Bank Loan Portfolio, Monetary Policy Transmission and Financial Downturns

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Abstract

This paper studies the change in the financial sector's asset portfolio following a monetary policy contraction, as well as a tightening of financial conditions measured by loan-to-value (LTV) ratios in the residential mortgage market. By using three different datasets relating to bank loans and private sector liabilities in the U.S., the paper provides indirect support to active portfolio composition changes in the banking sector. This evidence is from the observed differences in the dynamics of loan responses between these datasets and over time. In terms of econometrics, both fixed and time-varying parameter vector autoregressive models are employed to identify these findings. Specifically, under a monetary contraction, results confirm the puzzling commercial and industrial (C&I) loan increase found in the literature. However, different degrees of the puzzling increase materialize depending on the dataset employed. Along the business cycles, this business loan puzzle is found to be more prominent in the 1980s, but varying over time, and slightly weaker after the Great Recession. Also, banks tend to favor real estate loans after the 2000s following a monetary contraction. Under a negative LTV ratio shock, banks tend to adjust their asset portfolio by cutting C&I loans more than real estate loans; over time, this response pattern shows little time variation across datasets, other than a notable boom in real estate liabilities after the 2000s. The response of monetary policy to credit crunches (or booms) seems to be time-varying: more aggressive before the Great Recession but weaker near and after the recession.

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1 Introduction

The study of monetary policy transmission mechanisms has been an important topic in macroeconomic research. Researchers and policy makers are interested in understanding how policy innovations propagate and ultimately impact the real economy. Several well-established channels in the literature work through financial markets, such as those relating to balance sheets of borrowers, lenders (financial intermediaries), and the cost of loanable funds.[1]

One relatively subtle and less-studied channel influencing the monetary transmission relates to the financial intermediary's portfolio adjustment. This supply-side effect of credit is discussed in Den Haan et al. (2007) among other early works. They find that an unexpected monetary policy tightening leads to a real estate and consumer loan decline; meanwhile, perhaps surprisingly, commercial and industrial (C&I) loans increase, which in this paper I refer to as the "business loan puzzle." The authors argue that the initial increase in C&I loans indicates a supply-side effect from banks, more specifically the presence of portfolio behaviors of bank loans, as they try to change their asset composition by increasing more C&I loans. It is important to understand this mechanism as the banking sector behavior can alter the propagation of monetary policy and therefore its ultimate outcome.

In this paper, I study the impact of monetary policy shocks on the financial sector's asset composition, motivated by Den Haan et al. (2007). This paper tests empirically with financial and macro data the existence of the portfolio effect transmitting monetary policy. In addition, I investigate the portfolio behavior of the financial sector following a financial downturn, which is represented by a negative exogenous shock to the loan-to-value (LTV) ratio in the residential mortgage market. This exercise is of particular interest for the study of recessions relating to financial frictions, such as the Great Recession. The paper studies how the financial sector behaves following a financial disturbance and how the monetary authority reacts to it. To shed cross-sectional and historical insights about these issues, I use both fixed and time-varying parameter vector autoregressive models as econometric tools. I also collect and utilize three datasets measuring different view points of the U.S. financial sector.

The work in this paper is innovative along two dimensions. Regarding the data of the financial

[1] See for example Ciccarelli et al. (2015) for a clear review of the channels proposed in the literature.

sector, I collect three different datasets to reflect different measures of the financial sector in the U.S. First, I update the primary data set used by Den Haan et al. (2007), which is constructed based on the Consolidated Reports of Condition and Income (Call Reports). As noted by these authors, this dataset gives a good representation of the commercial bank universe. The second data set is from the H.8 category released by the Board of Governors of the Federal Reserve System on their website. I collect a third data set documenting liabilities of the private sector in the U.S. This data set takes liabilities issued by the entire financial sector into consideration including commercial banks, and thus represents the whole financial system in the U.S. Using these different datasets allow me to shed insights on identifying supply-side effects in the banking sector that previous studies are in general missing.

On the econometric side, I employ the time-varying coefficient stochastic-volatility vector autoregressive model (TVC-SV-VAR), following the work by Canova and Pérez Forero (2015). This state-of-the-art econometric tool gives a more flexible evaluation of data dynamics. In particular, whether the mechanisms studied in this paper evolve over the business cycle, and if so, how they evolve, are less addressed in previous studies. Using this approach allows me to examine this potentially time-varying property over business cycles. Also, I add to their algorithm an extra step sampling prior hyperparameters. Specifically, I impose priors over chosen prior hyperparameters in the model and add relevant sampling steps in the existing algorithm, following Amir-Ahmadi et al. (2018). This method provides a more flexible, data-driven approach to choose hyperparamter values of these priors. It is particularly beneficial for the current study given the variety of datasets and model specifications considered.

The results of the paper are as follows. The business loan puzzle exists following monetary contractions, verifying the findings in the literature. However, the severity differs across datasets and evolves along business cycles. Specifically, I find bank level datasets yield a more significant increase in business loans on impact than liability datasets. This observation indirectly supports the presence of portfolio behavior in the banking sector. Over time the degree of this puzzle also varies and is weaker after the recent recession. Between different loans, there seems to be substitutability, and real estate loans are favored by banks after the 2000s when contractionary monetary policy hits the economy. Under a negative LTV ratio shock, C&I loans drop more than real estate loans for bank-level data but less in aggregate liability data. I argue this particular pattern relates to the fact that banks reshuffle their asset portfolio holdings given possible demand side effects. Importantly, according to the time-varying model results, the monetary authority reacts to changes in financial conditions differently in the last decades compared to earlier periods. The reaction is found to be weaker near and after the Great Recession.

Related Literature

There is a vast, empirically-oriented literature on monetary policy transmission mechanisms. In early seminal works, Taylor (1995) generally distinguishes the transmission mechanisms into one relating to a financial market price (or interest rate) and others focusing on money or credit. He emphasizes the price mechanism which states that with nominal rigidities and rational expectations, the real interest rate increases following a monetary policy tightening. On the other hand, works including Bernanke and Blinder (1988, 1992) and Bernanke and Gertler (1995) study the money and credit-related channels, which relate to the financial intermediary's liability and asset sides respectively. For the "money" view, Bernanke and Blinder (1992) show that the deposits held by depository institutions fall under a positive innovation to the Fed funds rate (a policy tightening). For the "credit" view, Bernanke and Gertler (1995) have a detailed discussion of credit channels of the monetary transmission, including the borrower's balance sheet and the bank lending channels respectively.[2]

The loan supply adjustment on the intermediary's asset side, relating to the credit view by Taylor (1995), has been noticed by Bernanke and Blinder (1992). They show that with the fall in deposits after a monetary tightening, banks sell off securities while they do not change loans much since they are quasi-contractual commitments. At a longer horizon, banks reduce their loans and create an impact on the real economy, as an unemployment rate increase is observed with similar timing to a loan decrease.

Early works that have identified the business loan puzzle include Gertler and Gilchrist (1993) and Christiano et al. (1996).[3] Gertler and Gilchrist (1993) find C&I loans increase slightly following

[2]Under a contractionary monetary policy, the first channel implies a higher external finance premium when the borrowers' balance sheet strength weakens. The second mechanism is that, bank loan supply decreases due to its reduced access to loanable funds, which is caused by draining reserves and deposits under open market sales. This effect increases borrowers' funding costs, as other liabilities of borrowers are imperfect substitutes to bank loans.

[3]As pointed out by Den Haan et al. (2007) and other works, aggregation across different credits can conceal information. Therefore, these studies identify the business loan puzzle with different loan series which has been largely ignored in earlier studies.

a money tightening. Christiano et al. (1996) further find that the net funds raised by the business sector in financial markets increases for about four quarters before it drops. They also point out that mechanisms in theoretical models were not capable of explaining this empirical result. Kashyap and Stein (2000) find a "perverse result" such that there is a positive correlation between loan growth and the policy rate.[4]

On explaining the business loan puzzle, Bernanke and Gertler (1995) find that the fixed business investment contraction lags those of housing and consumer durable loans, albeit it does eventually decline in response to a monetary tightening. They also suggest inventories build-up to explain the increase in business loans under the monetary contraction, arguing that this increase can happen as long as relevant demand rises more than supply. Den Haan et al. (2007), however, finds this explanation implausible after empirically examining the relationship between inventories and business loans. They then refer to the supply side effect echoing Bernanke and Blinder (1992), and propose the portfolio adjustment mechanism (or "the portfolio channel") to explain this puzzle.

Given these studies, identifying supply and demand factors in credit markets has still been one of the tricky issues in this literature, which makes a precise study of supply related channels thornier, including the portfolio channel.[5] Recent empirical studies have made progress along different aspects to identify the supply factor and the portfolio mechanism. Black and Rosen (2016) spot loan supply changes by distinguishing between commitment and spot lending.[6] According to their study, the flow of lending increases but the stock of loans outstanding may not, given tighter money reduces the loan maturity supplied by banks. Orzechowski (2017) uses the ratio of real estate loans to C&I loans in banks in the study and finds evidence of shifting portfolio composition to monetary policy innovations. He argues that the portfolio shift at banks can explain the perverse result between commercial loan growth measures and monetary policy. Barraza et al. (2018) look into contractual characteristics of loans, and suggest the puzzling increase of business loans is driven by drawdowns from existing commitments at larger banks who attempt to shorten maturities of

[4]Interestingly, the business loan puzzle is also found to exist in other countries. The increase in business loans after a monetary tightening is identified by Giannone et al. (2012) for the whole Euro Area and Busch et al. (2010) for Germany. More recently, Leblebicioglu and Valcarcel (2018) find this feature prevalent in emerging markets.

