes the time $t$ output of retail-good firm $j$. The parameter $\lambda_f$ governs the degree of price mark-up over marginal cost for retail-good firms. As a result of profit maximization, the demand for retail good $j$ is

$$Y_{jt} = Y_t \left(\frac{P_{jt}}{P_t}\right)^{\frac{\lambda_f}{1-\lambda_f}}, \tag{11}$$

where $P_{jt}$ is the per unit money prices of retail good $j$. Integrating 11 and imposing 10 yields a relationship between the final good's price and retail good prices:

$$P_t = \left[\int_0^1 P_{jt}^{\frac{1}{1-\lambda_f}} \mathrm{d}j\right]^{1-\lambda_f}. \tag{12}$$

## 4.4 Retail Goods Firms

There is a continuum of retail good firms who each make differentiated retail good $Y_{jt}$ with linear production technology

$$Y_{jt} = \chi_{jt}, \tag{13}$$

where $\chi_{jt}$ is the input of intermediate good used by retail firm $j$. While the retail goods firms are price takers in the input market, they are monopolistic competitors in the product markets. As a result, retail goods firms set prices for their products, taking as given the demand schedule 11 and the price index 12.

As in Rotemberg (1982), I assume that each firm $j$'s price is subject to quadratic adjustment costs and is proportional to nominal GDP:

$$\frac{\xi_p}{2}\left(\frac{P_{jt}}{P_{jt-1}} - \pi\right)^2 P_t Y_t,$$

where the parameter $\xi_p \geq 0$ governs the cost of adjusting prices in period $t$ and $\pi$ denotes the steady-state inflation rate, where $\pi_t = P_t/P_{t-1}$. As a result, retail firm $j$'s nominal profits can be written as

$$\begin{aligned} \Pi^f_{jt} &= P_{jt}Y_{jt} - Q_t\chi_{jt} - \frac{\xi_p}{2}\left(\frac{P_{jt}}{P_{jt-1}} - \pi\right)^2 P_t Y_t, \\ &= \left(P_{jt} - Q_t\right)\underbrace{Y_t\left(\frac{P_{jt}}{P_t}\right)^{\frac{\lambda_f}{1-\lambda_f}}}_{=\chi_{jt}} - \frac{\xi_p}{2}\left(\frac{P_{jt}}{P_{jt-1}} - \pi\right)^2 P_t Y_t, \end{aligned} \tag{14}$$

where $Q_t$ denotes the competitive price of the intermediate good. To arrive at equation 14 I substitute out $\chi_{jt}$ using 13 and impose retail firm $j$'s output demand 11. Thus, in each period $t$ retail firm $j$ chooses $P_{jt}$ to maximize expected real lifetime profits:

$$\mathbb{E}_t \sum_{s=0}^{\infty} \beta^s \frac{\lambda_{1,t+s}}{\lambda_{1,t}} \frac{\Pi^f_{jt+s}}{P_{t+s}},$$

subject to 14, where $\beta^s \frac{\lambda_{1,t+s}}{\lambda_{1,t}}$ denotes the household's stochastic discount factor. In a symmetric equilibrium, $P_{jt} = P_t \; \forall j$, and the optimality condition is

$$q_t = \frac{1}{\lambda_f} + \xi_p \frac{\lambda_f - 1}{\lambda_f}\left[\pi_t(\pi_t - \pi) - \beta\mathbb{E}_t\left\{\frac{\lambda_{1,t+1}}{\lambda_{1,t}}\frac{Y_{t+1}}{Y_t}\pi_{t+1}(\pi_{t+1} - \pi)\right\}\right] \tag{15}$$

where $q_t = Q_t/P_t$ and denotes the real marginal cost. Under no price adjustment cost, i.e., $\xi_p = 0$, the real marginal cost is simply the inverse of the markup.

## 4.5 Labour Market

At the beginning of each period $t$, there are $u_t$ unemployed workers searching for jobs and there are $v_t$ vacancies posted by intermediate-good firms. Following Mortensen and Pissarides (1994), the number of successful worker-firm matches occur according to a constant returns to scale matching function $\mu(v_t, u_t)$. The probability of an open vacancy matching with a searching worker is

$$p^v(\vartheta_t) \equiv \frac{\mu(v_t, u_t)}{v_t} = \mu(1, 1/\vartheta_t),$$

and the probability of an unemployed and searching worker matching with a firm posting an open vacancy is denoted

$$p^u(\vartheta_t) \equiv \frac{\mu(v_t, u_t)}{u_t} = \mu(\vartheta_t, 1), \tag{16}$$

where $\vartheta_t = \frac{v_t}{u_t}$ denotes labour market tightness.

At the beginning of period $t$ there are $n_{t-1}$ workers. Of these workers, fraction $\delta$ separate from their job leaving $(1-\delta)n_{t-1}$ workers remaining employed. Following job separation—but before the production cycle—last period's unemployed workers and newly separated workers begin to search for jobs with match probability 16. Consequently, the total number of job searchers in period $t$ evolves according to

$$u_t = 1 - n_{t-1} + \delta n_{t-1}. \tag{17}$$

As in Blanchard and Galí (2010) and Leduc and Liu (2016), I assume newly matched workers begin working in the period the match is made. Moreover, I assume full participation and define the unemployment rate as the fraction of the population who are left without a job after hiring takes place in period $t$. As a result, aggregate employment in period $t$ evolves according to

$$n_t = (1-\delta)n_{t-1} + \mu(v_t, u_t). \tag{18}$$

while the unemployment rate, $\mathscr{U}_t$, is found as

$$\mathscr{U}_t = u_t - \mu(v_t, u_t) = 1 - n_t. \tag{19}$$

## 4.6 Intermediate-Good Firm

There is a continuum of identical intermediate-good firms index by $i$ with a common production technology $F(k_{it}, n_{it}; z_t)$, where $k_{it}$ is the level of capital service input, $n_{it}$ denotes labour input and $z_t$ is a common TFP shock known at the beginning of period $t$. Each firm can only produce output if she has successfully hired a worker. Moreover, in each period a hired worker supplies the firm with exactly one unit of labour ($n_{it} \in \{0,1\}$). As a result, firm $i$'s output following period $t$'s production cycle is

$$\chi_{it} = \begin{cases} z_t f(k_{it}), & \text{if successful match} \\ 0, & \text{otherwise.} \end{cases}$$

where $z_t f(k_{it}) \equiv F(k_{it}, 1; z_t)$ and $f' > 0$ and $f'' < 0$. Since the wage bill and capital rental costs must be paid in advance of production, a successfully matched intermediate-good firm must obtain a loan from the bank to finance its operational costs. Thus, total loans given to firm $i$ are

$$W_t + P_t r_t^k k_{it}.$$

A matched firm obtains marginal flow value of labour of $Q_t z_t f(k_{it}) - (1+R_t^l)W_t$ in the current period. In following period, the match survives with probability $1-\delta$ and the firm continues producing; with probability $\delta$ the match is destroyed and the firm may post a new job vacancy. As a result, the Bellman equation for a matched firm is written as

$$J_{it}^F = Q_t z_t f(k_{it}) - (1+R_t^l)W_t + \beta \mathbb{E}_t \left\{ \frac{\lambda_{1,t+1}}{\lambda_{1,t}} \left[ (1-\delta) J_{it+1}^F + \delta J_{it+1}^V \right] \right\}, \quad (20)$$

where $J_{it}^F$ is the value of a matched firm and $J_{it}^V$ is the value of an unmatched firm who posted a vacancy. Following a successful match, a firm then choses its quantity of capital services to employ that satisfies

$$Q_t z_t f'(k_{jt}) = (1+R_t^l) P_t r_t^k. \quad (21)$$

Since firms are price takers in the capital rental market, from condition 21 I find that $k_{it} = k_{jt}\ \forall\ i \neq j$, which implies $J_{it}^F = J_{jt}^F$ and $J_{it}^V = J_{jt}^V\ \forall\ i \neq j$. As a result, I drop intermediate-good firm index subscripts. See the Appendix for a complete derivation of the firms' optimization problem.

A firm who is unmatched and posts a new vacancy in period $t$ must pay nominal cost $P_t \kappa$, where $\kappa > 0$ is a quantity of final goods. With probability $p^v(\vartheta_t)$ the firm obtains a match and the vacancy is filled yielding value $J_t^F$. Otherwise, with probability $1 - p^v(\vartheta_t)$ the vacancy remains into the following period yielding the value $J_{t+1}^V$. Thus, the Bellman equation for a firm with a vacancy is written as

$$J_t^V = -P_t\kappa + p^v(\vartheta_t)J_t^F + \mathbb{E}_t\left\{\beta\frac{\lambda_{1,t+1}}{\lambda_{1,t}}(1-p^v(\vartheta_t))J_{t+1}^V\right\}. \tag{22}$$

## 4.7 Worker Value Functions

During period $t$, an employed worker receives wages $W_t$ in monetary units but sustains a utility cost—in monetary terms—of $P_t\psi_L/\lambda_{1,t}$. In the following period, if the match is sustained the worker receives value $J_{t+1}^W$; whereas if the match is destroyed the worker begins their search for a new match. With probability $p^u(\vartheta_{t+1})$ a worker searching for a job obtains a new match an receives value $J_{t+1}^W$, while a worker who is unsuccessful at obtaining a match receives value $J_{t+1}^U$ for being unemployed. As a result, the Bellman equation for an employed worker is written as

$$J_t^W = W_t - P_t\frac{\psi_L}{\lambda_{1,t}} + \beta\mathbb{E}_t\left\{\frac{\lambda_{1,t+1}}{\lambda_{1,t}}\left[(1-\delta)J_{t+1}^W + \delta\left\{p^u(\vartheta_{t+1})J_{t+1}^W + (1-p^u(\vartheta_{t+1}))J_{t+1}^U\right\}\right]\right\}. \tag{23}$$

An unemployed worker obtains flow benefits $P_t\mathscr{B}$ from the government and can search for a job in period $t+1$. With probability $p^u(\vartheta_{t+1})$ an unemployed worker successfully matches with a firm and becomes employed and with probability $1-p^u(\vartheta_{t+1})$ she remains unemployed and reveives value $J_{t+1}^U$. As a result, the Bellman equation for an unemployed worker is written as

$$J_t^U = P_t\mathscr{B} + \beta\mathbb{E}_t\left\{\frac{\lambda_{1,t+1}}{\lambda_{1,t}}\left[p^u(\vartheta_{t+1})J_{t+1}^W + (1-p^u(\vartheta_{t+1}))J_{t+1}^U\right]\right\}. \tag{24}$$

## 4.8 Nash Bargaining & Wage Rigidity

Workers and intermediate-good firms bargain over wages by solving the following problem

$$\max_{W_t}\left\{\left(J_t^W - J_t^U\right)^b\left(J_t^F\right)^{1-b}\right\}, \tag{25}$$

where $b\in(0,1)$ denotes the workers bargaining power. The first-order condition looks like

$$bJ_t^F\frac{\partial\left(J_t^W - J_t^U\right)}{\partial W_t} + (1-b)\left(J_t^W - J_t^U\right)\frac{\partial J_t^F}{\partial W_t} = 0.$$

The solution to the bargaining problem is shown in propsition 4.3.

**Proposition 4.3** *The solution to the Nash bargaining problem gives the worker surplus,* $J_t^W - J_t^U$*,* *and firm surplus,* $J_t^F$*, as*

$$J_t^W - J_t^U = \omega(R_t^l;b)S_t \quad \text{and} \quad J_t^F = \left(1-\omega(R_t^l;b)\right)S_t,$$

*respectively, where*

$$\omega(R_t^l;b) \equiv \frac{b}{1+(1-b)R_t^l},$$

*and* $S_t \equiv J_t^F + J_t^W - J_t^U$ *denotes the total net surplus value generated by a match in period* $t$*.*

I leave its proof in the Appendix. Unlike the standard search-and-matching literature without working capital loans, the equilibrium surplus shares depend on the loan interest rate $R_t^l$. It is clear to see that when the firms' cost of borrowing rises, the worker's share of surplus falls. In this sense the credit market frictions allow part of the firms' borrowing costs to be transferred to workers. Notwithstanding, the economic effect of this wedge is insignificant.[17]

Subtracting 24 from 23 and using proposition 4.3, the Nash bargaining wage is determined by the following relationship

$$\omega(R_t^l;b)S_t = W_t^N - P_t\frac{\psi_L}{\lambda_{1,t}} - P_t\mathscr{B} + \beta\mathbb{E}_t\left\{\frac{\lambda_{1,t+1}}{\lambda_{1,t}}(1-\delta)\left(1-p^u(\vartheta_{t+1})\right)\omega(R_{t+1}^l;b)S_{t+1}\right\}, \quad (26)$$

where $W_t^N$ denotes the wage which solves the Nash bargaining problem 25.

As in Leduc and Liu (2016), I assume a wage rigidity between the equilibrium market wage and the Nash bargaining wage. Specifically, I assume

$$\frac{W_t}{P_t} = \left(\frac{W_{t-1}}{P_{t-1}}\right)^{\iota}\left(\frac{W_t^N}{P_t}\right)^{1-\iota},$$

where $\iota \in [0,1]$ is a model parameter which governs the mix between the previous period's market wage and the Nash bargaining wages.

## 4.9 Policy, Market Clearing & Search Equilibrium

Each period the government's fiscal policy is limited to collecting lump-sum taxes, $Tax_t$, from the household which it uses to exclusively finance the unemployment benefits of unemployed workers.

[17] Assuming a bargaining weight of $b = 0.5$, under the benchmark calibration with steady-state interest rate $R^l = 0.011$ implies a bargaining share of $\omega = 0.497$, whereas in the standard model $\omega = 0.5$.

As a result, the period $t$ government budget constraint is written as

$$P_t \mathscr{B}(1-n_t) = Tax_t.$$

The monetary authority conducts monetary policy according to two different rules. The first is a money base growth rule that takes the following form:

$$x_t - x = \rho_x(x_{t-1} - x) + \varepsilon_t^x$$

where $x_t = \frac{X_t}{M_t^{\text{base}}}$ and $x$ denotes the steady-state money base growth rate and $\rho_x$ denotes the persistence of money base growth rate. The term $\varepsilon_t^x$ represents an unanticipated monetary policy shock to the money base growth rate that follows an exogenous process described below. The second rule is an interest rate rule governing the short-term demand deposit rate that takes the form of a general Taylor Rule:

$$R_t^d - R^d = \rho_r(R_{t-1}^d - R^d) + (1-\rho_r)\left[\alpha_\pi^r \log(\frac{\mathbb{E}_t \pi_{t+1}}{\pi}) + \alpha_y \log(\frac{Y_t}{Y_{t-1}})\right] + \varepsilon_t^r,$$

where $R^d$ denotes the steady-state deposit interest rate and $\rho_r$ governs the rate's persistence. The parameters $\alpha_\pi$ and $\alpha_y$ denote the policy wights on the deviation of expected inflation from its steady-state rate and GDP growth rate respectively. The term $\varepsilon_t^r$ represents an unanticipated monetary policy shock to the deposit rate that follows an exogenous process described below.

In a search equilibrium, the markets for final consumption goods, intermediate goods, capital, and loans all clear. The final good's market clearing condition yields the resource constraint

$$C_t + I_t + \kappa v_t + \frac{\xi_p}{2}(\pi_t - \pi)^2 Y_t + a(\varkappa_t)K_t = Y_t.$$

Capital services market clearing implies

$$\int_{i \in \mathscr{M}_t} k_{it} \mathrm{d}i = \varkappa_t K_t,$$

where the intermediate-good's market clearing condition implies

$$Y_t = \int_{i \in \mathscr{M}_t} z_t f(k_{it}) \mathrm{d}i.$$

Finally, the bank loan market clearing condition implies

$$NetWorth_t + \int_{i\in\mathscr{M}_t} D^d_{it}\mathrm{d}i = \int_{i\in\mathscr{M}_t} \left\{W_t + P_t r^k_t k_{it}\right\}\mathrm{d}i. \tag{27}$$

With free entry of intermediate-good firms, in equilibrium $V_t = 0$ and 22 implies that

$$\frac{\kappa}{p^v(\vartheta_t)} = \frac{J^F_t}{P_t}. \tag{28}$$

### 4.10 Calibration, Steady-State & Comparative Statics

I assume the household's real liquidity preference has the following functional form

$$\mathscr{V}(x) = \gamma\frac{x^{1-\sigma_q}}{1-\sigma_q},$$

where $\gamma > 0$ and $\sigma_q$ are parameters which govern the utility weight and utility curvature of real money, respectively. Following Christiano et al. (2010) I assume capital utilization cost function takes the following form

$$a(\varkappa_t) = \frac{r^k}{\sigma_a}\left\{\exp[\sigma_a(\varkappa_t - 1)] - 1\right\},$$

where $r^k$ denotes the steady-state capital rental rate in real terms and $\sigma_a > 0$ is a parameter governing the cost function convexity. As is standard in the search literature, I assume the number of successful worker-firm matches, $\mu(v_t, u_t)$, is governed by a Cobb-Douglas matching technology:

$$\mu(v_t, u_t) = \bar{\mu} u_t^{\alpha} v_t^{1-\alpha},$$

where the parameters $\bar{\mu} > 0$ governs the matching efficiency and $\alpha \in (0,1)$ governs the elasticity of job matches with respect to the number of searching workers. Following Christiano et al. (2014) I assume the investment adjustment cost function, $S(\cdot)$, takes the following functional form

$$S(x) = \frac{1}{2}\left\{\exp\left[\sqrt{S''}(x-1)\right] + \exp\left[-\sqrt{S''}(x-1)\right] - 2\right\},$$

and has the following properties: $S(1) = S'(1) = 0$, $S''(1) = S'' > 0$, where $S''$ is a model parameters governing the curvature of the function.

The model's parameters are grouped into three categories: calibrated, targeted and estimated. For reference, one period in the model corresponds to one quarter. The calibrated parameters are

Table 4: Calibrated Parameters

| Variable | Description | Value | Source/Target |
|---|---|---|---|
| $\alpha_f$ | production function curvature | 1/3 | standard |
| $\Delta$ | capital depreciation rate | 0.025 | standard |
| $\alpha$ | matching function elasticity | 0.5 | Leduc and Liu (2016) |
| $\delta$ | job destruction rate | 0.1 | Leduc and Liu (2016) |
| $\kappa$ | vacancy cost | 0.017 | 2% of GDP |
| $b$ | Nash bargaining weight | 0.5 | Leduc and Liu (2016) |
| $\mathscr{B}$ | unemployment benefits | 0.25 | Leduc and Liu (2016) |
| $\rho^s$ | saving deposit reserve ratio | 0.0 | Feinman (1993) |
| $\rho^d$ | demand deposit reserve ratio | 0.1 | Feinman (1993) |
| $\tau$ | bank dividend rate | 0.05 | Langlais (2023a) |

*Notes*: One period corresponds to one quarter.

set to values which are common in the related literature and are listed in Table 4. As is standard, production function curvature on capital, $\alpha_f$, and capital depreciation rate, $\Delta$, are set to to 1/3 and 0.025 (10% per year), respectively. Following Leduc and Liu (2016), I set the elasticity of matching, $\alpha$, to 0.5, job separation rate, $\delta$, to 0.1, Nash bargaining weight, $b$, to 0.5, unemployment benefits, $\mathscr{B}$, to 0.25, and the cost of posting a vacancy, $\kappa$, such that it is 2% of steady-state GDP. As a result, I find $\kappa = 0.017$. Following the Federal Reserve's minimum reserve requirements for non-transaction and transaction deposits, I set the minimum reserve ratios for savings deposits, $\rho^s$, and demand deposits, $\rho^d$, to be 0% and 10%, respectively.[18] Finally, I set the bank dividend rate, $\tau$, to 5%.

Table 5 lists the second group of parameters (panel B) which are endogenously determined based on targeted steady-state moments (panel A) in the data or literature. Data for computing sample averages span the period 1987:Q1-2008:Q2. Given a targeted annual nominal savings rate of 5% and annual inflation rate of 2%, the household's subjective discount factor, $\beta$, is found to be 0.998. The steady-state inflation rate of 2% annually implies a steady-state growth rate of the money base, $x$, to be 0.005. I set the steady-state level of the FMC shock, $\zeta_b$, such that the interest rate spread, $R^l - R^d$, matches the sample average 'GZ' spread in the data. Following Leduc and Liu (2016) I set the steady-state unemployment rate to 6.4% and the steady-state vacancy filling rate, $p^v$, to 0.7. This implies that the matching function efficiency parameter, $\bar{\mu}$, is 0.644. The firms' mark-up parameter, $\lambda_f$, is set such that the steady-state term structure is upward sloping: $R^d < R^l < R^s$. This results in a mark-up of 17.5% over marginal cost. Following Leduc and Liu (2016) I set the steady-state utility benefit of non-work to 0.75, implying a labour disutility weight, $\psi_L$, of 0.809. The steady-state level of TFP, $z$, is set such that the steady-state capital-output ratio, $K/Y$, is 10.7 as in Christiano et al. (2010). However, the steady-state level of TFP also depends on

[18] Although the Federal Reserve has eliminated all minimum reserve requirements as of 2020, over the period in which the model is estimated minimum reserve requirements on transaction deposits were positive. https://www.newyorkfed.org/medialibrary/media/research/epr/02v08n1/0205bennpdf.pdf

Table 5: Targeted Steady-State Variables & Endogenous Parameters

| Variable | Description | Value | Source/Target |
|---|---|---|---|
| *Panel A: Targeted Steady-State Variables* | | | |
| $U$ | unemployment rate | 6.4% | Leduc and Liu (2016) |
| $\mathscr{B}+\frac{\psi_L}{\lambda}$ | total benefit of non-work | 0.75 | Leduc and Liu (2016) |
| $\pi$ | inflation rate | 1.005 | 2% (apr) |
| $\frac{K}{Y}$ | capital-output ratio | 10.7 | Christiano et al. (2010) |
| $p^v$ | vacancy filling rate | 0.7 | den Haan et al. (2000) |
| $D^s/M^{\text{base}}$ | savings deposit share | 0.09 | currency to money base ratio = 91%[a] |
| $R^s$ | savings deposit rate | 5% annual | 3% real rate |
| $R^l - R^d$ | interest rate spread | 1.84% annual | GZ spread[b] |
| $R^d < R^l < R^s$ | interest rate term structure | — | upward sloping yield curve |
| *bank leverage* | assets to net worth ratio | 13.6 | financial sector leverage[c] |
| *Panel B: Endogenous Parameters* | | | |
| $\beta$ | discount rate | 0.998 | |
| $x$ | steady-state money base growth | 0.005 | |
| $\zeta_b$ | steady-state FMC | 2.731 | |
| $\bar{\mu}$ | matching function efficiency | 0.644 | |
| $\lambda_f$ | mark-up | 1.175 | |
| $\psi_L$ | labour disutility | 0.809 | |
| $z$ | steady-state productivity | 0.426 | |
| $\gamma$ | liquidity preference weight | 0.041 | |
| $\sigma_q$ | liquidity preference curvature | 1.209 | |
| $\phi$ | lump-sum banking fees | 0.004 | |

*Notes*: Unless stated otherwise, sample averages are computed over the sample period 1987:Q1-2008:Q2.
[a] Currency component of M1 divided by monetary base. Source: Board of Governors of the Federal Reserve System H.6 and H.3, FRED codes CURRSL and MBCURRCIR.
[b] Sample average of the 'GZ spread'. Source: Gilchrist and Zakrajšek (2012).
[c] Sample average of financial sector assets to equity. Financial sector consists of chartered depository institutions, security brokers and dealers, finance companies, credit unions, and life insurance companies. Source: Board of Governors of the Federal Reserve System under Z1/OTHER.

the consumption habit persistence parameter, $h$. As a consequence, $z$ can only be attained once $h$ has been estimated.[19] A targeted steady-state savings deposit to money base ratio, $D^s/M^{\text{base}}$, of 0.09 and interest rate, $R^s$, yield liquidity preference weight parameter, $\gamma$, and liquidity curvature parameter, $\sigma_q$, of 0.041 and 1.209, respectively. The steady-state ratio $D^s/M^{\text{base}}$ is computed as $1-\frac{M}{M^{\text{base}}}$, where $\frac{M}{M^{\text{base}}}$ is the sample average of currency in circulation to base money ratio. Finally, bank leverage is targeted to 13.6 implying real banking fees, $\phi^b$, of 0.004;

The remaining parameters—all of which do not affect the model's steady-state—are estimated using Bayesian estimation techniques in Section 5.1.[20] For reference, I refer to the model with parameter value set to those in Tables 4, 5 and 6 (see below) as the benchmark model.

[19]Once $h$ is known, $z$ is found using a solution algorithm described in the Appendix.

[20]There is, however, one exception: the consumption habit persistence parameter, $h$, which affects the steady-state level of money's marginal utility.

**Comparative Statics** Before I estimate the remaining parameters, I pause to describe the key relationship of this paper: that between bank credit supply and the labour market equilibrium. In this first exercise, I detail the steady-state relationship between the level of bank FMC and the unemployment rate. For expositional purposes, I simplify the analysis in this first exercise by assuming the capital-labour ratio and marginal utility of money are constant.[21] These assumptions are relaxed in the second exercise.

The main result of the first exercise can be summarized in proposition 4.4.

**Proposition 4.4** *For a given capital-labour ratio and marginal utility of money, the steady-state unemployment rate is decreasing in $\zeta_b$ (i.e., the value of the FMC shock).*

*Proof*—Under the benchmark model when firms are required to borrow funds to pay their wage bill in advance of production, the job-creation condition—living in the $\vartheta$-$w$ plane—is found by combining 20 with equilibrium condition 28 yielding

$$w = \frac{1}{1+R^l}\left[qz\left(\frac{\varkappa K}{n}\right)^{\alpha_f} - \Phi\frac{\kappa}{p^v(\vartheta)}\right], \tag{29}$$

where variables without time subscripts denote the variable's non-stochastic steady-state value and $\Phi \equiv 1-\beta(1-\delta) > 0$. Here $w$ is the steady-state value of the real wage rate $W_t/P_t$. It is clear to see that the financial frictions introduced in this paper—showing up as $R^l > 0$ in equation 29—have the effect of shifting the standard job-creation condition downward and rotating it counter-clockwise.

Noting that $S_t = J_t^F / \left(1-\omega(R_t^l|b)\right)$ and $W_t^N/P_t = w$ in steady-state, the wage condition—also living in the $\vartheta$-$w$ plane—under the benchmark model is found by combining 26 with the equilibrium condition 28 yielding

$$w = \frac{\psi_L}{\lambda_1} + \mathscr{B} + \frac{1}{1+R^l}\left(\frac{b}{1-b}\right)\left[\Phi + (1-\Phi)p^u(\vartheta)\right]\frac{\kappa}{p^v(\vartheta)}, \tag{30}$$

where $\lambda_1$ denotes the Lagrange multiplier on the household's asset accumulation equation 8. Combing the job-creation rule 29 with the wage rule 30 yields an expression which, for a given capita-labour ratio and marginal utility of money, pins down the equilibrium market tightness, $\theta^*$:

$$qz\left(\frac{\varkappa K}{n}\right)^{\alpha_f} - (1+R^l)\left[\frac{\psi_L}{\lambda_1} + \mathscr{B}\right] = \frac{\kappa}{p^v(\vartheta^*)}\left(\Phi + \frac{b}{1-b}\left[\Phi + (1-\Phi)p^u(\vartheta^*)\right]\right). \tag{31}$$

From this last expression, given $\Phi < 1$ it is clear to see that $\frac{\partial \vartheta^*}{\partial R^l} < 0$. In words, as firms' cost of obtaining bank financing rises, the labour market tightness falls. Note that this relationship

[21] There is a relatively inelastic relationship between both capital-labour ratio and marginal utility of money with the bank's level of FMC (not reported). As the second exercise below shows, when these assumptions are relaxed the main result holds.

between the cost of borrowing and the labour market tightness is a crucial link between the level of bank FMC and the unemployment rate. To see this, consider the standard relationship that arising between labour market tightness and the unemployment rate through the Beveridge curve. Under the labour search timing convention adopted in this paper, the Beveridge curve—living in the $\vartheta$-$\mathscr{U}$ plane—is found by combining equations 17, 18 and 19 yielding

$$\mathscr{U} = \frac{[1-p^u(\vartheta)]\delta}{\delta + (1-\delta)p^u(\vartheta)}.$$

Therefore, higher loan interest rates is associated with a higher unemployment rate since $\frac{\partial \mathscr{U}}{\partial \vartheta} < 0$. Given propositions 4.1 and 4.2, there is an unambiguosly negative relationship between the loan interest rate spread, $R^l - R^d$, and the level of bank FMC, $\zeta_b$. Since $R^d$ represents the short-term policy interest rate it is considered exogenous. As a result, any changes in the level of FMC has a direct effect on $R^l$.[22] Therefore, we have established the critical negative relationship between bank credit supply and the unemployment rate found in the data. ■

Consider this relationship graphically. Panel A of Figure 5 plots the job-creation curve and wage curve under two different levels of bank FMC: $\zeta_b = 2.731$ (solid line) and $\zeta_b = 2.731/10$ (dashed line). Below, panel B plots the associated Beveridge curve. When $\zeta_b$ is reduced, $R^l$ rises shifting both curves downward (dashed lines). However, the effect on the job-creation curve is relatively stronger leading to a fall in the labour market tightness. As discuss above, a lower market tightness is associated with a higher unemployment rate through the Beveridge curve.