[5]This issue has been noted by multiple works such as Walsh (2010), Beck et al. (2014), Ciccarelli et al. (2015). Other identification challenges include disentangling borrower's balance sheet channels and the bank lending channel as in Bernanke and Gertler (1995).

[6]These authors find that banks increase total lending (which is a flow) with a monetary contraction, in line with Kashyap and Stein (2000)'s perverse result. However, in the meantime, banks sharply reduce the supply of commercial loan commitment by shortening the loan maturity.

new loans in response to the monetary tightening. Complementing these works, my study does not intend to provide a direct identification strategy to the financial sector's portfolio behavior, but instead examines the presence of the business loan puzzle with different datasets as well as along the business cycles. Thus, it provides indirect support to the existence of the financial sector's portfolio activities.[7]

Financial frictions on the borrower side and impact for monetary policy transmission are also explored in recent empirical studies. Den Haan et al. (2007) study the effect of a non-monetary shock (real income decrease) controlling for interest rate variation and find that C&I loans decrease while real estate and consumer loans show no significant responses. Sanjani (2014) conducts a joint study of default risk and the maturity mismatch channels of the monetary transmission and finds the latter to have a stronger impact over business cycles. Bachmann and Rüth (2018) study the macroeconomic impact of changes in residential mortgage market LTV ratios. They show the monetary authority in the U.S. tends to respond to increases in the LTV ratio changes directly. They further argue accordingly that an exogenous increase of the LTV ratio is unlikely to create a housing market boom in times of conventional monetary policy. In this paper, I include their LTV ratio data series to study the mechanism relating to financial and mortgage market conditions. I do find similar results as Den Haan et al. (2007), namely that the C&I loans are more sensitive than real estate loans to non-monetary downturns. For systematic monetary policy, I find that the Federal Reserve did not react as aggressively to financial condition tightening after the Great Recession, complementing the results by Bachmann and Rüth (2018).

The literature has noticed the changes in these channels passing through monetary policy along the business cycles. Using two subsamples 1959-1984, and 1984-2012, Endut et al. (2018) suggest a nontrivial role in the bank lending channel at the aggregate level but note it has been significantly diminished since the early 1980s. Berka and Zimmermann (2018) also claim a decline in importance of this channel with deregulation on banks' capital requirement, referring to the point raised by Bernanke and Gertler (1995) emphasizing deregulation on reserve requirement. Specific to the portfolio channel, Barraza et al. (2018) find the mechanisms relating to the business loan puzzle

[7] Other than these empirical works, theoretical studies have been exploring different mechanisms in structural models to explain the business loan puzzles and bank portfolio choice behaviors; see Zhang (2009) for a model focusing on credit demand to explain the business loan puzzle, and Aksoy and Basso (2014) for a model with bank portfolio choice and related implications over the yield curve and unconventional monetary policy.

have changed after the Great Recession with business loans significantly decreasing following a monetary contraction. In the current study, I employ the TVC-SV-VAR approach to investigate the evolution of the channels of interest. The literature on this econometric methodology includes important works by Cogley and Sargent (2005), Primiceri (2005), Koop and Korobilis (2010), and Canova and Pérez Forero (2015). Recently, the approach has been applied by Ellington (2018) to investigate time-varying interactions between money and the real economy, as well as the forecasting power of the money index.

The remainder of the paper is organized as follows. Section 2 discusses the data construction and difference between datasets. Section 3 introduces the empirical methodology used in the analysis based on Canova and Pérez Forero (2015), as well as the identification strategy. Results from the benchmark model are demonstrated in Section 4. Section 5 considers different model specifications as extended discussion and robustness checks. Section 6 concludes.

2 Data

2.1 Source and Definition

I consider three datasets in this study.[8] These datasets measure the U.S. financial system from different view points. Comparing results from them can help in identifying the differences transmitting monetary policy and financial disturbance between the banking sector and a broader range of the financial system, including the possible supply-side effect of credit.

The loan series are from different sources for these datasets. The first dataset (dataset "Call") includes the bank loan series from the Consolidated Reports of Condition and Income (Call Reports). This sample starts in 1976Q1. I closely follow the data definition in Den Haan et al. (2007) and extend the aggregated loan series in this dataset to 2011Q4.[9]

The second dataset (dataset "H8") consists of bank loan data for commercial banks from table H.8 provided by the Board of Governors of the Federal Reserve System. This sample runs from 1954Q3 to 2018Q3. As noted by Den Haan et al. (2007), the drawback of this dataset is that banks voluntarily submit credit reports to the Federal Reserve and is "blown up" to represent the whole

[8] Without causing ambiguity, I refer to them in later discussion as dataset "Call", "H.8", and "Liability" respectively (based on their definitions) for the sake of brevity.

[9] This ending date of the sample is determined by data availability.

commercial bank universe. The Call Report dataset is of better quality from this aspect for that the related survey is compulsory to all federally insured banks. Nevertheless, I show later that the results from these two datasets are similar.[10]

The last dataset (dataset "Liability") contains liabilities born by private parties in the United States, corresponding to the three loan categories in the first two datasets. The source of the data is table Z.1 measuring financial accounts of the U.S. provided by the Board of Governors. I use this dataset to represent the whole financial system in the United States, which contains the scope measured by the first two datasets. Employing this dataset is essential in identifying the portfolio mechanism in the banking sector. In theory, if the banks play no active role altering the supply of loans to different borrowers given fundamental disturbances in the economy (such as monetary policy innovations), the entire financial system and its subset, the banking system, should behave similarly supplying credit. Therefore, the three datasets would yield very similar results under this premise. I show later that the business loan puzzle is significant in the first two datasets but not the third. This finding serves as indirect support of the portfolio mechanism in the banking sector.

Besides the difference, all datasets share three common variables: the effective Federal Funds rate (FFR), the headline consumer price index (CPI), and a loan-to-value (LTV) ratio measure used by Bachmann and Rüth (2018). This LTV ratio is on the conventional mortgage loans from the Monthly Interest Rate Survey (MIRS) by the Federal Housing Finance Agency (FHFA). These authors suggest that the series is extensive over the terms and conditions of U.S. mortgages and measures all type of homeowners. I use it to measure the financial condition in the economy as it also closely relates to the most recent crisis. This series runs from 1973Q1 to 2017Q4, which therefore limits the effective sample length for all three datasets.

The effective FFR is the chosen monetary policy measure, following classical papers such as Bernanke and Blinder (1992) among others. However, I investigate the sample covering the recent crisis during which this policy rate decreased to near zero. To circumvent the restriction of the zero lower bound identifying the monetary policy innovations, I refer to the previous study by Wu and Xia (2016) and replace the effective FFR by their shadow policy rate measure between 2009Q1 and 2015Q4.

[10]This finding is in line with Den Haan et al. (2007). The second dataset relating to table H.8 has wider bands for impulse responses in general, possibly because of noises generated by the nature of voluntary survey.

2.2 Processing and Sample Lengths

I describe the details of the final data used in the regression analysis in this subsection. I use the original series of the (shadow) effective FFR directly in the study; therefore, it is kept intact. Except for the effective FFR, all other series are seasonally adjusted.[11] The loan or liability series are then deflated using the GDP deflator.[12] Further, I transform these deflated credit quantity data and LTV ratio to year-to-year growth rates to remove secular trends.[13] Last, I transform CPI to the annualized quarterly growth rate after seasonal adjustment.[14]

For sample spans used in the study in the fixed-parameter VAR case, I consider the period starting in 1976Q1 and ending in 2011Q4 for all three datasets as the benchmark case. Using the same period for all samples ensures comparability of results across datasets. The availability of the first dataset (relating to the Call Reports) dictates the start and end dates. In the TVC-SV-VAR study, I examine each dataset to its longest possible sample length. This approach can guarantee better identification for the model parameters. Also, the results can shed important insights on the monetary and financial transmission mechanisms during and after the Great Recession. Specifically, for the first dataset relating to the Call Report, the ending period is 2011Q4. The second and third datasets span till 2017Q4, where the availability of the LTV ratio dictates the end of both samples. The last two datasets also start in an earlier period in 1973Q1, determined by the availability of LTV ratio. To visualize, Figures 1 and 2 plot the data for all three datasets with year-to-year transformation (when necessary) and full sample length for each dataset.

[11] I follow the practice in previous studies such as Bachmann and Rüth (2018) and use the X-13ARIMA-SEATS package in `R` developed by the United States Census Bureau to carry out seasonal adjustment. Note that a few time series have already been seasonally adjusted when obtained from the data source (such as those from dataset "H8") Therefore, no seasonal adjustments are applied to them.

[12] I deflate the nominal series with the GDP deflator following Bachmann and Rüth (2018). Alternatively when loans or liabilities are deflated with headline CPI, I get very similar results.

[13] I also consider the quarterly growth rate transformation in the extended discussion in Section 5.

[14] I use CPI as the price level measure following Den Haan et al. (2007). Using the GDP deflator instead yields similar results.

3 Methodology

3.1 Model

Fixed-Parameter VAR

A reduced-form VAR model can be expressed as

$$y_t = B_0 + \sum_{i=1}^{p} B_i y_{t-i} + u_t \tag{1}$$

where y_t is a $M \times 1$ vector of M time series variables observed at t ($t = 1, 2, \ldots, T$). B_0 denotes a $M \times 1$ vector of intercepts. B_i ($i = 1, 2, ..., p$) are square matrices of coefficient parameters, and p is the lag order. The error term follows a normal distribution as $u_t \sim \mathcal{N}(\mathbf{0}_{M\times 1}, \Omega)$, with Ω as the covariance matrix of reduced-form error term u_t. The total number of intercept and slope coefficients to estimate is $K = M + M \times p = M(p + 1)$.

For short-run identification, it is necessary to assume a relationship between u_t and the structural or fundamental shocks to the economy denoted as ϵ_t. Such a relationship can be written as

$$u_t = D\epsilon_t \tag{2}$$

where D is an $M \times M$ square matrix of coefficients. ϵ_t is a $M \times 1$ vector of structural shocks with unit standard deviations, i.e. $\epsilon_t \sim \mathcal{N}(\mathbf{0}_{M\times 1}, I_M)$. To identify structural shocks, I follow the classical approach by Sims (1980) and impose a recursive identification scheme. This strategy implies that D is lower triangular and is the Cholesky decomposition of Ω. It follows that $DD' = \Omega$. Under this setup, the ordering matters: innovations of a variable ordered first will contemporaneously affect all variables ordered afterward. However, the variable only reacts to innovations of the other variables with a one-period delay. The more a variable is ordered to the front of this system, the more exogenous or 'fundamental' it is as it only reacts to shocks to itself on impact.[15]

[15] In section 3.3 I explain the details of the orderings used in this study as related to economic intuition.

TVC-SV-VAR

A time-varying coefficient stochastic volatility vector auto-regression (TVC-SV-VAR) in its reduced-form is

$$y_t = B_{0,t} + \sum_{i=1}^{p} B_{i,t} y_{t-i} + u_t \tag{3}$$

where the notations are largely consistent with the fixed-parameter VAR case, but now the intercepts and slope coefficients, $B_{0,t}$ and $B_{i,t}$ $(i = 1, 2, ..., p)$, are time-varying. Moreover, the reduced-form error term follows a normal distribution with its covariance matrix evolving over time, such that $u_t \sim \mathcal{N}(\mathbf{0}_{M\times 1}, \Omega_t)$.

The structural representation of this model can be written as

$$y_t = X_t' B_t + D_t \epsilon_t \tag{4}$$

where $X_t' = [I_M \otimes 1, I_M \otimes y_{t-1}', ..., I_M \otimes y_{t-p}']$, $B_t = [\mathrm{vec}(B_{0,t}')', \mathrm{vec}(B_{1,t}')', ..., \mathrm{vec}(B_{p,t}')']'$ are a $M \times K$ matrix and a $K \times 1$ vector. D_t is the identification matrix similar to the fixed-parameter case. To introduce stochastic volatility and a (possibly non-recursive) short-run identification scheme, I follow Canova and Pérez Forero (2015) and denote

$$D_t = A_t^{-1} \Sigma_t \tag{5}$$

where $\mathrm{A}_t \equiv \mathrm{A}(\alpha_t)$ is the contemporaneous coefficient matrix, with α_t as a $n_\alpha \times 1$ column vector as a result of affine transformation following Amisano and Giannini (1997).[16] n_α denotes the number of unrestricted parameters in the identification matrix, and A_t is nonsingular for (almost) all α_t. $\Sigma_t = \mathrm{diag}([\sigma_{1,t}, \sigma_{2,t} \ldots, \sigma_{M,t}]')$, where the operator 'diag' converts a column vector to a diagonal matrix with elements in this vector on the matrix's diagonal positions.[17] The parameter $\sigma_{m,t}$ $(m = 1, 2, ..., M)$ denotes the time-varying standard deviation associated to shock m. The structural

[16]Specifically, $\mathrm{vec}(A(\alpha_t)) = S_A \alpha_t + s_A$, where S_A and s_A are matrices of zeros and ones. This transformation facilitates the sampling algorithm.

[17]This operator can also perform its inverse function if the input is a square matrix (not necessarily diagonal), mapping the matrix to a column vector containing all and only diagonal elements of this matrix in order from top left to bottom right. One can think of it as the `diag` function in `Matlab`.

shock follows a multivariate normal distribution, i.e. $\epsilon_t \sim \mathcal{N}(\mathbf{0}_{M\times 1}, I_M)$. Albeit the flexibility of this framework with which one can impose non-recursive identification in A_t, I keep using the same recursive identification strategy as in the fixed-parameter case for consistency. Therefore, A_t is a M-dimensional lower-triangular matrix with ones as elements on its diagonal.

Also, I follow the literature as in Primiceri (2005) and assume the laws of motions for the time-varying parameters are

$$B_t = B_{t-1} + q_t, \tag{6}$$

$$\alpha_t = \alpha_{t-1} + v_t, \tag{7}$$

$$\log(\sigma_{m,t}) = \log(\sigma_{m,t-1}) + w_{m,t}, \text{ for } m = 1, 2, \ldots, M. \tag{8}$$

Denote $w_t = [w_{1,t}, w_{2,t}, \ldots w_{M,t}]'$. All the innovations in the model are assumed to follow a joint normal distribution with zero mean and covariance matrix $\mathcal{V}$ which is block diagonal. More specifically,

$$\mathcal{V} = \text{Var}\left(\begin{bmatrix} \epsilon_t \\ q_t \\ v_t \\ w_t \end{bmatrix}\right) = \begin{bmatrix} I_M & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & V & 0 \\ 0 & 0 & 0 & W \end{bmatrix} \tag{9}$$

where Q, V, and W are covariance matrices of q_t, v_t, and w_t respectively with dimensions being K, n_α, and M. These matrices follow inverse-Wishart distributions defined later in the model specification part, in which hyperparameters κ_Q, κ_V, and κ_W control means of these distributions. Therefore, this framework captures the time variation in lag structure (B_t), contemporaneous reaction coefficients (A_t), and structural variances (Σ_t). When the hyperparameters κ_Q, κ_V, and κ_W decrease to zero, the model degenerates to the fixed-parameter VAR presented above.

To tune these prior hyperparameters efficiently and appropriately given different data and the model setup, I impose priors over κ_Q and κ_V to facilitate choosing their values for different datasets.[18] The details of the sampling procedure follows the method proposed by Amir-Ahmadi

[18] I fixed $k_W = 0.01$ following the value used in the literature. I did not impose a prior on it for two reasons. Firstly, as Lubik et al. (2016) argue, the TVC-SV-VAR approach tends to account erroneously excessive time variation to stochastic volatilities based on a simulation study. Fixing κ_W can prevent the stochastic volatility from changing too much. Secondly, the results are not particularly sensitive to different values of κ_W for the cases I considered, and fixing this parameter has the benefit of reducing dimensions of priors for these hyperparameters.

et al. (2018). They suggest a Metropolis-Hasting (MH) step drawing these parameters given chosen priors on them. Under some nonrestrictive independence assumptions, the acceptance probability of hyperparameter draws can be written as terms only relating to prior and proposal distributions of the sampler. Specifically,

$$\min\left\{1, \frac{p(K|\kappa^*)p(\kappa^*)\cdot q(\kappa^-|\kappa^*)}{p(K|\kappa^-)p(\kappa^-)\cdot q(\kappa^*|\kappa^-)}\right\}, \tag{10}$$

where κ represents generic hyperparameters, and K denotes model parameters that depend on κ. κ^* and κ^- denote newly proposed and current draws. $p(K|\kappa)$ and $p(\kappa)$ are prior density functions. $q(\cdot)$ represents the (possibly asymmetric) proposal density. These densities are known in closed form in general, which are fast and easy to evaluate. This algorithm is therefore also computationally efficient. Accordingly, an extra step sampling these hyperparameters is added in the algorithm by Canova and Pérez Forero (2015).

3.2 Sampling Algorithm of TVC-SV-VAR

The sampling algorithm for TVC-SV-VAR follows the one described in Canova and Pérez Forero (2015), which employs a routine of a MH step within a Gibbs sampler. The use of a MH step is because the parameters α_t cannot be drawn directly from a closed-form distribution.

One difficulty in sampling is the nonlinearity of stochastic volatilities (Σ_t) due to the multiplicative format in which they enter the model. This issue is tackled in the literature by taking logarithms of these random variables and draws from the transformed distribution, which is approximated by a mixture of normal distributions; see Kim et al. (1998), and Del Negro and Primiceri (2015). For this study, I use a seven-component normal mixture setup following Canova and Pérez Forero (2015).

For notation, I use superscript T to denote the entire history of a time series (can be parameter or data), for instance $\alpha^T = \{\alpha_t\}_{t=1}^T$. I use subscripts with parenthesis to keep track of the number of draws. The MCMC algorithm sequentially samples $\{B^T, \alpha^T, \Sigma^T, \mathcal{V}\}$ conditional on chosen data y^T. Details of the sampling step follows Canova and Pérez Forero (2015). A brief description of the MH within Gibbs sampling procedure is as below.

Step 1 Set the initial values of $\left\{B^T_{(0)}, \alpha^T_{(0)}, \Sigma^T_{(0)}, \mathcal{V}_{(0)}\right\}$. Start from $i = 1$ as the first posterior draw.

Step 2 Draw $B^T_{(i)}$ from $p\left(B^T_{(i)}|y^T, \alpha^T_{(i-1)}, \Sigma^T_{(i-1)}), \mathcal{V}_{(i-1)}\right) \cdot \mathbb{I}_B(B^T_{(i)})$, where the indicator function

$\mathbb{I}_B(B^T_{(i)})$ truncates the non-stationary draws of $B^T_{(i)}$ when roots of their companion form's characteristic polynomials are inside the unit circle. The algorithm follows Carter and Kohn (1994) using the Kalman filter to compute the smoothed value of latent states based on which draws are generated.