In the next exercise, I plot the steady-state relationship between the level of FMC and the unemployment rate (see Figure 6) allowing the capital-labour ratio and marginal utility of money to vary. I perform this exercise under several different calibrations: specifically, I change the values of required demand deposit reserve ratio (panel A), steady-state inflation rate (panel B), matching efficiency (panel C), and unemployment benefits (panel D). As expected, under the benchmark calibration (solid lines) the relationship between the level of FMC and the unemployment rate is negative.

When the monetary authority raises the minimum required reserve ratio on demand deposits (dotted line panel A), the unemployment rate rises for each level of FMC. This result highlights the fact that bank credit supply is also governed by forces outside the bank's control—in this case by policy. Increasing $\rho^d$ while holding $\zeta_b$ constant reduces the bank's excess reserves and increases the firm's cost of borrowing (see Propositions 4.1 and 4.2). Lower excess reserves and higher borrowing costs reduce the total financing available to matched firm's to purchase their inputs. As a result, labour market tightness falls the unemployment rate rises.

[22] It is also worth noting that $R^s$ in proposition 4.2 is governed by household time preference and the steady-state inflation rate.

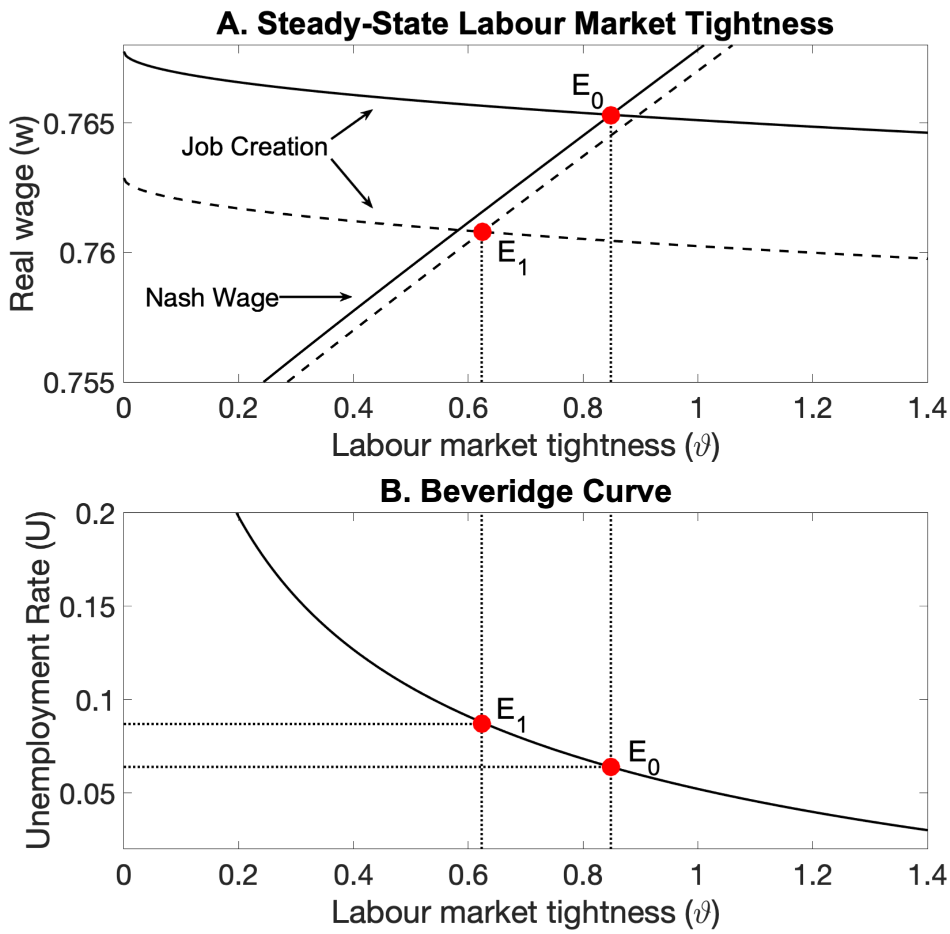


Figure 5: Comparative Statics—Reduction in the level of FMC ($\zeta_b$)

*Notes*: Comparative statics are computed for parameter values listed in Tables 4 and 5. I assume $h = 0.47$. Equilibrium $E_0$ is associated with $\zeta_b = 2.731$, whereas equilibrium $E_1$ is associated with $\zeta_b = 2.731/10$. I assume a constant capital-labour ratio and constant marginal utility of money under both equilibria.

When the steady-state inflation rate is raised from 2% to 3%, holding $\zeta_b$ constant, increases the steady-state unemployment rate. This is because the inflation rate determines the nominal savings rate faced by the household—i.e., $R^s$—and this rate is a determinant the interest rate spread (see Proposition 4.2).[23] A higher interest rate spread is associated with higher cost of borrowing for the firms. As a result, labour market tightness falls the unemployment rate rises.

Consistent with the standard labour-search models without financial frictions, a rise in matching efficiency or a rise in unemployment benefits have the predicted effect on the steady-state unemployment rate. A higher matching efficiency, for a given level of $\zeta_b$, increases the probability of

[23] Combining the household's first-order conditions with respect to $D_t^s$ and $M_{t+1}^{base}$, yields steady-state savings rate of $R^s = \left(\frac{\pi}{\beta}\right)^2 - 1$. See Appendix for further details.

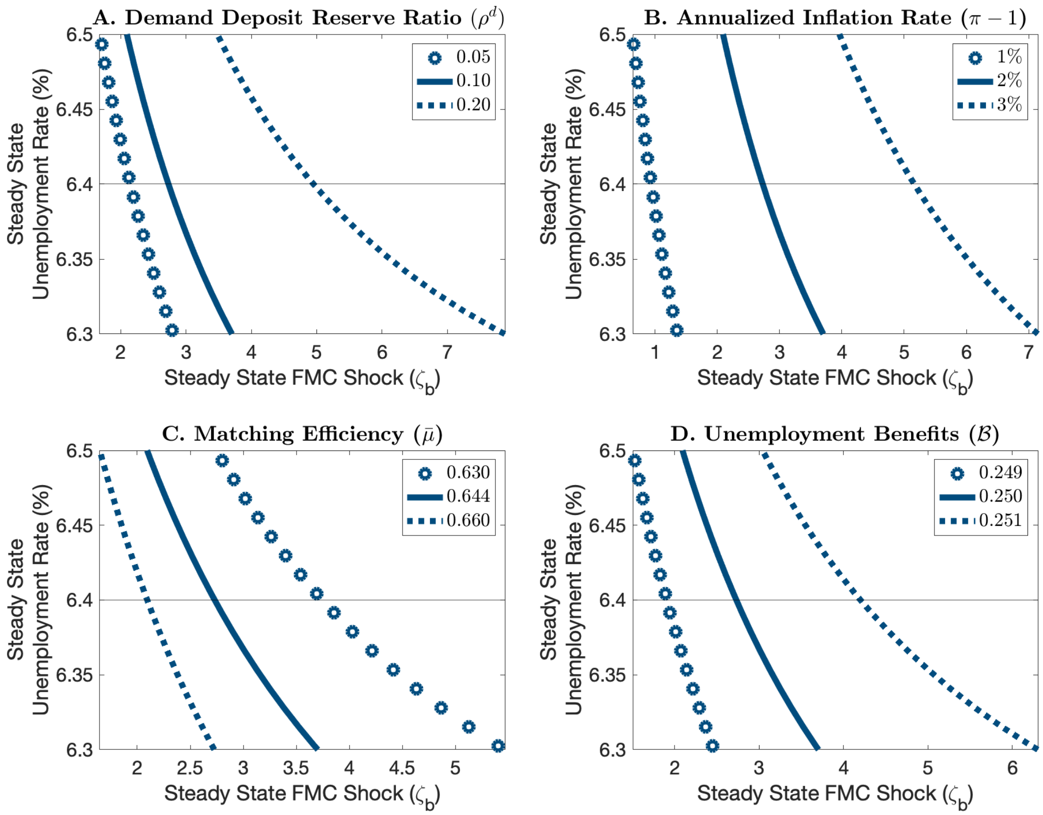


Figure 6: Comparative Statics

*Notes*: Comparative statics are computed for parameter values listed in Tables 4 and 5. I assume $h = 0.641$.

workers and firms finding a match. As a result, more matches are made and the unemployment rate falls. On the other hand, when unemployment benefits rise, again holding $\zeta_b$ constant, the value of unemployment rises which reduces the surplus generated from a match. As a result, labour market tightness falls and unemployment rate rises.

# 5 Dynamic Analysis

In this section I describe the macroeconomic data used to estimate the remaining parameters of the model and analyze the model's dynamic properties in response to bank credit supply shocks. The primary objective of this section is to quantify the relative importance that bank credit supply shocks have on the unemployment rate.

## 5.1 Data & Parameter Estimation

I use Bayesian techniques to obtain estimates of the mode and posterior distribution of each estimated parameter. Except for the household's consumption habit persistence parameter, $h$, the estimated parameter does not affect the model's stead-state. The dataset is comprised of five macroeconomic variables, in quarterly frequency, describing the US economy over the period 1989:Q1–2019:Q4.[24] The variables are: real per capita GDP growth, unemployment rate, inflation rate, external finance premium and the federal funds rate. The real per capita GDP is logged then first-differenced. Inflation rate is computed as the first difference of the logged implicit price GDP deflator. The measure used for the external finance premium is the 'GZ' spread. All series then have their respective sample means removed to ensure consistency with their model counterpart. Further details regarding dataset construction and sources see Section F.4 of the Online Appendix.

In addition to the four shocks in the model (FMC, TFP, monetary policy rate, and monetary policy money growth rate) I include a measurement error on the observed external finance premium. This is motivated by the fact that the model, and therefore the model counterpart to the external finance premium—i.e., the interest rate spread $R^l - R^d$—does not incorporate any risk or information about economic uncertainty which the 'GZ' spread has been shown to contain (Gilchrist and Zakrajšek, 2012). As a result of not having risk or uncertainty in the model's loan market, the measurement error placed on the 'GZ' spread can be thought of as a misspecification factor of the model in failing to capturing observed economic uncertainty in the loan market. Notwithstanding, the estimation procedure will still be useful in quantifying the relative importance that bank credit supply shocks have on the observe external finance premium.

Table 6 lists the estimated parameters, their associated prior distributions and their posterior distribution's mode and standard deviations. Figures 15 and 16 of the Appendix plot the parameter priors and posterior distributions. For each analyses performed below I set each estimated parameter to its respective posterior mode.

## 5.2 Model Response to Bank Credit Supply Shock

*What happens following a contraction in the supply of bank credit*? The solid blue line in Figure 7 represents the model response to an unexpected one-standard deviation contraction in the bank's FMC. A deep recession ensues following the shock: GDP and bank loans contract by about 1.5 and 1.7 percent, respectively, while unemployment rate rises 1.4 percentage points. Since the estimated FMC shock process is persistent, the economic recession persists beyond the five-year horizon.

[24]The actual starting period is 1985:Q1 and was chosen to minimize the impact of potential structural breaks from the 'Volker Period'. The first 16 quarters are utilized as a training sample for the Kalman filter iterations. As a result, the likelihood estimation is performed over the period 1989:Q1–2019:Q4

Table 6: Estimated Parameters—Baseline Model

| | | Prior | | | Posterior | |
|---|---|---|---|---|---|---|
| | | Type | Mean | Std. dev. | Mode | Std. dev. (Hess.) |
| *Panel A: Economic Parameters* | | | | | | |
| $h$ | Habit persistence | Beta | 0.5 | 0.1 | 0.641 | 0.039 |
| $\xi_p$ | Price adj. cost | Norm. | 80 | 50 | 45.982 | 5.799 |
| $S''$ | Investment adj. cost curvature | Norm. | 5 | 3 | 14.807 | 1.991 |
| $\sigma_a$ | Capital utilization cost curvature | Gamma | 6 | 5 | 0.000 | 0.002 |
| $\iota$ | Real wage rigidity | Beta | 0.5 | 0.15 | 0.952 | 0.004 |
| *Panel B: Monetary Policy Parameters* | | | | | | |
| $\rho_r$ | Interest rate smoothing | Beta | 0.75 | 0.1 | 0.944 | 0.012 |
| $\alpha_\pi$ | Interest rate weight on inflation | Norm. | 1.5 | 0.25 | 1.709 | 0.216 |
| $\alpha_{\Delta y}$ | Interest rate weight on output growth | Norm. | 0.25 | 0.1 | 0.226 | 0.090 |
| $\rho_x$ | Money base smoothing | Beta | 0.5 | 0.1 | 0.556 | 0.105 |
| *Panel C: Shock Autocorrelations* | | | | | | |
| $\rho_z$ | Firm technology | Beta | 0.5 | 0.2 | 0.814 | 0.013 |
| $\rho_b$ | FMC technology | Beta | 0.5 | 0.2 | 0.979 | 0.005 |
| *Panel D: Shock Standard Deviations & Measurement Error* | | | | | | |
| $\sigma_z$ | Technology | Invg. | 0.01 | 0.05 | 0.008 | 0.0006 |
| $\sigma_b$ | Inter-period FMC technology | Invg. | 0.03 | 0.3 | 1.077 | 0.1253 |
| $\sigma_r$ | Monetary policy rate | Invg. | 0.58 | 0.825 | 0.279 | 0.019 |
| $\sigma_x$ | Money base growth injection | Invg. | 0.01 | 0.05 | 0.008 | 0.002 |
| | Std. dev. measurement error on spread | Weibull | 0.01 | 5 | 0.0043 | 0.0004 |

*Notes*: Invg. denotes 'Inverse gamma type 1'. Data used for estimating parameters represents the US economy and span the period 1985:Q1–2019:Q4. Data description and sources are found in Table 8 of the Appendix. The Laplace approximation of marginal density is 2517.11. The posterior distribution is obtained from 8,000,000 draws equally distributed across 8 chains of the Metropolis-Hastings algorithm. For each chain the first 20% of the draws are discarded.

Notwithstanding, consumption returns to its steady-state level around the four-year mark. Moreover, the response is consistent with a typical recession: GDP, investment and labour market tightness fall, while the external finance premium and the unemployment rate rise.