Step 3 Draw $\alpha^T_{(i)}$ from $p\left(\alpha^T_{(i)}|y^T, \Sigma^T_{(i-1)}, B^T_{(i-1)}, \mathcal{V}_{(i-1)}\right)$. As noted earlier, α_t is the affine transformation of the contemporaneous coefficient matrix A_t, following Amisano and Giannini (1997). The latent states relating to $\alpha^T_{(i)}$ are again computed following Carter and Kohn (1994). The posterior densities of current and newly proposed draws of $\alpha^T_{(i)}$ are then evaluated and compared. Draws are accepted according to the standard MH algorithm.

Step 4 Draw VAR covariance matrix $\Sigma^T_{(i)}$. This step involves a draw of mixture indicators $s^T_{(i)}$ (each $s_{t(i)}$ is a M-tuple column vector) that selects the mixture component at each date, following Kim et al. (1998). This step is done prior to sampling the log volatility (logarithm transformation of matrices Σ^T's diagonal elements), as noted in Del Negro and Primiceri (2015).

Step 5 Draw $\mathcal{V}_i$ from $p\left(\mathcal{V}_{(i)}|y^T, B^T_{(i-1)}, \alpha^T_{(i-1)}, \Sigma^T_{(i-1)}\right)$, which follows inverse-Wishart distributions in each block as noted in equation (9) therefore can apply Gibbs sampling.

Step 6 Draw hyperparameters κ_Q and κ_V with the acceptance rate defined in equation (10), following Amir-Ahmadi et al. (2018).

Step 7 Repeat steps 2 to 6 for $i = 1, 2, \ldots N_{sim}$ (N_{sim} times). Discard the first N_{burn} draws as the burn-in sample and thin the remainder by taking one draw out of every N_{thin} draws. The final result from this routine approximates the posterior distribution of parameters in the TVC-SV-VAR model.

3.3 Model Specification

In this section I present details of the model specifications including the chosen variables, orderings and lag lengths. Then I specify the prior and simulation details for TVC-SV-VAR models.

Variables. The benchmark specification of the VAR model contains four variables: The Federal Funds rate (r_t), LTV ratio (θ_t), and two loan or liability measures relating to the business sector (l^I_t) and real estate sector (l^H_t) respectively. I choose this four-variate model for parsimonious consideration. This specification includes the fewest possible variables relating to measures on portfolio decision, monetary policy, and financial conditions. In the extended discussion, a richer specification of the VAR contains another two variables: the annualized inflation rate measured by headline CPI (π_t), and consumer loans or liabilities (l_t^C).

Orderings and Lag Lengths. As mentioned in Section 3.1, the VARs are all identified with the classical recursive identification strategy by imposing a Cholesky decomposition to the covariance matrix of the reduced-form VAR error term. Therefore, the variable ordering in the VAR is important.

In the benchmark case, the time series variables are ordered as $y_t = \left[r_t \; l_t^I \; l_t^H \; \theta_t\right]'$. The FFR, as the proxy of the monetary policy stance, is ordered first. This ordering assumes that the Federal Reserve does not respond to contemporaneous innovations in other variables. This assumption implies lags exist in the information set of the monetary authority which seems plausible. With quarterly data, this might be less obvious, but the data in use is not real time and may have been updated using information after the current period as commented by Den Haan et al. (2007) .[19] For the loan variables, I order the C&I loans in front of the real estate loans by assuming the former does not react to contemporaneous changes in real estate credit markets. The C&I sector does influence the housing market on impact, because it relates more closely to output in the economy. The LTV ratio is ordered last implying its determination is influenced on impact by innovations of other variables in the system.[20]

The ordering of the six-variate VAR considered in the extended discussion is $y_t = \left[r_t \; l_t^I \; l_t^H \; l_t^C \; \pi_t \; \theta_t\right]'$. I use this setup as a robustness check of the results from the benchmark specification, as well as to obtain more results on the portfolio behavior of the financial sector regarding consumer loans.

The lag order is chosen to be $p = 1$ for regressions of all three samples according to the Schwarz information criterion (SIC) under the fixed-parameter VAR cases. I also use $p = 1$ as the benchmark

[19]Another support of this ordering is Christiano et al. (1996), in which the Federal Funds rate is also ordered in front of loan variables. Also, with the lag length equal to one (chosen by this paper), the loan puzzle tends to disappear with the Federal Funds rate ordered last. This result may be caused by the contemporaneous restriction to loan responses under this ordering. Also, the small lag length limits the dynamics of the VAR system, for that with two lags, the loan puzzle still exists (results are suppressed and available upon request).

[20]The ordering of the last three variables follows the benchmark specification in Den Haan et al. (2007). They assume that the non-monetary shock only has contemporaneous effect on itself and not on other variables. However, they have the less restrictive assumption on the ordering of loan variables by imposing a block-triangular structure of the identification matrix as in Christiano et al. (1998). The ordering of loan variables is not as important in my study because the associated structural shocks are not the focus of this paper. Reordering the loan variables in the benchmark specification also will not overturn the main results.

specification for all TVC-SV-VAR cases for consistency.[21]

Priors and Simulations. For the TVC-SV-VAR models, priors are needed to complete the Bayesian model and identify posterior distributions. In the benchmark case, I consider empirical priors, which are caculated by OLS utilizing all data available. This prior setup gives appropriate values for the parameters to be identified in the model, as well as reflecting the researcher's belief *a priori* demonstrated in the fixed-parameter VAR section below. However, the associated drawback is that empirical priors could drive too much of the posterior draws, as calculating these priors uses the whole dataset. I make the scaling parameter of variances larger than the value in the literature to remedy this potential issue.[22]In the extended discussion, I also use the training sample approach to choose priors and compare the results from these two different setups.[23]

To be clear, I present the forms of prior distributions here in detail. The priors for intercept, slope, and contemporaneous coefficients are (for $t = 1, 2, \dots, T$)

$$B_{t,(0)} \sim \mathcal{N}(\overline{B}, \kappa_b^2 \cdot \overline{V}_B), \tag{11}$$

$$\alpha_{t,(0)} \sim \mathcal{N}(\overline{\alpha}, \kappa_a^2 \cdot \overline{V}_A). \tag{12}$$

Let $\sigma_{t,(0)} = \text{diag}(\Sigma_{t,(0)})$ and is a $M \times 1$ column vector. Then the stochastic volatility prior is (for $t = 1, 2, \dots, T$)

$$\log \sigma_{t,(0)} \sim \mathcal{N}(\log \overline{\sigma}, \kappa_\sigma^2 \cdot \overline{V}_\sigma). \tag{13}$$

Innovations in the random walks (6), (7) and (8) follow normal distributions, i.e. $q_t \sim \mathcal{N}(0, Q)$,

[21]SIC occasionally selects $p = 2$ for four-variate models due to the longer sample length used in time-varying cases. To support the robustness of the primary results, I also checked TVC-SV-VAR with $p = 2$ for all three datasets. Under this setup, the loan puzzle, observed differences between datasets and other conclusions in the main text hold in general, while the degree of time variation is minor (results available upon request). Another consideration of having the lag order equal to one is parsimony.

[22]Specifically as mentioned below, I set the scaling parameters κ_b^2, κ_a^2 and κ_σ^2 to 10, 10, and 1 in the benchmark case, where in general the previous studies use values of 4, 4, and 1 respectively: for instance see Primiceri (2005). Another consideration of choosing κ_b is to tune the acceptance rate of B^T near a reasonable value (around 40%).

[23]I also consider uninformative priors in this study. However, the related results are not reported as the sampling convergence, in general, is not ideal. Also, this approach may be incapable of identifying interesting regions in the parameter space, as opposed to the other two priors in the main text.

$v_t \sim \mathcal{N}(0, V)$, and $w_t \sim \mathcal{N}(0, W)$. The priors for the random walk covariance matrices are[24]

$$Q \sim IW\left(\kappa_Q^2 \cdot df_q \cdot (\kappa_b^2 \cdot \overline{V}_B), df_q\right), \tag{14}$$

$$V \sim IW(\kappa_V^2 \cdot df_v \cdot (\kappa_a^2 \cdot \overline{V}_A), df_V), \tag{15}$$

and for $m = 1, 2, \ldots, M$,

$$W_m \sim IW(\kappa_W^2 \cdot df_W \cdot 1, df_W), \tag{16}$$

where IW denotes inverse-Wishart distributions and the degrees of freedom defined for them are $df_Q = t$, $df_V = 1 + n_\alpha$ $df_W = 1 + 1 = 2$. For df_Q, parameter $t = T$ is the size of the full sample length when using empirical priors. For priors chosen by the training sample approach, $t = \tau$, and τ denotes the size of training sample.

With OLS priors, vectors $\overline{B}, \overline{\alpha}$ and $\overline{\sigma}$, and matrices $\overline{V}_B$ and $\overline{V}_A$ are set to their OLS estimates based on either the entire sample (empirical prior) or a subset of it (training sample). The matrix $\overline{V}_\sigma = I_M$ is arbitrarily chosen by assumption following Primiceri (2005) and the parameter κ_σ reflects the prior belief of this conjecture.

Lastly, the priors on hyperparameters κ_Q and κ_V are assumed to be inverse gamma distributions, following Amir-Ahmadi et al. (2018), as

$$\kappa_Q \sim IG(a_Q, b_Q), \tag{17}$$

$$\kappa_V \sim IG(a_V, b_V), \tag{18}$$

where a_Q, a_V and b_Q, b_V are shape and scale parameters for corresponding inverse gamma distributions (denoted as IG above) respectively. I set their values to meet the following two standards: (1) the modes of κ_Q and κ_V are 0.05 and 0.1 respectively; (2) the standard deviations are 0.1 for both cases.[25] To sum, all fixed prior parameters are listed in the following table.