Considering the comparative static exercise performed above, the transmission mechanism generating this response is straight forward. When the bank unexpectedly contracts the supply of loans, firms are faced with a shortage of funds—i.e., money—required to purchase their inputs. As a result, demand for inputs fall leading to less capital and labour being employed and output contracts. Digging deeper, the contraction in bank credit supply has both a *quantity* and *price* effect that reinforce one another. The price effect (red dotted line in Figure 7) is estimated by holding $\zeta_b$ constant in the loan market clearing condition 27. As a consequence, the price effect operates through the bank's optimality condition (see proposition 4.2) and raises borrowing costs imposed on firms. This lowers the firms' value of matching with a worker leading firms to post less vacancies. As a result, labour market tightness—$\vartheta = v/u$—falls and the unemployment rate rises. On the other hand, the quantity effect (green dashed line in Figure 7) is estimated as the difference between

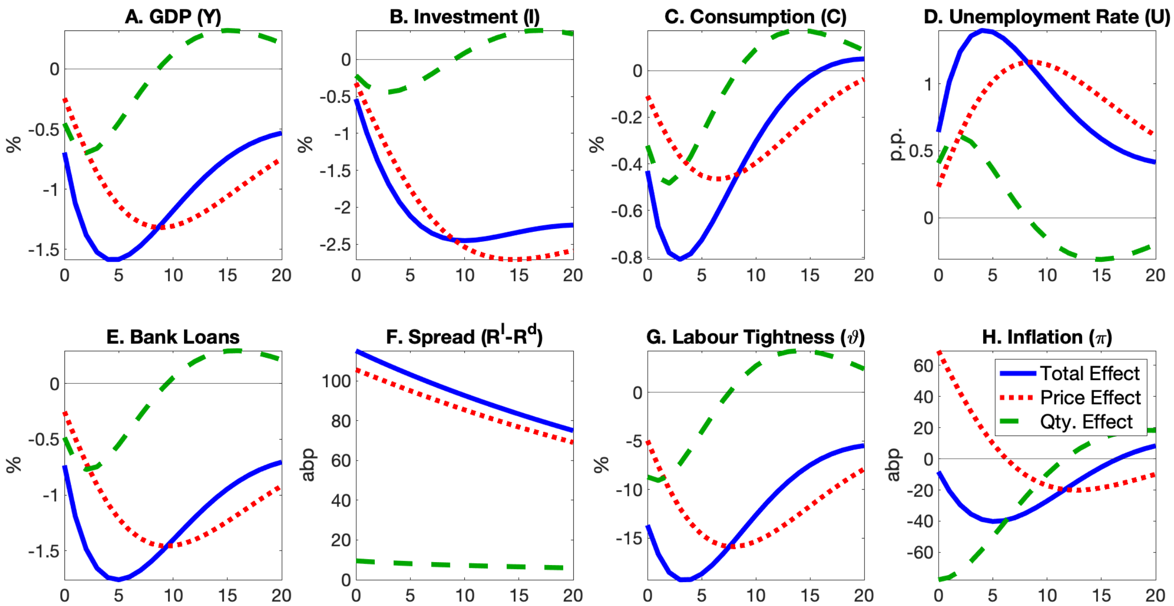


Figure 7: Impulse Responses to a FMC shock

*Notes*: Estimated parameters are set to their posterior mode.

the total effect and price effect.[25,26] Save for investment and interest rate spread, for each plotted variable the quantity effect dominates the price effect upon impact. After eight quarters, however, the quantity effect dissipates while the price effect persists beyond the plotted horizon.

## 5.3 Variance & Historical Decomposition

Now that the mechanism linking the bank's supply of credit and the firm's hiring decisions has been established, I now compare the relative importance of each of the four structural shocks in generating the observed economic volatility. Table 7 shows the variance decomposition of each observed variable used in estimation (panel A) as well as other interesting variables (panel B). Each table cell entry denotes the percentage contribution of the column shock at generating the volatility of the row variable at business cycle frequencies.[27] Surprisingly, the bank's FMC shock is the most important source of volatility for GDP (48%), unemployment (46%) and interest rate spread (39%). Moreover, the FMC shock accounts for the majority of investment volatility and is the main contributor of labour market tightness volatility. Compared to the empirical estimates in Table 1, the model results suggest bank credit supply shocks play a stronger role in driving economic volatility.

[25] Note: while the quantity effect operates directly through total loans available to firms, there are general equilibrium effects operating through the household's savings rate, $R^s$, which feedback into the interest rate spread.

[26] Since the model is solved via log linearization, the total effect is the sum of the quantity and price effects.

[27] Business cycle frequencies range between 6 and 32 quarters.

Table 7: VAR Variance Decompositions

| Variable | FMC $\zeta_b$ | TFP $z$ | Policy Rate $\varepsilon^r$ | Money Base Growth Rate $x$ | ME |
|---|---|---|---|---|---|
| *Panel A: observed variables* | | | | | |
| GDP ($Y$) | 48 | 21 | 1 | 30 | – |
| Unemployment Rate ($\mathscr{U}$) | 46 | 25 | 1 | 28 | – |
| Policy Rate ($R^d$) | 12 | 15 | 22 | 51 | – |
| Inflation Rate ($\pi$) | 6 | 42 | 1 | 51 | – |
| Spread ($R^l - R^d$) | 39 | 0 | 0 | 0 | 61 |
| | [100] | [0] | [0] | [0] | [–] |
| *Panel B: other variables* | | | | | |
| Real Credit ($wn + r^k \varkappa K$) | 40 | 34 | 0 | 26 | – |
| Investment ($I$) | 56 | 26 | 1 | 17 | – |
| Consumption ($C$) | 45 | 19 | 0 | 36 | – |
| Labour Market Tightness ($\vartheta$) | 45 | 26 | 1 | 28 | – |

*Notes*: Each cell entry denotes the percentage contribution attributed to the column shock in explaining the volatility of the row variable at a business cycle frequency (i.e., 6-32 quarters). Entries in square brackets denote variance decomposition when measurement error is omitted. Estimated parameters are set to their posterior mode. ME denotes measurement error.

Notwithstanding, the model estimates lie within the 95 percent confidence intervals of the empirical estimates at various horizons.

Figure 8 plots the historical decomposition of year-over-year GDP growth (panel A) and deviations in the unemployment rate from its mean (panel B) over the sample horizon. The solid black lines denote the observed data as represented by the model's response to all the estimated shocks and initial conditions. The various coloured bars denote the model simulation of the panel variable when only the associated shock is turned on. For example, the blue bars denote the GDP growth and the unemployment rate deviations when the only source of variation in the model is the estimated FMC shock. Consistent with the results above, the FMC shock plays an important role at generating the observed cyclicality of both variables. This is particularly true during the period surrounding the 2007-09 financial crises. Between 2005 and 2007, there were a series of positive FMC shocks driving unemployment down and GDP up. By the time the recession began, however, the FMC shocks suddenly reversed themselves (see Figure 9 below) leading to a contraction in bank credit supply and GDP. While GDP had already begun contracting prior to the official recession began, the contraction in bank credit greatly exacerbated the downturn.

Unsurprisingly, the estimated monetary policy shocks—$R^d$ and $x$—are countercyclical and, according to the model, played an important role at stabilizing the economy during the 2007-09 recession. Had there not been any monetary policy shocks during the financial crises, the

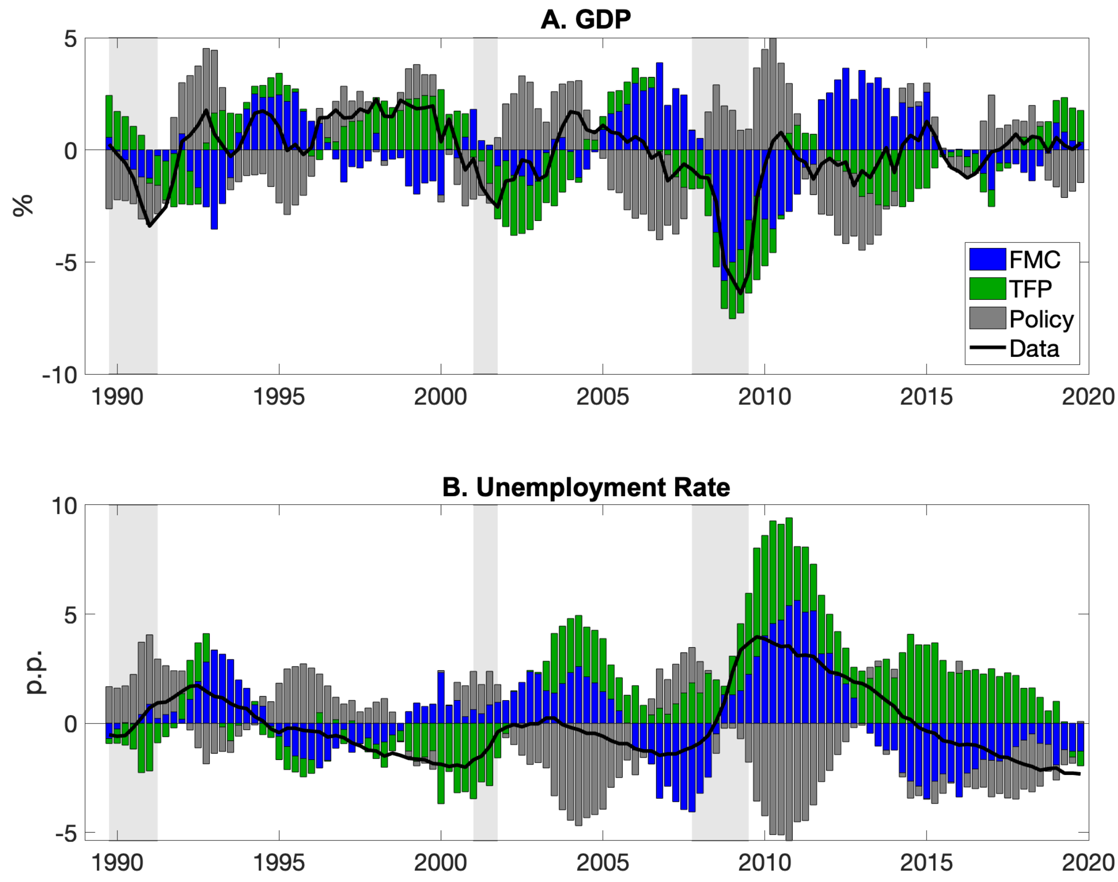


Figure 8: Historical Decomposition

*Notes*: Each series is demeaned. Model simulations are conducted when the estimated parameters are set to their posterior mode. Shaded areas denote NBER recession dates.

unemployment rate would have been about 5 percentage points higher, and GDP would have experienced a deeper and longer contraction. These results are broadly consistent with Jannsen et al. (2015) and Farmer (2015) who evaluate the Federal Reserve's unconventional monetary policy during the financial crises.

# 6 Out of Sample Tests & Alternative Identification Method

**Out-of-Sample Tests:** Since the FMC shock is inferred from the macroeconomic data used in the estimation procedure outlined in Section 5.1 and, therefore, is not directly observed in the data, it is possible the estimated FMC shock may be capturing other sources of variation in the economy. In this section I test to see whether the model implied FMC shock accurately captures bank credit supply shocks observed in the real world. To accomplish this task, I compare the cyclical properties

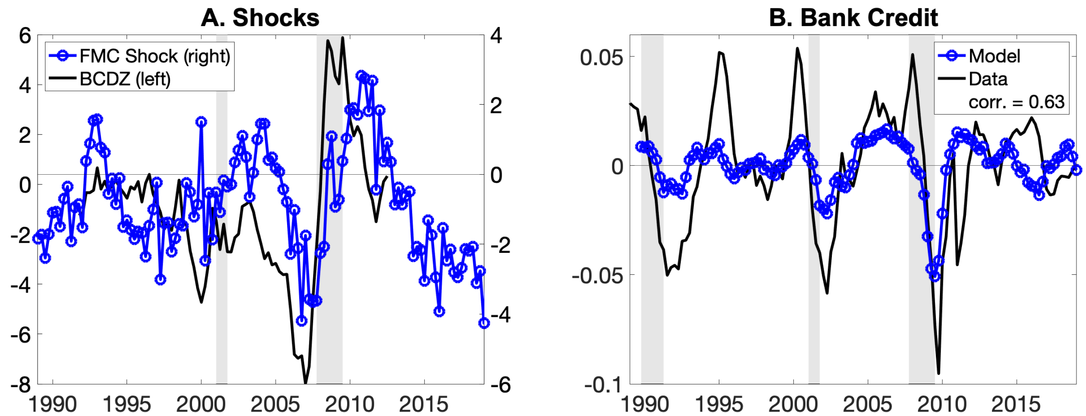


Figure 9: Out of Sample Tests

*Notes*: Estimated model parameters are set to their posterior mode.

of the model implied FMC shock with the BCDZ bank credit supply shock used in Section 3. Because the BCDZ shock is estimated using *qualitative* senior loan officer opinion survey data that is not used in the model's estimation procedure, makes it the ideal candidate for an *out-of-sample* test. In other words, the BCDZ series should, in theory, be measuring the same thing as the model implied FMC shock—i.e., exogenous shifts in the supply of bank credit—and, therefore, should exhibit a similar pattern over the business cycle.

Figure 9 panel A plots the cumulative sum of BCDZ shock (solid black line) and the model implied smoothed FMC shock (blue circled line). To maintain consistency between the empirical and model derived bank credit supply shocks, I plot the negative of the FMC shock implying that a rise (fall) corresponds to a contraction (expansion) in the supply of bank credit. Early in the sample period there appears to be little consistency between the shocks. From the 2004 up until the financial crises, however, both series predict a marked increase in the supply of bank credit followed by a sudden reversal during the recessionary period.

It is important to note that data on bank credit was not included in the set of observed variables in the model estimation procedure. This means that the cyclical properties of the model implied FMC shock are largely dependent on the underlying mechanisms of the model. Although the FMC and BCDZ are similar, it would be important to know if the model implied bank credit series is consistent with its observed data counterpart. Panel B of Figure 9 displays the model implied bank credit (blue circled line) and its observed counterpart.[28] While the model predicts a much lower level of volatility, the cyclical pattern of each series are remarkable similar over the sample period.

Going further, I ask: In the context of the VAR model, can the model implied FMC shock generate a VAR response consistent with that of the BCDZ shock? I replace the BCDZ shock with

[28]Observed bank credit is the sum of FDIC commercial banks' commercial and industrial loans, and construction and development loans. The series is then put into per capita terms. Source: FDIC call reports.