[24] I put the scaling hyperparameter in the mean of these prior distributions to reflect the tightness of priors obtained from data (either empirical prior or training sample) in line with (11) and (12). For stochastic volatility, the interpretation and setup could be different as the prior variance is assumed and not from the data directly.

[25] I set modes of these priors referring to past studies. In Primiceri (2005), $\kappa_Q = 0.01$ and $\kappa_V = 0.1$. Lubik et al. (2016) consider higher values of κ_Q and κ_V (0.03 and 0.5) while regarding values from Primiceri (2005) as lower bounds. Amir-Ahmadi et al. (2018) choose modes and standard deviations to be 0.05 and 0.1 respectively for all hyperparameter priors.

Table 1: Fixed-Parameters in Prior (Benchmark)

Parameter	κ_W	df_Q	df_V	df_W	κ_b^2	κ_a^2	κ_σ^2	a_Q	b_Q	a_S	b_S
Value	0.01	t	7	2	10	10	1	3	0.2	4.48	0.55

Notes: The sample size $t = 139, 175, 175$ for dataset "Call", "H8", and "Liability" respectively.

For the simulation, I run $Nsim = 150,000$ draws in total and discard the first $Nburn = 100,000$ draws. The thinning factor is chosen to be $Nthin = 100$, meaning for every 100 draws starting from the non-burned part, one last draw is kept and all the other draws are discarded. This practice is standard in the MCMC literature to reduce the serial correlations of draws. Convergence is checked for posterior draws using inefficient factor statistics, and related results are reported in the appendix.

4 Results

Before digging into the discussion, some general comments are useful to present the results. All impulse response function plots demonstrate variable responses with one standard deviation error bands (68%). For the fixed-parameter VAR, bands are obtained by the bootstrap method using 10,000 simulations. For the time-varying parameter models, the bands are credible sets obtained directly from posterior draws.

Impulse responses are shown at chosen time horizons for time-varying models. These dates are mostly NBER peak dates, including 1980Q1, 1990Q3, 2001Q1, and 2007Q4. I choose the peak dates because both shocks considered in this paper are contractionary.[26] The demonstration also includes 2011Q4 for all datasets and 2017Q4 for dataset "H8" and "Liability" as they are the ending dates of the samples.

Importantly, all shocks are normalized by their standard deviations when they hit the economy; in other words, all impulse response results are under one standard deviation (positive or negative) innovations of corresponding shocks. This normalization facilitates comparison of results between the time-varying and fixed-parameter models. Also, the stochastic volatility effects are isolated from the impulse responses in the time-varying parameter models. Therefore, time variations of

[26] Choosing other dates in the neighborhood would not overturn key results in this paper as time variations of propagation mechanisms seem to be smooth.

impulse responses presented below are solely due to the changes in propagation mechanisms over time rather than through shock sizes.

Lastly, under the time-varying cases, I also plot the fixed-parameter VAR impulse response results with dotted lines along with time-varying results. I also fix the vertical axis range for each variable across different dates. The purpose is to demonstrate time variations in impulse responses more clearly.

4.1 Monetary Tightening

Results from fixed-parameter VAR. Figure 3 plots the fixed-parameter structural VAR impulse response results under a one standard deviation contractionary monetary policy shock.[27] With the Federal Funds rate increase, the business loan puzzle appears in all three datasets. The on-impact responses for these three cases are 40.64 bps, 51.72 bps and 16.18 bps at their medians. It is interesting to notice that dataset "Liability" has a smaller increase in business loan quantities compared to the first two datasets. Meanwhile, the decrease of real estate loans are slightly less than the first dataset.[28] Given the dataset definition, one possible explanation of this observation is that there are portfolio behaviors in the banking sector. Under the contractionary monetary policy, banks want to hold relatively more C&I loans and less real estate or mortgage related loans. Several explanations are discussed in the literature and briefly mentioned in the introduction. For instance, on the supply side, banks are in general "borrow short and lend long." They have the incentive to align the maturities on the asset and liability sides of their balance sheets mentioned by Den Haan et al. (2007) which is quite intuitive. Under an interest rate hike, the maturity of liabilities becomes shorter as interest payments increase. Therefore, banks adjust their portfolios by holding more short-term assets (C&I loans) and less long-term ones (real estate loans).

Notice that the LTV ratio increases on impact for all three cases, but these responses decrease rather quickly and are statistically insignificant after the second quarter. This pattern possibly relates to the higher LTV requirement after a contractionary policy. Then the credit standard falls

[27] The absolute size of the shock is between 92.39 to 92.48 bps.

[28] The median responses at the tenth quarter for these three cases are 19.56 bps, 9.85 bps, and 18.53 bps respectively. All responses are negative. The contraction in dataset "H8" is small in magnitude and statistically insignificant, but is of comparable size with dataset "Call" if the sample span stops at 2007Q4 (before the Great Recession) for this comparison study. In this case the real estate loan contractions are larger in the first two datasets than the one in dataset "Liability".

back to zero and tends to contract for the rest of time.

Results from TVC-SV-VAR. Figures 4a to 4c present the variable responses for a one standard deviation Federal Funds rate increase. Impulse responses from the TVC-SV-VAR models shift away from those under the fixed-parameter VAR case, showing clearly the time-variation patterns. Given so, overall these responses are still quite stable (not varying much) over chosen dates for all datasets. Therefore, the result in the fixed-parameter case across datasets relating to business loans still goes through, as a more significant business loan puzzle is still observed in the first two datasets than the last.

I focus on C&I loans first to investigate the business loan puzzle. For dataset "Call", the on-impact responses of C&I loans are more prominent in 1980Q1. Responses on other dates are quite in line with the fixed-parameter reference and tend to be weaker in general. The positive response of C&I loans also lasts longer in 1980Q1 than those from other chosen dates. For datasets 2 and 3, response patterns of C&I loans change little over time. It is worth pointing out that, for dataset "H8", the C&I loans have less response on impact in 2017Q4 than other dates. These observations echo findings by Barraza et al. (2018), who claim the business loan puzzle is fading away after the Great Recession.[29]

I also find some evidence of substitution between C&I loans and real estate loans in the banking sector. For the dates when the two loan components both contract, the decreases are of different magnitudes. I take the measure of contraction as the difference between the median responses of time-varying and fixed-parameter models. I mainly refer to this difference after five to ten quarters when the business loan puzzle disappears. For instance, business loans contracts more than real estate loans (1990Q3, 2007Q4, 2011Q4 in dataset "Call"; 1990Q3 in dataset "H8"), or the other way around (1980Q1 in dataset "Call"; 1980Q1 in dataset "H8"). While one can interpret the results as changes in complementarity ratios between the different loans, it can also be thought as a change in the loan bundle that favors a particular component. Capital requirements are also different between loans and change overtime. In general, the results are mixed at this point.

[29]On explaining this result, these authors suggest transmission mechanisms of monetary shocks driven by the demand side of credits. They argue that firms reduce their use of commitment loans in response to a monetary tightening after the recent recession. Possible interpretations include that the uncertainty about future recoveries leads to firms postponing their business expansions. Also, with an anticipated low interest rate given monetary policy practices during and after the Great Recession, firms may have an incentive to refrain from increasing new commitments instantaneously to prevent the possibly higher interest rate faced in the future.

Further, notice that for dataset "H8", movements in opposite directions (comparing to the time-invariant responses) occur at later dates (2007Q4, 2011Q4, 2017Q4). The fixed-parameter VAR impulse responses can be regarded as the 'average' levels of responses for (almost) the entire samples. It follows that real estate loans contract less than average but business loans more at these dates. There, of course, are demand-side forces driving this result, as the smaller contraction in real estate loans corresponds to the housing boom before the last recession. Nevertheless, there has been a drastic contraction in housing demand after the boom in the 2000s.[30] The pattern of credit quantity responses observed here is quite stable over time given the radical changes of housing demands which directly influences the related credit demand. Therefore, the real estate loans could be favored by banks around the crisis under a monetary contraction, and this supply-side effect is of non-negligible importance. For dataset "Liability", these patterns are in general weaker.[31]

This second observation supports portfolio behaviors in the banking sector, as the first two datasets measure the banking sector while the last is broader by measuring the liabilities. Under a monetary contraction, the banking sector seems to prefer business loans more in the earlier part of the sample and real estate loans later on. Opposite movements (relative to fixed-parameter impulse responses) even occur in dataset "H8" near and after the Great Recession. This substitution between loan categories can be another source weakening the business loan puzzle in the last decade.[32]

For the last variable in the system, the LTV ratio tends to have a short-lived positive response for all dates and datasets. The deviation falls back to zero quickly (within two to three quarters in general), and the error bands contain zero for most periods. These results are in line with the fixed-parameter VAR findings.

[30] For related studies suggesting housing (or land) demand shocks as a significant force driving the last boom and bust cycles, see Liu et al. (2013), Iacoviello and Neri (2010), Iacoviello (2015) among others.

[31] There is a minor exception in 2007Q4, i.e., before the Great Recession. The real estate liabilities tend to increase in quantities (comparing to the fixed-parameter response), which seems to be quite abnormal comparing to all other dates. This boom may be caused by a demand increase in the real estate loan market or other unidentified credit supply factors.

[32] These conclusions are drawn under the premise that the demand side does not vary much under a monetary contraction. It is not unreasonable to think so. For firms, alternative channels financing loans can be more costly with higher interest premium than banks under contractionary monetary policy. Mortgage borrowers such as households also have limited choices other than bank loans when financing mortgages.

4.2 Financial Downturn

Results from fixed-parameter VAR. Figure 5 demonstrates results after a one standard deviation negative LTV ratio shock. The Federal Funds rate decreases unambiguously for almost all time horizons plotted in all three cases. This observation is in line with the result by Bachmann and Rüth (2018) who argue that the Federal Reserve directly responds to the collateral requirement contraction. For the loan variables, stark differences appear in the impulse responses across datasets. For the bank level data (Call and H.8), business loans significantly decrease and reach troughs around the sixth quarter. Contractions in real estate loans are also observed but not as deep in magnitude. The median response of real estate loans is negative 45.76 bps at its lowest point for dataset "Call", which is less than half of the deepest contraction in C&I loans in this case (104.4 bps). For dataset "H8" the real estate loan contraction is even less (33.2 bps lowest median response) compared to the C&I counterpart (116.6 bps).

For dataset "Liability", results are different: although the C&I liabilities still decrease more than its real estate counterpart, this difference is less. The absolute magnitude of decrease for both loan series is less as well: for C&I loans (liabilities), the deepest contraction appears in the fifth quarter after the contractionary financial shock hits and the median response is only negative 13.89 bps. Also, the impulse response of real estate loans tends to be positive but statistically insignificant for all time horizons.

These observations can again give support to portfolio behaviors in the banking sector under financial downturns. It seems that banks react to the collateral requirement contraction by cutting business loans more than real estate loans. One possible explanation is that the banking sector is more sensitive in supplying business loans than the real estate loans given a financial condition tightening, possibly due to higher risk associated with the business sector. The real estate loans, on the other hand, are usually collateralized and relatively safer in general. For the entire financial system, the contraction magnitudes of these two credits are closer. As facing similar demand side effects, it seems that at the bank level, the bankers try to filter the fundamental shock by altering loan supplies between different categories.

Note that the demand side effect could also play a prominent role for the C&I loan contractions in the banking sector. With credit crunches, firms have a variety of alternatives for financing their business such as bonds, equities, or commercial paper. Therefore they may switch away from the bank lending market relatively easier than mortgage borrowers such as households. Therefore the demand contractions can be deeper and drive loan quantity responses down much more for C&I loans than real estate loans in the bank lending market. Financial innovations facilitating these credit demand shifts also play essential roles as more C&I loan quantity contractions are found in later dates. This deeper quantity contraction in the C&I bank-level credit market washes away with less credit quantity decrease in other financial markets (bonds, stocks, commercial papers etc.) for business sectors when considering the entire financial system as a whole, explaining less contraction in C&I liabilities in dataset “Liability”. However, with similar arguments in the monetary contraction scenario, the demand increase in alternative credit markets is limited as the shock is contractionary and directly relates to tighter financing conditions for all financial markets. Switching lenders can also be costly as noted by Bernanke and Gertler (1995). Therefore, the supply side effects from the banking sector are essential for explaining the observed impulse response dynamics.

Results from TVC-SV-VAR. Figures 6a to 6c show the results for the TVC-SV-VAR under a one standard deviation negative LTV ratio shock.[33] The response patterns are in general similar to the fixed-parameter counterparts while some time variations are observed.

I focus on the results for loan series first. For C&I loans, the decrease seems to become deeper from the early 1980s to 2000s and stable then after in dataset “Call”. Little time variation is observed in dataset “H8” which represents a subset of the banking sector universe. In the third dataset representing the entire financial sector, the contraction in C&I liabilities is more significant before the 2000s but insignificant after.

For real estate loans, the responses hardly vary for bank level datasets. If anything is to be noticed, contractions in real estate loans become slightly milder overtime in dataset “H8”. However, for the third case, real estate liabilities have a puzzling boom in 20001Q1 and 2007Q4. This pattern is especially apparent in 2001Q1 where the boom is statistically significant for all time horizons in the plotted impulse response.

The conflicts in impulse responses across datasets show different transmission mechanisms in the banking sector compared to the entire financial system following an exogenous LTV ratio dis-

[33]The absolute size of the shock is between 129.4 to 130.7 bps.

turbance. There seems to be evidence such that the C&I loans become less favorable for banks over time, assuming minor demand-side changes. Also, there is not much change in the response dynamics of real estate loans over time. From the entire financial sector's point of view, real estate loans are significantly favored before the recession. Given stable patterns of impulse responses in the bank level datasets over time, this boom is likely to be driven by housing demand or unmeasured intermediary credit supplies beyond these datasets (such as shadow banking). These findings are in line with the housing market boom before the Great Recession.

Importantly for the last variable and the monetary policy measure in the system, the Federal Funds rate displays notable time variation. The Fed combats financial condition tightening by cutting the short-term interest rate in general, but this reaction becomes weaker prior to the Great Recession and after. This pattern is observed in all datasets with mixed magnitudes, due to different loan variables used in each case.

A brief takeaway from the observed changes in the Federal Funds rate responses is that the systematic monetary policy has evolved in the last decade. The central bank seems to be not vigilant to the credit boom (the opposite of credit contraction) before the eve of the Great Recession. After that, the changes can be linked to the fact that the Federal Funds rate drops to zero due to the latest recession and unconventional monetary policies in use. The shadow rate measure by Wu and Xia (2016) used in this study takes into account these unconventional monetary policies. Therefore, in the post-recession era, the interest rate still responds less aggressively to financial condition tightening compared to earlier dates.

5 Extended Discussion

In this section, I extend the study along three aspects. First, I look into the time variation of the business loan puzzle and changes in the monetary policy response to LTV ratio shocks more closely under the benchmark specification. I further check the robustness of results presented in section 4 under alternative model specifications including training sample priors, quarterly growth data of credit quantities, and more variables used in the VARs. In general, the main results presented earlier still hold under these cases. Lastly, I examine the effect of the algorithm relating to hyperparameter priors by comparing the posterior results of these hyperparameters across different model specifications. In short, the posterior distributions of hyperparameters vary significantly, implying the advantage of using this flexible setup compared to fixed hyperparameters.

5.1 Time Variations of Interests

Business loan puzzle over time. Figure 7 plots the business loan puzzle across time for all three datasets. The puzzle is measured by the on-impact response of the C&I loans to a one standard deviation increase in the Federal Funds rate. The associated bands represent 95% credible sets obtained from posterior draws.

The first two subplots obtained from bank level datasets have a more significant degree of this puzzle than the last subplot obtained using dataset "Liability". Quantitatively, the first two subplots have responses between 0.2% to 0.6% at their medians for almost all dates. The response in the third subplot has its median smaller than 0.2% in general. In all, the business loan puzzle is found to be more pronounced in the bank level datasets than the liability dataset as mentioned in the previous section.

The degree of time variation is also different across datasets. The response from the liability dataset shows a smaller degree of time variation than those from the bank level datasets through the entire sample span. For bank-level data, the change in this puzzle is more significant along the business cycles in the dataset "Call" than "H8". For instance, during the double-dip recession in the early 1980s, the observed drop for the business loan puzzle is around 40 basis points (measured at median) according to dataset "Call"; on the other hand, there is only about 15 basis points drop for the response in dataset "H8", and the drop smoothly reaches its bottom after 1985 (rather than before this date in dataset "Call"). The contraction of this puzzle is seen in both datasets during the Great Recession but the magnitude is larger in dataset "Call".[34] Possible reasons behind these observed differences in magnitude are nonidentical individual banks included in these datasets. For H.8 dataset, only banks who are willing to provide their credit reports can be observed and therefore subject to sample selection issue if it is used to represent the whole banking sector. On the other hand, banks who are willing to submit credit reports may be in better shape than their peers who do not do so. This assumption could be another possible reason why the observed pattern of the

[34] One exception is around the early 1990s. The hike in the business loan puzzle is prominent in dataset "H8" during and after the building and loan crisis, but not as obviously seen in dataset "Call".

business loan puzzle is more stable in the H.8 dataset.

Last, the timing of peaks and troughs appear to be similar across datasets given the differences stated above. This observation should not be too surprising, as the datasets measure different view points of the same financial sector, and time variations in the business loan puzzle are related to the same fundamental reasons. The degree of this puzzle appears to be larger in the early part of the sample (especially for dataset 'Call'"), and also some years during the Great Moderation. For dataset "Call", it peaks before the recession in the early 2000s; for dataset "H8" the peak appears around 1992, but the response plateaus after then and changes little in the following fifteen years. After the Great Recession, the financial sector recovers, and there is an increase in this puzzle in the first three years after the recession for all datasets. However as seen in dataset "H8", the magnitude of this puzzle is mildly decreasing after the increase, which has been mentioned earlier in the last section.

Monetary policy reactions to changes in the LTV ratio. Figure 8 shows the IRF surface under negative LTV ratio shocks (one standard deviation shock for all dates) from the 'Call' dataset. The three-dimensional surface is composed of median responses from 1976Q1 to 2011Q4 in quarterly frequency. The x-axis represents the timeline, and the y-axis represents the forecast horizon of IRFs with its maximum being 20 quarters. The z-axis measures the magnitude of the response in the annualized percentage rate.

In general, the response pattern of monetary policy to the LTV ratio change is very stable over time especially before 1995. In the following decade, the monetary authority reacted more mildly to changes in credit standards of the residential mortgage market, especially around the 2000s. This period corresponds to the housing boom before the Great Recession. One possibility is that the central bank drastically lowered the policy rate in 2001 to combat the brief recession in the early 2000s. However, this observation may also demonstrate that the monetary authority was not vigilant to the credit expansion in the housing market, which could be a potential cause of the Great Recession. Also from around 2006Q1 to 2011Q4 (ending date of dataset "Call"), there is a notable decrease in the maximum magnitude of the (shadow) FFR impulse response. Potentially this could indicate a regime switch in the conduct of monetary policy. Another reason could simply be that the monetary authority is limited in exerting efforts given the extremeness of the recession.[35]

5.2 Robustness

Alternative prior. I consider training samples to calculate OLS priors for the TVC-SV-VAR model, which is another commonly used approach in the literature. A drawback of this method is that the training sample will be unavailable when drawing posteriors with data. I choose the length of training samples as $\tau = 40$, i.e., ten-year data to obtain prior values. The time horizon 1980Q1 hence drops out from the IRF results for that it is included in the training sample. Figures 9a to 9c and 10a to 10c present the results. To compare with the benchmark case, I keep the fixed-parameter VAR impulse responses (in dotted lines) as in section 4 and fix the vertical axis range to demonstrate the time variations in IRFs.