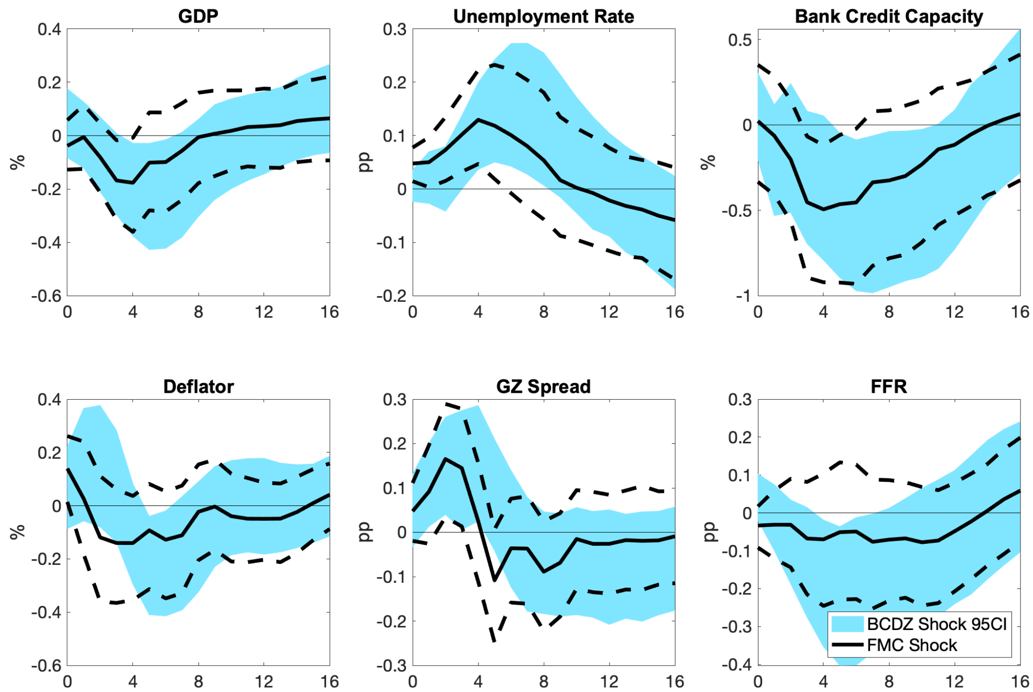


Figure 10: Impulse Responses—BCDZ & FMC shock

*Notes*: Shaded area denotes the 95% confidence interval of the original VAR model impulse responses estimate in Section 3. The solid lines denotes the VAR model impulse responses when the BCDZ shock is replaced with the model implied FMC shock. Dashed lines denote the respective 95% confidence intervals. See text for further details.

the first difference of the model implied FMC shock in the VAR model. For consistency I also maintain the same sample period as the original VAR model. Looking at Figure 10, it is clear both BCDZ and FMC shocks exhibit similar model response. Moreover, there is considerable overlap in the respective model's 95 percent confidence intervals.

**Alternative FMC Shock Identification:** Next I employ an entirely different methodological approach to estimating the FMC shock process. Following Jermann and Quadrini (2012) I use the model equations to directly isolate the targeted shock process. In this case the equation of interest is 4 where the FMC shock in log-deviations is

$$\hat{\zeta}_{bt} = -\left[1+(1+\zeta_b)\rho^d\right]\left(\frac{1+\zeta_b}{\zeta_b}\right) \times \hat{\tilde{\rho}}_t^d, \tag{32}$$

where $\tilde{\rho}^d$ and $\zeta_b$ denote the steady-state levels of the bank's desired reserve ratio and FMC, respectively. The $\hat{}$ denotes log difference. Since the growth in bank's desired reserve ratio is not directly observable, I infer it using corollary 4.1.1. As a result, log-deviations in desired reserve ratio can be written as

$$\hat{\hat{\rho}}_t^d = -\left(\widehat{\int_{i\in\mathcal{M}_t} D_{it}^d \mathrm{d}i} - \hat{D}_t^s\right),$$

where the righthand side denotes the negative difference between the growth in bank loans to firms, $\widehat{\int_{i\in\mathcal{M}_t} D_{it}^d \mathrm{d}i}$, and growth of total reserves held by the bank within period $t$, $\hat{D}_t^s$.[29] The data used to for bank loans is the same series plotted in panel B of Figure 9.[30] As for total reserves held by the bank, I use data of total reserve balances held by depository institutions in master accounts and excess balance accounts at Federal Reserve Banks.[31] After $\hat{\hat{\rho}}_t^d$ is estimated it is straight forward to impute the FMC shock series using equation 32. The alternative FMC shock process estimates imply $\hat{\rho}_b = 0.9799$ with standard error 0.0157, and $\hat{\sigma}_b = 0.4769$. The remaining parameters are kept at their benchmark values.

Figure 11 panel A shows the alternative FMC measure (blue circled line). Again, to maintain consistency between the empirical and model derived bank credit supply shocks, I plot the negative of the alternative FMC shock. One obvious feature of the alternative measure is the sustained downward trend from the 1990s and then the sudden reversal during the financial crises. Compared to the BCDZ shock (black line), the alternative measure predicts less of a contraction during the 2001 recession; however, both measures predict a period of sustained bank credit expansion prior to, and sudden contraction during, the 2007-2009 recessionary period.

How does the alternative FMC measure influence the unemployment rate? Panel B of Figure 11 addresses this question. Save for the 1990 recessionary period, the observed (black line) and model implied unemployment rate (blue circled line) exhibit a similar cyclical pattern. Notwithstanding, the sustained credit expansion predicted by the alternative FMC shock prior to the financial crises has the effect of lowering the unemployment rate below the observed value. Had there been only FMC shocks hitting the US economy, the model predicts that the unemployment rate would have been about 4 percentage point lower than it had been prior to the financial crises. Additionally, the unemployment rate would have also been 2 percentage points higher towards the end of the crises. Regarding bank credit, the model implied series (panel C blue circled line) does a poor job at capturing the cyclical pattern of the observes series (black line). During the period surrounding the financial crises, however, the model implied credit series tracks the observed counterpart remarkably close, especially during the contractionary phase which the benchmark model has trouble replicating.

[29] While total bank loans in the model are also comprised of bank net worth, as has been shown in the literature bank net worth is 'sticky' quarter-over-quarter (Adrian et al., 2013). As a result, I assume growth in bank loans is driven by changes in deposit liabilities and not bank net worth.

[30] See footnote 28.

[31] Sourced via FRED; code BOGMBBM.

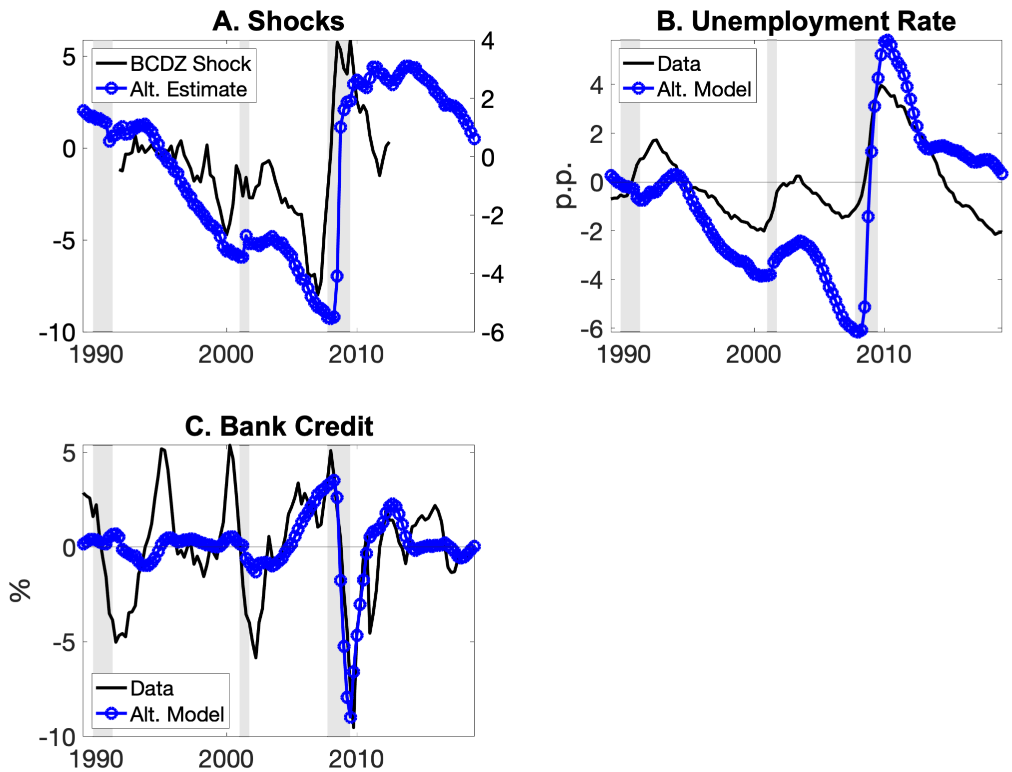


Figure 11: Alternative FMC Shock

*Notes*: Alternative model parameters are set to the benchmark values except for $\rho_b$ and $\sigma_b$ which are estimated using the alternative method in the text. Shaded areas denote NBER recession dates.

I cautiously interpret the results presented in this section as evidence that the benchmark model and associated estimated FMC shock do capture the macroeconomic effects of bank credit supply shocks.

# 7 Conclusion

This paper asked: Is there a causal connection between changes in the supply of bank credit and the observed fluctuations of the unemployment rate; and, if there is, what are the transmission mechanisms governing such a relationship? Using a bank credit supply shock estimated in Bassett et al. (2014) I find that bank credit supply shocks contribute 30% of the volatility in the unemployment rate. To shed light on the mechanism behind this relationship, I used a model with labour search frictions and nominal rigidities that incorporates a banking sector endowed with a financing through money creation technology allowing it to expand and contract the supply of bank credit. When the bank contracts loans less funds are available to firms to purchase inputs and the cost of borrowing rises. Faced with higher borrowing costs, the value of being a matched firm falls and less vacancies are posted. As a result, labour market tightness falls and the unemployment rate rises. Both empirical and estimated model suggest that shocks to the supply of bank credit supply play an important role in generating economic fluctuation overall. Moreover, disruptions to bank credit supply generates fluctuations consistent with a stylized business cycle: the unemployment rate and credit spread are countercyclical while investment and labour market tightness are procyclical.

Reasons banks adjust their supply of credit, no doubt, depend on a host of factors. For example, changes in expectations or economic outlook and industry competition have been found to be important determinants of the position of the credit supply curve over the business cycle. While this paper remains agnostic regarding the source of changes affecting the bank credit supply curve, this paper provides evidence that the bank credit supply channel plays an important role in generating cyclical fluctuations in economic activity. As to which sources of variation are driving the results, I leave for future research.

## Disclosures

Perplexity, an AI-powered search engine, was used as an aid when completing the literature review.

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# A Representative Bank's Optimization Problem

Although the bank accumulates net worth, the bank's optimization problem is static. Ultimately, in each period the bank's optimization problem is to take previous periods net worth, $\{NetWorth_t\}$, interest rates, $\{R^d_t, R^s_t\}$, and it's level of FMC, $\{\zeta_{b,t}\}$, as given and choose a level of savings deposits, $D^s_t$, to issue to the household that maximizes end-of-period profits. To show this first I first note that combining 2 and 3, total demand deposits created by the bank can be written as

$$\int\limits_{i\in\mathscr{M}_t} D^d_{i,t}\mathrm{d}i = \frac{1-\rho^s}{\tilde{\rho}^d_t} D^s_t. \tag{A.1}$$

Moreover, using the balance sheet identity, total reserves are simply equal to the amount of savings deposits the bank holds—i.e., $D^s_t$. Using this fact and using A.1 to substitute out total demand deposits from bank's profit function 6, the bank's optimization problem can be formally written as

$$\max_{D^s_t}\left\{(1+R^l_t)\left[\frac{1-\rho^s}{\tilde{\rho}^d_t}D^s_t + NetWorth_t\right] + D^s_t - (1+R^s_t)D^s_t - (1+R^d_t)\frac{1-\rho^s}{\tilde{\rho}^d_t}D^s_t - NetWorth_t\right\}.$$

The associated first order condition yields the result from 4.2.

# B Representative Household's Optimization Problem

Using equation 1 to substitute out $M_t$, the household's optimization problem can written as

$$\max_{\{C_t, M^{\text{base}}_{t+1}, D^s_t, K_{t+1}, I_t, \varkappa_t\}} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left\{ \log(C_t - hC_{t-1}) - \psi_L n_t + \mathscr{V}\left(\frac{M^{\text{base}}_t - D^s_t}{P_t}\right)\right\},$$

subject to

$$\begin{aligned} M^{\text{base}}_{t+1} \le {} & W_t n_t + [\varkappa_t r^k_t - a(\varkappa_t)]P_t K_t + P_t\mathscr{B}(1-n_t) \\ & + (1+R^s_{t-1})D^s_{t-1} + M^{\text{base}}_t - D^s_t + X_t + \text{Lump}_t - P_t C_t - P_t I_t, \end{aligned} \tag{B.1}$$

and

$$K_{t+1} = (1-\Delta)K_t + \left[1 - S\left(\frac{I_t}{I_{t-1}}\right)\right] I_t. \tag{B.2}$$

The associated first order conditions are

$$
\begin{aligned}
C_t: &\quad \lambda_{1,t} = \frac{1}{C_t - hC_{t-1}} - \beta \mathbb{E}_t \left\{ \frac{h}{C_{t+1} - hC_t} \right\}, \\
M_{t+1}^{\text{base}}: &\quad \lambda_{1,t} = \beta \mathbb{E}_t \left\{ \frac{1}{\pi_{t+1}} \left[ \lambda_{1,t+1} + \mathscr{V}'(\frac{M_{t+1}^{\text{base}} - D_{t+1}^s}{P_{t+1}}) \right] \right\}, \\
D_t^s: &\quad \lambda_{1,t} = -\mathscr{V}'(\frac{M_t^{\text{base}} - D_t^s}{P_t}) + \beta \mathbb{E}_t \left\{ \frac{\lambda_{1,t+1}}{\pi_{t+1}} (1 + R_t^s) \right\}, \\
K_{t+1}: &\quad \lambda_{2,t} = \beta \mathbb{E}_t \left\{ \lambda_{1,t+1} r_{t+1}^k + \lambda_{2,t+1} (1 - \Delta) \right\}, \\
I_t: &\quad \lambda_{1,t} = \lambda_{2,t} + \left[ 1 - S(\frac{I_t}{I_{t-1}}) - S'(\frac{I_t}{I_{t-1}}) \left( \frac{I_t}{I_{t-1}} \right) \right] + \beta \mathbb{E}_t \left\{ \lambda_{2,t} S'(\frac{I_{t+1}}{I_t}) \left( \frac{I_{t+1}}{I_t} \right)^2 \right\}, \\
\varkappa_t: &\quad r_t^k = a'(\varkappa_t),
\end{aligned}
$$

where $\pi_t = P_t / P_{t-1}$. The variable $\lambda_{1,t} \equiv \tilde{\lambda}_{1,t} P_t$, where $\tilde{\lambda}_{1,t}$ and $\lambda_{2,t}$ are the Lagrange multipliers on B.1 and B.2, respectively.

# C Intermediate-Good Firm Optimization Problem

The intermediate-good firm $i$'s optimization problem can be written as

$$
\max_{\{n_{it}, k_{it}, v_{it}\}} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \frac{\lambda_{1,t+1}}{\lambda_{1,t}} \left\{ Q_t F(k_{it}, n_{it}; z_t) - (1 + R_t^l)[W_t n_{it} + P_t r_t^k k_{it}] - P_t \kappa v_{it} \right\},
$$

subject to

$$
n_{it} = (1 - \delta) n_{it-1} + p^v(\vartheta_t) v_{it}. \tag{C.1}
$$

Let $J_{it}^F$ be firm $i$'s Lagrange multiplier on C.1, then the associated first order conditions are

$$
\begin{aligned}
n_{it}: &\quad \frac{J_{it}^F}{P_t} = q_t \frac{\partial F(k_{it}, 1; z_t)}{\partial n_{it}} - (1 + R_t^l) w_t + \beta \mathbb{E}_t \left\{ \frac{\lambda_{1,t+1}}{\lambda_{1,t}} (1 - \delta) \frac{J_{it+1}^F}{P_t} \right\} \\
k_{it}: &\quad Q_t \frac{\partial F(k_{it}, 1; z_t)}{\partial k_{it}} = (1 + R_t^l) P_t r_t^k \\
v_{it}: &\quad \kappa = p^v(\vartheta_t) \frac{J_{it}^F}{P_t},
\end{aligned}
$$

where the value of posting a vacancy, $J_{it}^V$, is assumed to be zero.