In general, the main results obtained in the benchmark case largely go through, with some differences spotted. First, regarding the monetary policy contractions, the variation in IRFs from dataset "H8" do not change as much compared to the benchmark case. This result is ambiguous for identifying potential substitute or complementary relationships between loans. For dataset "Liability", there are pronounced upward shifts in real estate loan responses after 2007Q4. This 'perverse' result may relate to the real estate liability overhang in the U.S. financial sector, as after the Great recession till recently, the monetary policy stance has been quite relaxed to help the economy recover. As can be seen in the raw data plot, real estate liabilities reached its bottom around 2015. Therefore, the liability quantity could move in the same direction with the (shadow) interest rate in the economy. Second, for the LTV ratio shock, the contraction of real estate loan responses seems to be deeper than the benchmark case. The dampened response in the monetary policy reaction near and after the Great Recession still exists in all datasets but with larger magnitudes especially in dataset "Liability".

In all, these differences compared to the main results from the benchmark case can be naturally attributed to the intrinsic differences between these two methodologies. With the training sample setup, the prior contains partial information only from earlier parts of the sample, and the rest of the dataset is used to obtain the final posterior distribution. Therefore a slight difference in

[35] Of course, it could also be the shadow FFR rate used in this study that caused this structural break. However given the description in Wu and Xia (2016), unconventional monetary policies are taken into consideration when constructing the shadow rate, making this argument less likely.

parameter space is preselected, and different information is used during the MCMC procedure.

Quarterly growth data. The benchmark case results are obtained from using year-to-year growth rates of credit quantities. Alternatively, Figures 11a to 11c and 12a to 12c present results from using annualized quarterly growth rates for loan or liability variables. The empirical prior setting is used in this case. To clearly present time variations in IRF results, the fixed-parameter IRFs are again plotted with dotted lines; however, they are obtained from using quarterly growth rate data as well.[36]

One stark difference between these two cases is the volatility of the processed data used in regressions, with the year-to-year growth rates being smoother than the quarterly changing rates. There could be, however, information concealed due to using the annual rather than quarterly differencing, such as how changes in variables between two adjacent quarters react to shocks.

It turns out that the main results are, perhaps surprisingly, not so different from the benchmark case. Under a monetary policy contraction, the business loan puzzle is still more prominent in the bank level datasets than the liability dataset. The LTV ratio also shows an on-impact positive response and then tends to be negative, sometimes insignificantly, for the following quarters. For the negative LTV ratio shock, credit quantities drop in general and C&I related loans tend to be more sensitive than real estate loans. The change in the FFR response over time is also clearly observed.

On the other hand, the IRFs are back to zero faster under this case compared to the benchmark case. Time variation patterns are somewhat different from the benchmark case as well. For instance, the real estate loan has positive responses in the bank level datasets sometimes, mostly after the 2000s, under a monetary contraction. For the LTV ratio shock, differences between drops of the two loans are less than the benchmark case. Again, these observations are present because of new information contained in the quarterly growth rate data and can reflect higher frequency changes in these credit markets over time.

More variables. Figures 13a to 13c and 14a to 14c show IRF results from VARs with six variables, including consumer-related credits and CPI as described in section 3.3. For variables already

[36]In essence, these fixed-parameter VAR IRFs correspond to the empirical priors used in this case.

included in the benchmark case, impulse response dynamics and corresponding time-varying patterns are very similar, if not almost identical, to those presented in section 4. Therefore, including additional variables does not overturn the main results.

For newly-added variables, the inflation rate responses suffer from the price puzzle under a monetary contraction for all cases.[37] For the consumer loan variables, the responses are very similar to the real estate loan variables. A tiny difference is that the contractions in consumer loans are slightly larger than real estate loans for bank-level datasets. As explained in Den Haan et al. (2007), there are two possible reasons intuitively. On the credit demand side, consumer balance sheets are relatively vulnerable to the monetary policy rate increase, for that the interest payments take a larger fraction of expenditure for consumers than for firms. On the credit supply side, rates on consumer loans tend to be sticky, and banks earn less marginal profits when the short-term policy rate increases. Therefore, banks potentially have the incentive to decrease the supply of consumer loans. Both these reasons can lead to a reallocation of loans within the banking sector, supporting the theory explaining the business loan puzzle on the supply side of credit.

5.3 Posteriors of Hyperparameters

In this study, a new step of sampling hyperparameters is introduced in the original algorithm by Canova and Pérez Forero (2015), based on the recent work by Amir-Ahmadi et al. (2018). Is this sampling step necessary in the current study? To answer this question, I plot the posterior distributions of the hyperparameters for various model specifications and see if there are differences among them.

Figures 15a to 15c show these posterior distributions for all three datasets under the benchmark model specification. The left two panels plot the posterior draws of hyperparameter κ_Q and κ_V, and the right two panels transform these draws into histograms. Solid red curves plot the prior distributions of κ_Q and κ_V as a reference. The vertical red lines represent the modes of these prior distributions.

The posterior draws center at different values compared to prior modes. In all three cases,

[37]As the inclusion of the price level does not influence the main results in this paper, I choose to stick to the current model specifications without particularly trying to solve the price puzzle. Most VAR setups do also lead to this puzzle, and extensive studies try to solve it or provide possible reasons for its existence. See Den Haan et al. (2007) and Ramey (2016) for a brief discussion on this issue.

draws of κ_Q are closely centered around 0.16. The posterior distribution of κ_V is more scattered and centered near 0.2 to 0.25. Both posterior distributions are significantly different from their priors. As data drive these results, this confirms that the data prefer a higher value of both hyperparameters in all these cases, corresponding to higher degrees of time variation in the lag and contemporaneous parameters in the TVC-SV-VAR models. Using the fixed values of these hyperparameters can potentially give less favorable results.

Across these three cases, however, it seems that the posterior distributions are similar, especially for κ_Q governing the degree of random walk in the lag coefficients in the VAR. Nevertheless, a slight variation can be seen in the posteriors of κ_V, as there are still some differences in the histograms among these three cases.

Figures 16a to 16c show the posterior draws of hyperparameters for dataset "Call" under three different specifications used in the robustness check. It is clear that with different model setups, the posteriors are significantly different for these hyperparameters. It seems that quarterly growth data prefer even larger time variation possibly due to higher volatilities with such data transformation compared to year-to-year growth data. Training sample priors setup yields a smaller value of κ_Q and slightly larger κ_V compared to the benchmark case. With more variables in the VAR, the posterior distributions of κ_Q and κ_V are both more to the left than those presented in Figure 15a, indicating smaller time variation are favored when additional variables are included in the specification.

In all, given multiple hyperparameters in the TVC-SV-VAR model, choosing priors by introspection is a daunting task as commented by Amir-Ahmadi et al. (2018). This situation is even worse with a large number of model specifications in the current study. The hierarchical model setup proposed by Amir-Ahmadi et al. (2018) can practically deal with this issue. All these observations above show that using priors over hyperparameters can bring out information about their values in the data, yielding specific *a posteriori* hyperparameter distributions driven by data under different model specifications.

6 Conclusion

This paper studies the propagation of monetary and financial condition disturbances along the dimension of asset compositions in the financial sector. Motivated by the business loan puzzle, the study verifies this result in the literature by using updated datasets and time-varying parameter models. Moreover, the presence of portfolio activities in the banking sector is supported by results in this paper as different degrees of business loan puzzles are spotted in the bank level and aggregate liability datasets. Along the business cycle, the degree of this puzzle varies and seems to become weaker in the last decade.

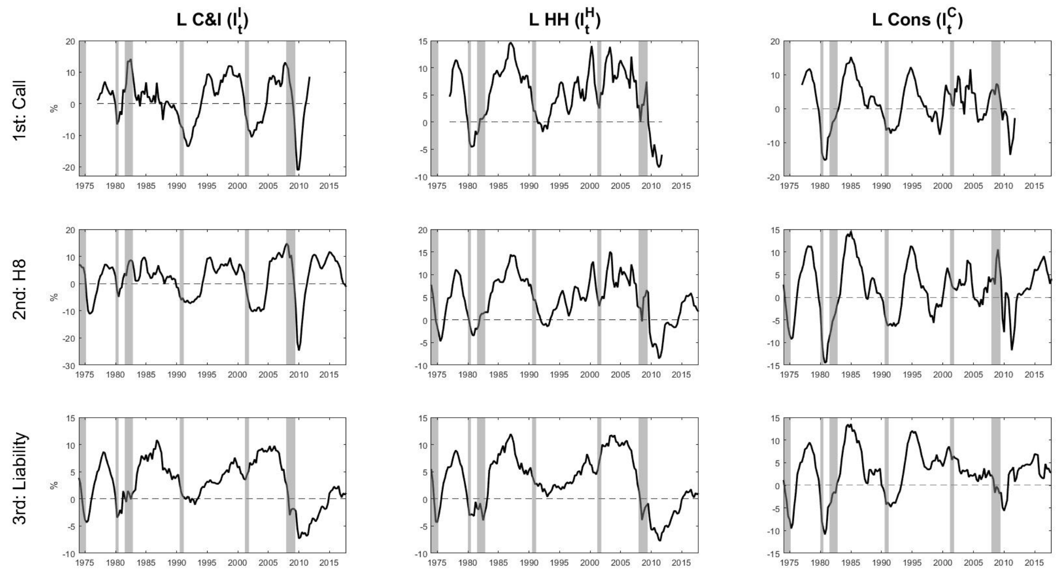
As to the financial condition change, the result shows deeper contractions in C&I loans relative to real estate loans, and the bank portfolio behavior substituting between these two loans could be responsible for this observation. Over time, the impulse response patterns for loans are relatively stable, although there seems to be a boom in real estate liabilities in the 2000s before the Great Recession. Given stable banking sector impulse responses, the boom is likely due to the demand-side effect or other unaccounted supply-side factors. Importantly, monetary policy reacts differently to financial condition disturbances. The response seems to be more active as the interest rate cuts are deeper in earlier dates when the LTV ratio contracts. In the last decade, the policy response becomes less aggressive. This change could be attributed to shifts in policy conduct or fundamental reasons due to the recent crisis.