# D Proofs

## D.1 Proposition 4.1

Invoking the balance sheet identity *Assets* $=$ *Liabilities* $+$ *Net Worth* on the bank's period $t$ balance sheet (Table 2) yields the following relationship:

$$\rho^s D_t^s + \tilde{\rho}_t^d \int\limits_{i \in \mathscr{M}_t} D_{i,t}^d \mathrm{d}i = D_t^s, \tag{D.1}$$

where the left hand side denotes total reserves held by the bank. Decomposing the reserves into *required* and *excess* reserves implies

$$\rho^s D_t^s + \tilde{\rho}_t^d \int\limits_{i \in \mathscr{M}_t} D_{i,t}^d \mathrm{d}i = \underbrace{\rho^s D_t^s + \rho^d \int\limits_{i \in \mathscr{M}_t} D_{i,t}^d \mathrm{d}i}_{\text{required reserves}} + \underbrace{E_t}_{\text{excess reserves}} \tag{D.2}$$

which can be rewritten as

$$\tilde{\rho}_t^d = \rho^d + \frac{E_t}{\int\limits_{i \in \mathscr{M}_t} D_{i,t}^d \mathrm{d}i}. \tag{D.3}$$

Noting that $\int\limits_{i \in \mathscr{M}_t} D_{i,t}^d \mathrm{d}i = (\zeta_{b,t} + 1) E_t$ from 2 yields the final result. This concludes the proof.

## D.2 Proposition 4.2

See the bank's optimization problem in Section A of the Appendix.

# E Tables

Table 8: Data Sources

| Variable | Description | Source(s) |
| --- | --- | --- |
| GDP | GDP in billions of dollars divided by population >= 16yrs and deflated by Implicit Price Deflators for GDP, index 2012=100 | Bureau of Economic Analysis: Table 1.1.5. and Table 1.1.9; Federal Reserve Economic Data: CNP16OV |
| Unemployment Rate | Unemployment Rate, Percent, Seasonally Adjusted, Transformed to quarterly rate | Bureau of Labor Statistics (via Federal Reserve Economic Data: UNRATE) |
| Bank Credit Capacity | Gross total loans & leases plus unused loan commitments in millions of dollars divided by population >= 16yrs and deflated by Implicit Price Deflators for GDP, index 2012=100 | FDIC Call Reports and Bureau of Economic Analysis: Table 1.1.9; Federal Reserve Economic Data: CNP16OV |
| Federal Funds Rate | Effective Federal Funds Rate, Percent, Transformed to quarterly rate | Board of Governors of the Federal Reserve System (via Federal Reserve Economic Data: DFF) |
| Inflation Rate | Log-difference of implicit price deflator for GDP, index 2012=100 | Bureau of Economic Analysis: Table 1.1.9 |
| GZ Spread | Corporate interest rate spread | Gilchrist and Zakrajšek (2012) |

# F Online appendix

## F.1 Bank Credit Supply Shock Derived from BVAR with Sign Restrictions

In this section I describe the method used to derive the 'SR' bank credit supply shock described in the main text.[32] The sign restriction method of identification, instead of assuming $B$ of equation **??** is lower triangular, relies on generating impulse responses—for a given set of parameters—which are consistent with underlying economic theory. For example, consider the VAR model

$$\mathbf{Y}_t = \alpha + \sum_{j=1}^{\rho} \mathbf{A}_j \mathbf{Y}_{t-j} + \mathbf{u}_t, \tag{F.1}$$

where where $\mathbf{A}_j$, $j = 1, \ldots, \rho$ are $n \times n$ matrices of coefficients, and $\mathbf{u}_t = \mathbf{B}\varepsilon_t$, where $\mathbf{B}$ is an $n \times n$ matrix and $\varepsilon_t$ is an $n \times 1$ vector of structural shocks with $\mathbb{E}\varepsilon_t = \mathbf{0}$ and $\mathbb{E}\varepsilon_t \varepsilon_t' = I$. The $n \times 1$ vector $\mathbf{u}_t$ are the reduced form shocks such that $\mathbf{u}_t \sim \mathcal{N}(\mathbf{0}, \Sigma_u)$, where $\Sigma_u = B\Sigma_\varepsilon B' = BIB'$.

While equation F.1 can be estimated using standard OLS techniques, under a sigh restriction approach it is desirable to uses Bayesian vector autoregression (BVAR) methods as it allows simple computation of impulse response function error bands. Moreover, as noted in Uhlig (2005), parameter draws from an estimated posterior distribution are candidate true values and therefore the true impulse responses should not violated the imposed sign restrictions discussed below. As a result, I follow a Bayesian approach which estimates the reduced form coefficients from equation F.1 using an uninformative Normal-Inverse-Wishart prior.

[32] The description here closely follows that in Langlais (2023b). To keep this paper self-contained, however, I reproduce parts of it here with some minor adjustments.

The estimation algorithm is as follows:

1. Estimate the reduced form VAR F.1 using Bayesian methods and obtain $S$ draws form the posterior distribution to get coefficient and covariance estimates $\{\hat{\alpha}^{(s)}, \hat{\mathbf{A}}_1^{(s)}, \hat{\mathbf{A}}_2^{(s)}, \hat{\Sigma}_u^{(s)}\}$ for $s = 1, 2, ..., S$.

2. Obtain the unique Cholesky matrix $C^{(s)}$ for each draw such that $C^{(s)}C^{(s)\prime} = \hat{\Sigma}_u^{(s)}$.

3. Generate a set of random $n \times n$ orthonormal matrices $\{Q^{(k)}\}$ for $k = 1, 2, ..., K$ and set $H^{(s,k)} = C^{(s)}Q^{(k)}$.

4. Check whether the model implied impulse responses for each $\{H^{(s,k)}\}$, $k = 1, 2, ..., K$, satisfy the sign restrictions imposed by the econometrician.

   *i*) if yes, the impulse responses bear a structural interpretation and are saved; set $s = s+1$ and go to step 2.

   *ii*) if no, set $s = s+1$ and go to step 2.

For the analysis below I set $\rho = 2$, $S = 2000$ and $K = 1000$.[33] Following the literature (Mandler and Scharnagl, 2020; Martínez and Rodríguez, 2021; Finck and Rudel, 2022), the variables I choose to include in the BVAR model are real GDP, total bank loan capacity, GDP deflator, interest rate spread and the federal funds rate. Total bank loan capacity is total bank loans plus unused loan commitments and is deflated using the GDP deflator. For the interest rate spread I use the 'GZ' spread from Gilchrist and Zakrajšek (2012). Except for the GZ spread and the federal funds rate, each variable is transformed into year-over-year growth rates.

What's more, **?** find that risk shocks—also referred to uncertainty shocks—and bank loan supply shock produce a very similar cyclical response in an estimated DGSE models. As a result, I follow Furlanetto et al. (2019) and include a sixth variable to the model meant to disentangle the model's response to risk and bank loan supply shocks. In particular, I assume that risk shocks have a relatively larger effect on economic uncertainty than they do on interest rate spreads compared to loan supply shocks. As a result, the (log) ratio of economic uncertainty relative to the GZ spread should increase (decrease) following a risk (loan supply) shock. The economic uncertainty measure used here is the 'total macro economic uncertainty' measure from Jurado et al. (2015) at the three month horizon. The BVAR sample period is 1985:Q2-2018:Q3.

Table 9 reports the sign restrictions on each of the model variables in response to four shocks: loan supply shock (panel a), aggregate demand shock (panel b), aggregate supply shock (panel c), and monetary policy shock (panel d). I assume the sign restrictions put on each variable may be

[33] This papers uses the MATLAB package developed in Breitenlechner et al. (2019) to perform the estimation algorithm. Further details regarding the algorithm used in this paper see Rubio-Ramirez et al. (2010).

Table 9: BVAR Sign Restrictions with Risk Shock

| | response variable | | | | | |
|---|---|---|---|---|---|---|
| horizon | GDP | Loans | GDP Deflator | GZ[a] | Overnight Rate | $\log(\frac{\text{Uncertainty}}{GZ})^b$ |
| *Panel A*: loan supply shock | | | | | | |
| 0 | $-$ | $-$ | | $+$ | $-$ | $-$ |
| 1 | $-$ | $-$ | | $+$ | $-$ | $-$ |
| 2 | $-$ | $-$ | $-$ | $+$ | $-$ | $-$ |
| *Panel B*: aggregate demand shock | | | | | | |
| 0 | $-$ | | $-$ | $-$ | $-$ | |
| 1 | $-$ | | $-$ | $-$ | $-$ | |
| 2 | $-$ | | $-$ | $-$ | $-$ | |
| *Panel C*: aggregate supply shock | | | | | | |
| 0 | $-$ | | $+$ | | $-$ | |
| 1 | $-$ | | $+$ | | $-$ | |
| 2 | $-$ | | $+$ | | $-$ | |
| *Panel D*: monetary policy shock | | | | | | |
| 0 | | | $-$ | | $+$ | |
| 1 | $-$ | $-$ | $-$ | | $+$ | |
| 2 | $-$ | $-$ | $-$ | | $+$ | |
| *Panel E*: risk shock | | | | | | |
| 0 | $-$ | | $-$ | $+$ | $-$ | $+$ |
| 1 | $-$ | | $-$ | $+$ | $-$ | $+$ |
| 2 | $-$ | $-$ | $-$ | $+$ | $-$ | $+$ |

*Notes*: The signs '$-$' and '$+$' denote a negative and positive response restriction, respectively. An empty cell denotes no restriction on variable response.
[a] 'GZ' refers to the GZ interest rate spread from Gilchrist and Zakrajšek (2012).
[b] 'Uncertainty' refers to the total macroeconomic uncertainty measure at the three month horizon from Jurado et al. (2015).

imposed for a maximum of 2 periods following each shock. See Langlais (2023b) for a detailed justification of the sign restrictions.

Out of the potential 2 million sets of impulse response functions computed, there were a total of 398 sets of impulse response functions in which the sign restrictions held.

Table 10: VAR Variance Decompositions

| horizon | GDP | Unemp. Rate | Bank Credit Capacity | Deflator | GZ Spread | Federal Funds Rate |
|---|---|---|---|---|---|---|
| $h = 4$ | 33 | 26 | 14 | 7 | 36 | 53 |
| | [12–51] | [7–47] | [1–36] | [1–23] | [18–54] | [31–73] |
| $h = 8$ | 29 | 28 | 17 | 23 | 34 | 54 |
| | [9–49] | [8–52] | [1–40] | [5–46] | [17–52] | [29–76] |
| $h = 16$ | 24 | 27 | 13 | 23 | 36 | 42 |
| | [9–43] | [11–46] | [3–31] | [6–46] | [19–54] | [19–66] |
| $h = 32$ | 26 | 28 | 18 | 22 | 34 | 40 |
| | [9–44] | [11–48] | [4–39] | [6–44] | [17–51] | [17–64] |

*Notes*: Each cell entry denotes the percentage contribution attributed to the bank credit supply shock in explaining the volatility of the column variable at horizon $h$. Entries in square brackets denote the 95% confidence interval.

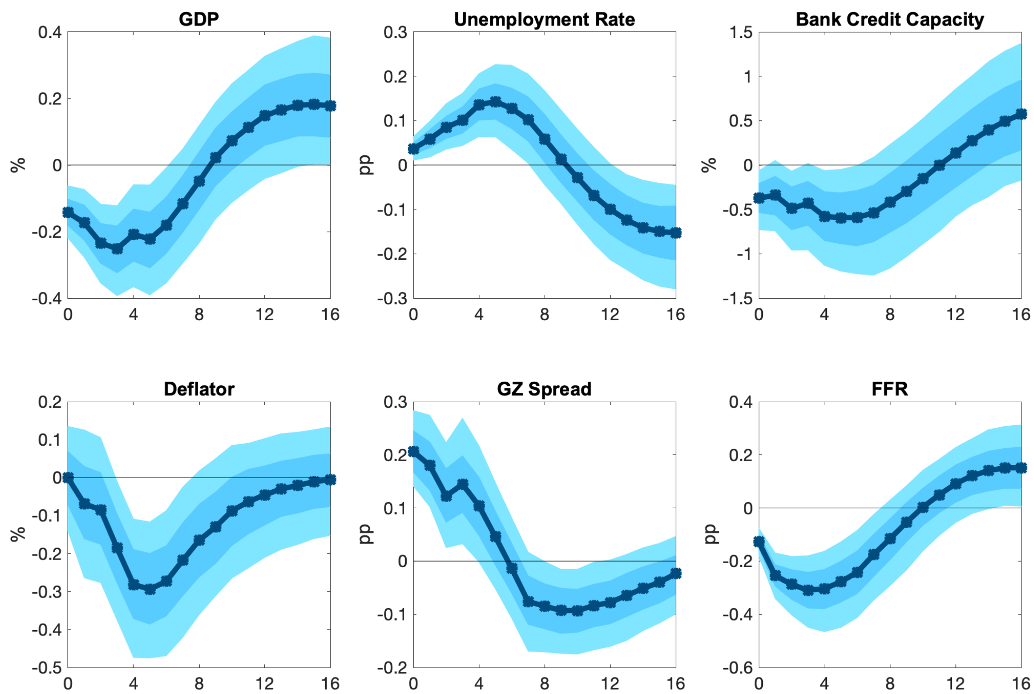


Figure 12: Impulse Responses of Contractionary SR Shock

*Notes*: Light shaded and dark shaded areas denote 95% and 68% confidence intervals, respectively. Confidence intervals are computed using 1000 bootstrap draws. See text for further details.

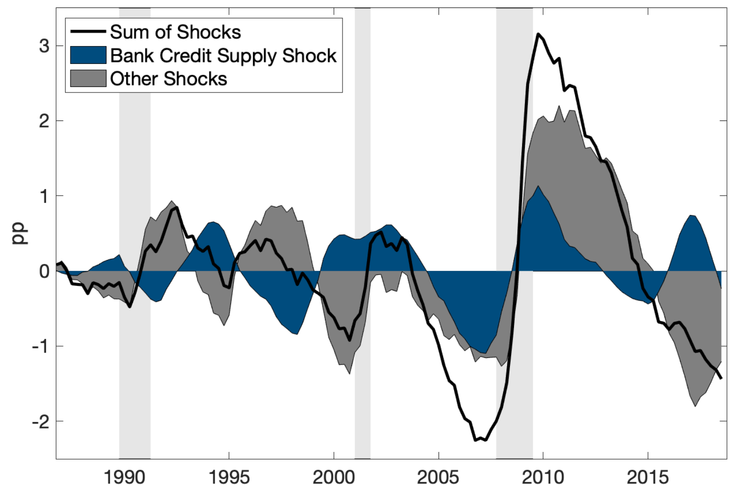


Figure 13: Historical Decomposition of the Unemployment Rate

*Notes*: See text for further details.

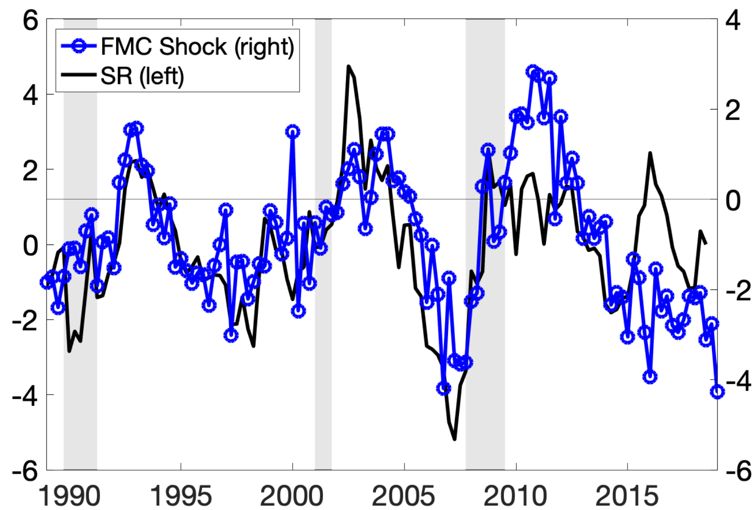


Figure 14: Out of Sample Test—SR Shock versus FMC Shock

*Notes*: SR shock process is derived from the closest-to-median model. Model simulations are conducted when the estimated parameters are set to their posterior mode. Shaded areas denote NBER recession dates.

The correlation coefficients between the BCDZ and the SR shock with the unemployment rate are 0.67 and 0.63, respectively.[34]

[34]Correlation coefficients were computed after removing linear trends in each of the series.

## F.2 Optimality Conditions

To solve to model requires to transform each of the nominal variables into real terms by deflating with the final good price level, $P_t$. Thus, $j_t^F = \frac{J_t^F}{P_t}$, $w_t^N = \frac{W_t^N}{P_t}$, $w_t = \frac{W_t}{P_t}$, $m_{t+1}^b = \frac{M_{t+1}^b}{P_t}$, $d_t^d = \frac{D_t^d}{P_t}$, $e_t = \frac{E_t}{P_t}$. The Lagrange multiplier on the households asset accumulation constraint is scaled by the price level: $\lambda_{1,t} = P_t \tilde{\lambda}_{1,t}$. The household's savings deposits are scaled by total money base: $d_t^s = \frac{D_t^s}{M_t^b}$. Likewise, the money base growth rate is scaled by total money base: $x_t = \frac{X_t}{M_t^b}$.

The model benchmark model can be summarized by 29 endogenous variables:

$$\{C_t, \lambda_{1,t}, \lambda_{2,t}, \pi_t, \mu_t, p_t^u, p_t^v, n_t, u_t, U_t, Y_t, r_t^k, K_{t+1}, I_t, R_t^s, v_t, q_t, j_t^F, w_t^N, w_t, m_{t+1}^b, d_t^s, d_t^d, e_t, R_t^l, R_t^d, x_t, networth_{t+1}, \varkappa_t\}$$

and 29 equations:

$$\zeta_{c,t}\lambda_{1,t} = \frac{\zeta_{c,t}}{C_t - hC_{t-1}} - \beta\mathbb{E}_t\left\{\frac{h\zeta_{c,t+1}}{C_{t+1} - hC_t}\right\} \quad \text{(F.2)}$$

$$\zeta_{c,t}\lambda_{1,t} = \beta\mathbb{E}_t\left\{\frac{\zeta_{c,t+1}}{\pi_{t+1}}\left[\lambda_{1,t+1} + \gamma\left(\frac{m^b_{t+1}}{\pi_{t+1}}(1-d^s_{t+1})\right)^{-\sigma_q}\right]\right\} \quad \text{(F.3)}$$

$$\zeta_{c,t}\lambda_{1,t} + \zeta_{c,t}\gamma\left(\frac{m^b_t}{\pi_t}(1-d^s_t)\right)^{-\sigma_q} = \beta\mathbb{E}_t\left\{\zeta_{c,t+1}\frac{\lambda_{1,t+1}}{\pi_{t+1}}(1+R^s_t)\right\} \quad \text{(F.4)}$$

$$\zeta_{c,t}\lambda_{2,t} = \beta\mathbb{E}_t\left\{\zeta_{c,t+1}[\lambda_{1,t+1}r^k_{t+1} + \lambda_{2,t+1}(1-\Delta)]\right\} \quad \text{(F.5)}$$

$$\zeta_{c,t}\lambda_{1,t} = \zeta_{c,t}\lambda_{2,t}\left[1 - S(\frac{I_t}{I_{t-1}}) - S'(\frac{I_t}{I_{t-1}})\left(\frac{I_t}{I_{t-1}}\right)\right] + \beta\mathbb{E}_t\left\{\zeta_{c,t+1}\lambda_{2,t}S'(\frac{I_{t+1}}{I_t})\left(\frac{I_{t+1}}{I_t}\right)^2\right\} \quad \text{(F.6)}$$

$$K_{t+1} = (1-\Delta)K_t + \left[1 - S(\frac{I_t}{I_{t-1}})\right]I_t \quad \text{(F.7)}$$

$$r^k_t - \tau^{oil}_t r^k \exp[\sigma_a(\varkappa_t - 1)] = 0 \quad \text{(F.8)}$$

$$q_t = \frac{1}{\lambda_f} + \xi_p\frac{\lambda_f - 1}{\lambda_f}\left[\pi_t(\pi_t - \pi) - \beta\mathbb{E}_t\left\{\frac{\lambda_{1,t+1}}{\lambda_{1,t}}\frac{Y_{t+1}}{Y_t}\pi_{t+1}(\pi_{t+1} - \pi)\right\}\right] \quad \text{(F.9)}$$

$$\mu_t = \bar{\mu}u^\alpha_t v^{1-\alpha}_t \quad \text{(F.10)}$$

$$p^u_t = \frac{\mu_t}{u_t} \quad \text{(F.11)}$$

$$p^v_t = \frac{\mu_t}{v_t} \quad \text{(F.12)}$$

$$n_t = (1-\delta)n_{t-1} + \mu_t \quad \text{(F.13)}$$

$$u_t = 1 - (1-\delta)n_{t-1} \quad \text{(F.14)}$$

$$U_t = 1 - n_t \quad \text{(F.15)}$$

$$Y_t = z_t\left(\frac{\varkappa_t K_t}{n_t}\right)^{\alpha_f} n_t \quad \text{(F.16)}$$

$$C_t + \frac{I_t}{\Upsilon_t} + \kappa v_t + \frac{\xi_p}{2}(\pi_t - \pi)^2 Y_t + \tau^{oil}_t a(\varkappa_t)K_t = Y_t \quad \text{(F.17)}$$

$$j^F_t = q_t z_t\left(\frac{\varkappa_t K_t}{n_t}\right)^{\alpha_f} - (1+R^l_t)w_t + \mathbb{E}_t\left\{\beta\frac{\lambda_{1,t+1}}{\lambda_{1,t}}(1-\delta)j^F_{t+1}\right\} \quad \text{(F.18)}$$

$$q_t z_t \alpha_f\left(\frac{\varkappa_t K_t}{n_t}\right)^{\alpha_f - 1} = (1+R^l_t)r^k_t \quad \text{(F.19)}$$

$$\frac{\kappa}{p^v_t} = j^F_t \quad \text{(F.20)}$$

$$\left(\frac{b}{1-b}\right)\frac{j^F_t}{1+R^l_t} = w^N_t - \frac{\psi_L}{\lambda_{1,t}} - \mathscr{B} + \mathbb{E}_t\left\{\beta\frac{\lambda_{1,t+1}}{\lambda_{1,t}}(1-\delta)\left(1-p^u_{t+1}\right)\left(\frac{b}{1-b}\right)\frac{j^F_{t+1}}{1+R^l_{t+1}}\right\} \quad \text{(F.21)}$$

$$w_t = (w_{t-1})^\iota (w^N_t)^{1-\iota} \quad \text{(F.22)}$$

$$R^l_t - R^d_t = \frac{1 + (1+\zeta_{b,t})\rho^d}{(1+\zeta_{b,t})(1-\rho^s)}R^s_t, \quad \text{(F.23)}$$

$$d_t^d + \frac{networth_t}{\pi_t} = w_t n_t + r_t^k \varkappa_t K_t \tag{F.24}$$

$$d_t^d = (1+\zeta_{b,t})e_t \tag{F.25}$$

$$e_t = (1-\rho^s)\frac{m_t^b}{\pi_t}d_t^s - \rho d_t^d \tag{F.26}$$

$$networth_{t+1} = (1-\tau)(1+R_t^l)\frac{networth_t}{\pi_t} + \phi_b \tag{F.27}$$

$$m_{t+1}^{\text{base}} = \frac{m_t^{\text{base}}}{\pi_t}(1+x_t) \tag{F.28}$$

$$x_t - x = \rho_x(x_{t-1}-x) + (1-\rho_x)\left[\alpha_\pi^x \log(\frac{\mathbb{E}_t\pi_{t+1}}{\pi}) + \alpha_y^x \log(\frac{Y_t}{Y_{t-1}})\right] + \varepsilon_t^x \tag{F.29}$$

$$R_t^d - R^d = \rho_r(R_{t-1}^d - R^d) + (1-\rho_r)\left[\alpha_\pi \log(\frac{\mathbb{E}_t\pi_{t+1}}{\pi}) + \alpha_y \log(\frac{Y_t}{Y_{t-1}})\right] + \frac{\varepsilon_t^r}{400} \tag{F.30}$$

## F.3 Steady State

Given $\pi$ and $R^s$, combining F.3 and F.4 to find $\beta = \frac{\pi}{\sqrt{1+R^s}}$. From F.5 capital rental rate is found as $r^k = 1/\beta - (1-\Delta)$. From F.8 $\varkappa = 1$. From F.28 we get $1+x = \pi$. Given unemployment rate $U$ implies $n = 1-U$, from F.13 implies matches $\mu = \delta n$ and from F.14 $u = 1-(1-\delta)n$, from F.12 vacancies is found as $v = \frac{\mu}{p^v}$ and F.10 implies a matching efficiency of $\bar{\mu} = \frac{\mu}{u^\alpha v^{1-\alpha}}$. From F.11 the probability of a searching worker finding a job is $p^u = \frac{\mu}{u}$. The real price of intermediate-goods from F.9 is found as $q = 1/\lambda_f$. Given the target interest spread, $R^l - R^d$, and savings rate, $R^s$, from F.23 the exogenous level of FMC is

$$\zeta_b = \left[\frac{R^l - R^d}{R^s}(1-\rho^s) - \rho^d\right]^{-1} - 1.$$

Next, I solve for the steady-state level of TFP, $z$. To do so, I solve the following minimization problem

$$\min_z \left(qz\alpha_f\left(\frac{K_i}{n}\right)^{\alpha_f-1} - (1+R_i^l)r^k\right)^2, \qquad \text{subject to} \tag{F.31}$$

$K_i$ and $R_i^l$ satisfying the following steps: for given targeted capital-output ratio, $\left(\frac{K}{Y}\right)$, make initial guess of the level of TFP, $z_i$, and use F.16 to solve

$$K_i = n \times \left[\left(\frac{K}{Y}\right)z_i\right]^{\frac{1}{1-\alpha_f}}. \tag{F.32}$$

Next I find $Y_i = \left(\frac{K}{Y}\right)^{-1} K_i$ and from F.7 $I_i = \Delta K_i$. Given we target vacancy posting costs of 2% of GDP, $\kappa_i = 0.02Y_i$ and using F.17 $C_i = Y_i - I_i - \kappa_i v$. From F.2 $\lambda_i = \frac{1}{C_i}\frac{1-\beta h}{1-h}$, from F.20 $j_i^F = \kappa_i / p^v$. Following Leduc and Liu (2016), total flow value of non-work $\mathscr{B} + \frac{\psi_L}{\lambda} = 0.75$, thus $(\psi_L)_i = \lambda_i(0.75 - \mathscr{B})$. Using F.18 and F.21 I solve for $R_i^l$ and $w_i^N$. Continue searching for $z$ which minimizes F.31 until $\left(qz\alpha_f\left(\frac{K_i}{n}\right)^{\alpha_f - 1} - (1+R_i^l)r^k\right)^2 < \varepsilon$, where $\varepsilon$ is a chosen threshold.

Once a steady-state TFP, $z$, and the associated steady-state loan rate of interest, $R^l$, are found, then for a given targeted interest rate spread, we get $R^d = R^l - [R^l - R^d]$. Next, I solve for $d^d$, $e$, $m^b$, $networth$, and $\phi^b$ using equations F.24, F.27, F.26, F.25 and

$$Lev = \frac{\pi d^d + networth + m^b d^s}{networth}$$

where $Lev$ denotes the bank's asset to net worth ratio and is targeted in the data. Lastly, using root a solving method I find parameters $\gamma > 0$ and $\sigma_q > 0$ which satisfy F.3 and F.4.

## F.4 Data & Estimation

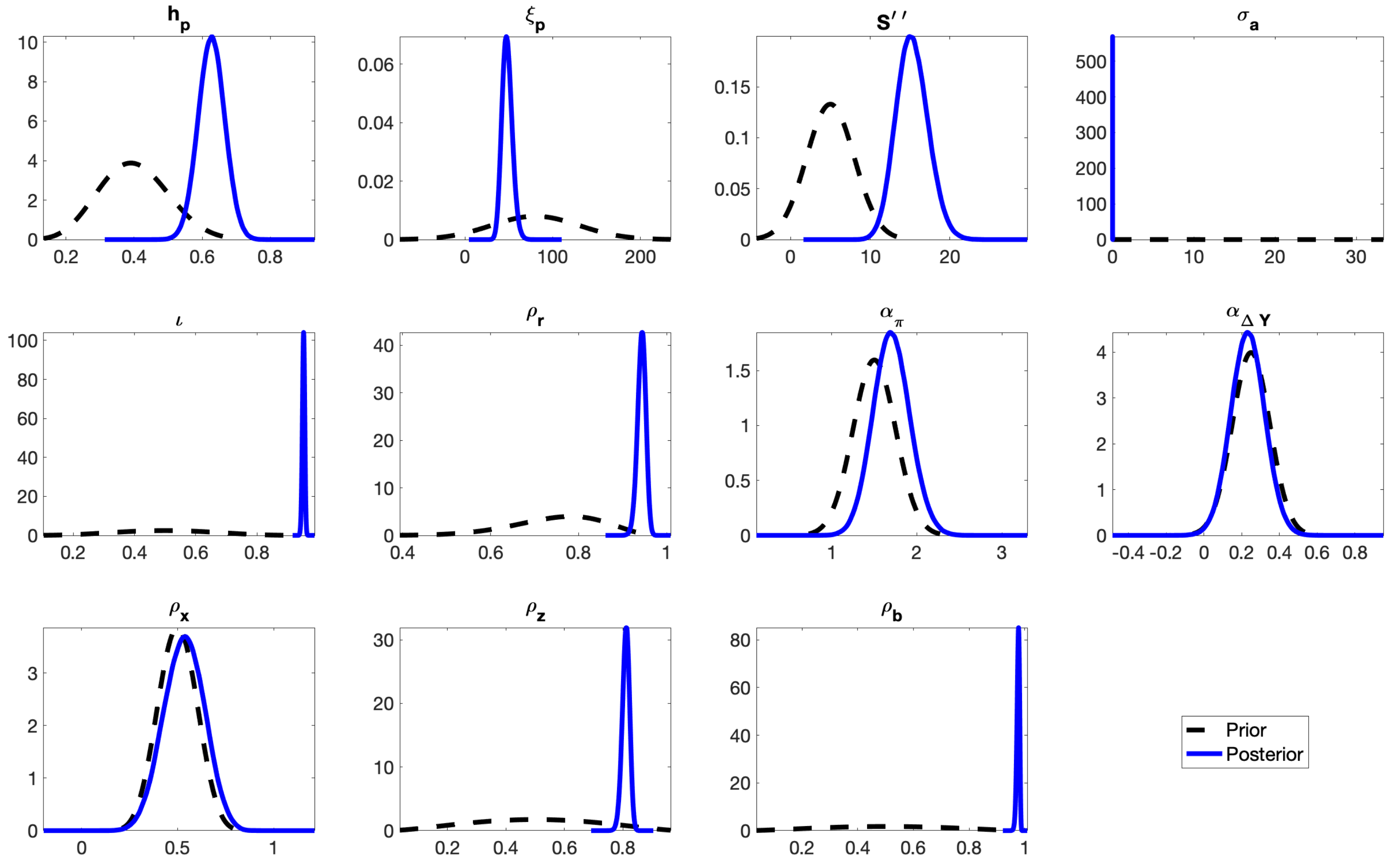


Figure 15: Prior & Posterior Densities: Parameters

*Notes*: The posterior distribution is obtained from 8,000,000 draws equally distributed across 8 chains of the Metropolis-Hastings algorithm. For each chain the first 20% of the draws are discarded.

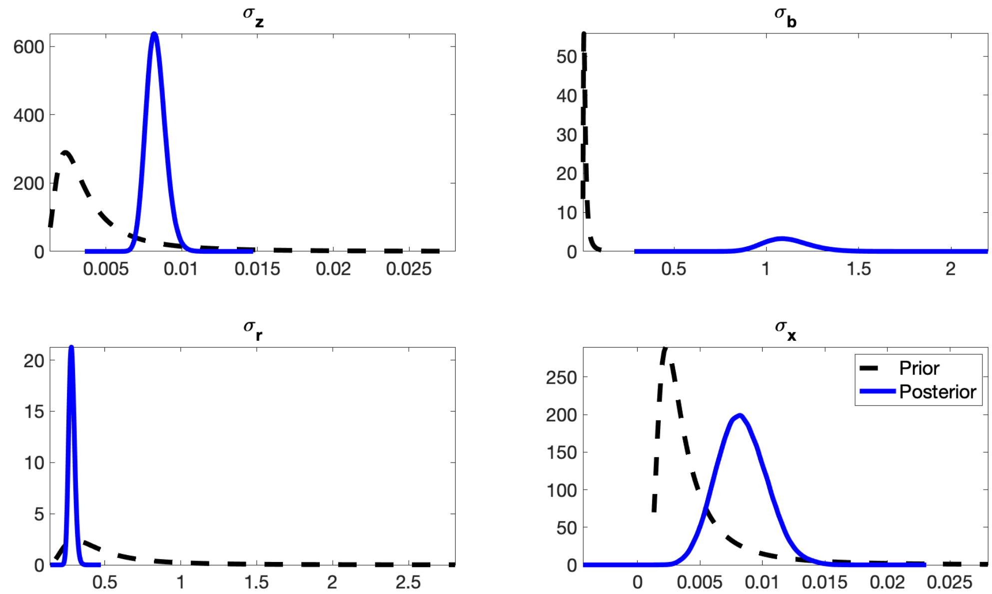


Figure 16: Prior & Posterior Densities: Shocks

*Notes*: The posterior distribution is obtained from 8,000,000 draws equally distributed across 8 chains of the Metropolis-Hastings algorithm. For each chain the first 20% of the draws are discarded.

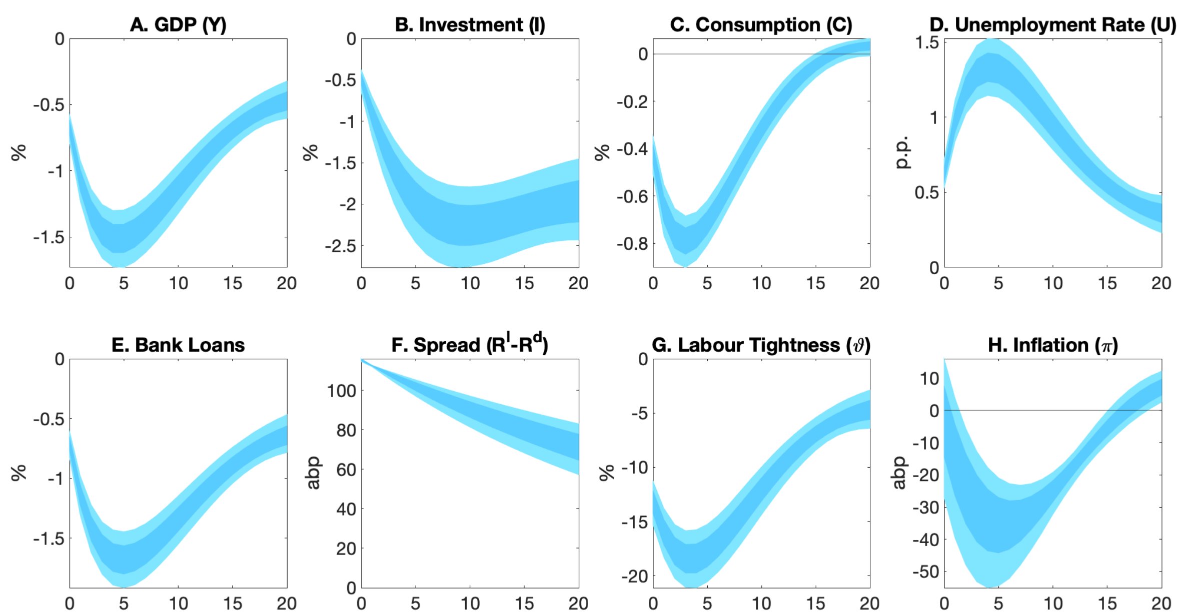


Figure 17: Bayesian Impulse Responses to a FMC Shock

*Notes*: Bayesian credible intervals are estimated using 10,000 draws from posterior parameter distribution. The light and dark shaded areas denote, respectively, the 95% and 68% equal-tailed credible intervals.

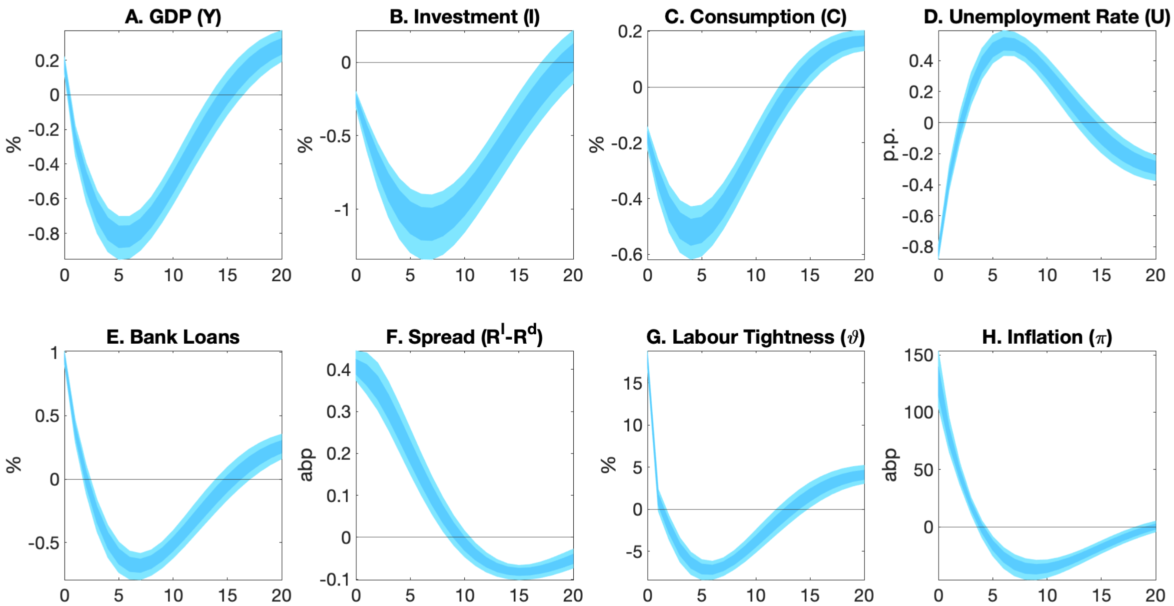


Figure 18: Bayesian Impulse Responses to a TFP Shock

*Notes*: Bayesian credible intervals are estimated using 10,000 draws from posterior parameter distribution. The light and dark shaded areas denote, respectively, the 95% and 68% equal-tailed credible intervals.

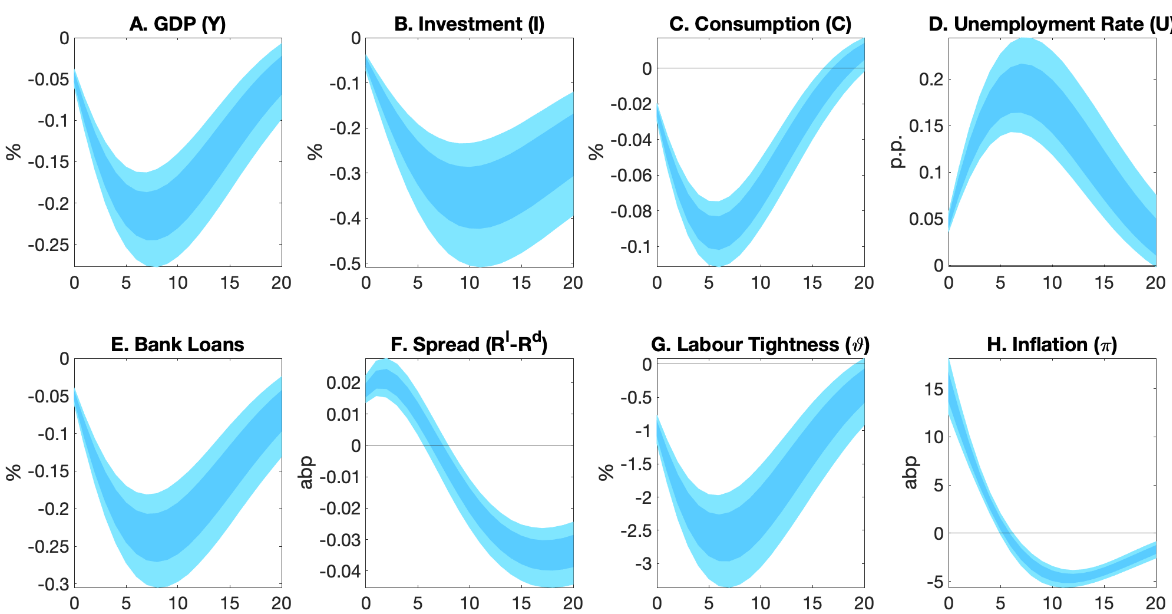


Figure 19: Bayesian Impulse Responses to a Monetary Policy Rate Shock

*Notes*: Bayesian credible intervals are estimated using 10,000 draws from posterior parameter distribution. The light and dark shaded areas denote, respectively, the 95% and 68% equal-tailed credible intervals.

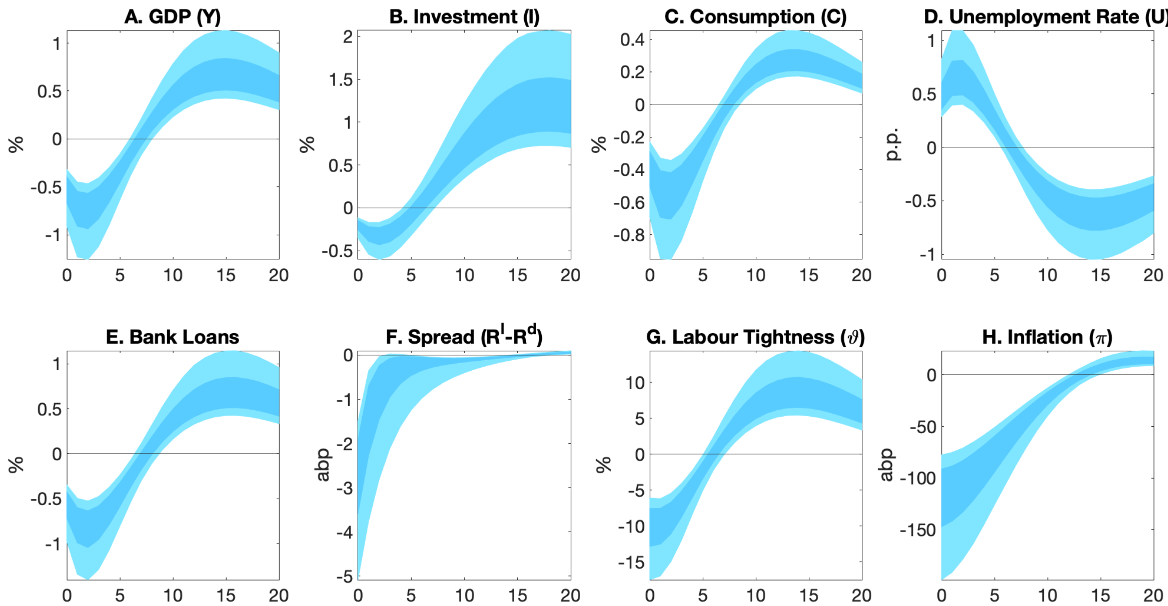


Figure 20: Bayesian Impulse Responses to a Money Base Growth Rate Shock

*Notes*: Bayesian credible intervals are estimated using 10,000 draws from posterior parameter distribution. The light and dark shaded areas denote, respectively, the 95% and 68% equal-tailed credible intervals.