The paper leads to several further research directions. Given the presence of the portfolio channel supported by this paper and related studies, a natural question is how important this channel is to the real side of the economy quantitatively. Incorporating output and other macroeconomic variables is the first step toward this direction.

Disentangling this impact of the financial sector from other effects, on the other hand, can be tricky. Similar studies have been conducted in the fixed-coefficient VAR literature. Bachmann and Rüth (2018) apply the impulse response decomposition used in Kilian and Lewis (2011) and others to isolate the effect of LTV shocks through systematic monetary policy to the real economy. The implementation idea is to generate exogenous shocks of monetary policy to offset the actual policy rate variation. Relating to the propagation mechanism of financial markets, Cafiso (2017) isolates the marginal contribution of private debt transmitting monetary policy to GDP quantitatively by setting related lag coefficients of the VAR to zero. Endut et al. (2018) apply sign restrictions and counterfactual experiments using a structural VAR to compare bank lending, exchange rate, and interest rate channels in the past half century in the U.S. An analog of such studies employing a time-varying framework is absent to the best of the author's knowledge.

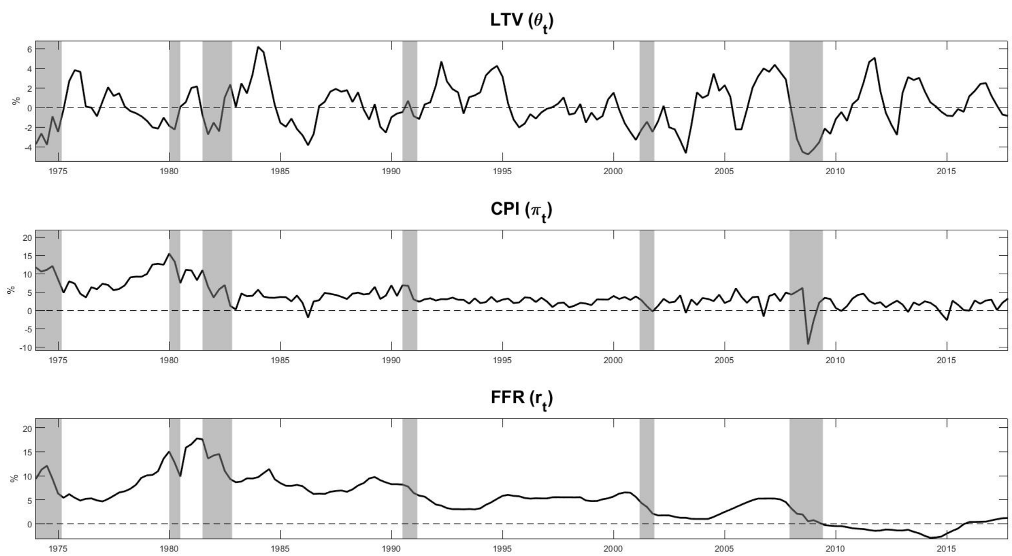
Further studies are also in need of providing alternative nonrecursive identifications with solid economic reasoning for this framework. A critical task for researchers though is to consider the choice of identification strategy with related theories carefully. On the technical side, the flexibility of the econometric framework by Canova and Pérez Forero (2015) does easily allow different specifications of short-run nonrecursive identifications. Under such studies, more detailed interactions of financial and other macroeconomic variables can be empirically unraveled.

Figure 1: Loans/Liabilities Data, All Three Datasets



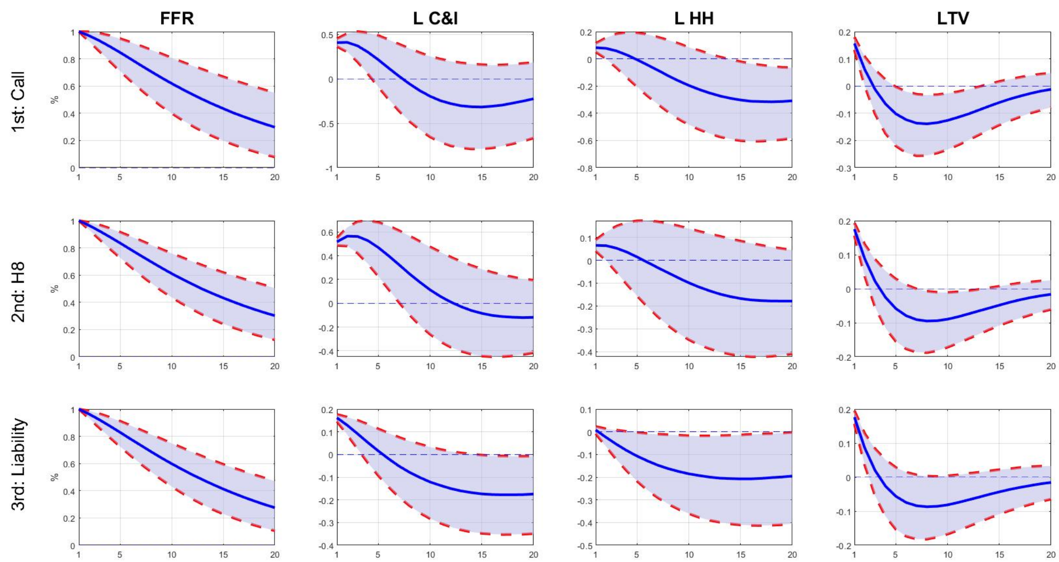
Notes: The figure displays the time series of credit quantities used in the benchmark case. The black solid lines represent the data. The shaded bars represent NBER recession episodes in the U.S. The row labels ("L C&I", "L HH", and "L Cons") represent loans or liabilities related to commercial and industrial (C&I), real estate, and consumer categories respectively. The column labels ("Call", "H8", and "Liability") indicate which dataset the credit quantity series on the corresponding row are from, namely the Consolidated Reports of Conditions and Income, table H.8, or table Z.1 provided by the Board of Governors, respectively. Data are at the quarterly frequency, and are transformed from the original data (see the detailed discussions of data definitions and sources in the main text) by the following steps: applying the seasonal adjustment, being divided by the GDP deflator, taking logarithm, calculating the year-to-year growth rate. The x-axis represents time, the y-axis represents (annualized) percentage points. Dataset "Call" runs from 1976Q1 to 2011Q4 due to limited data availability.

Figure 2: Common Data Series, All Three Datasets



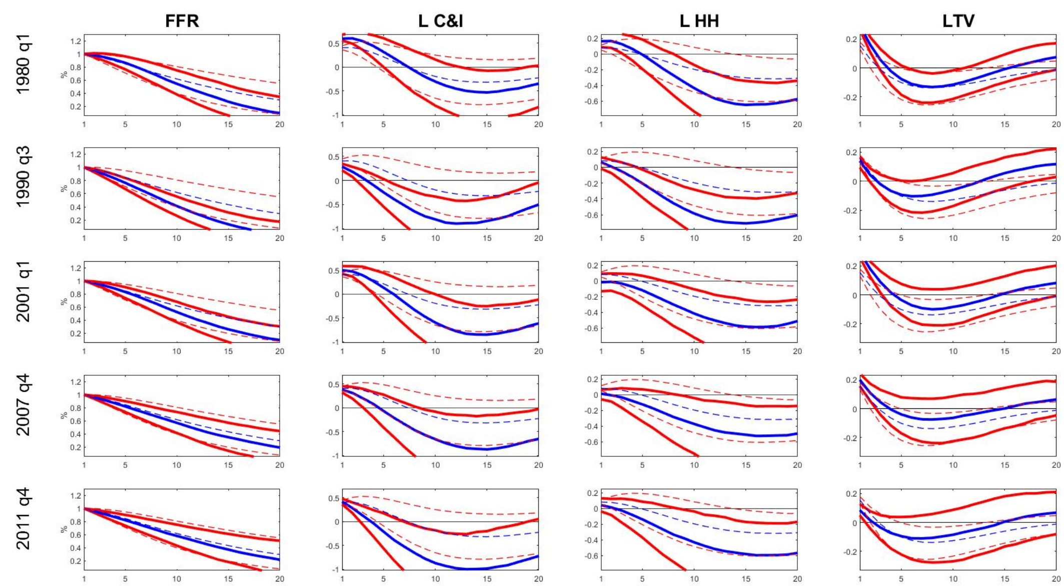
Notes: The figure displays the time series of all other common variables (across the three datasets) used in the benchmark case. The black solid lines represent the data. The shaded bars represent NBER recession episodes in the U.S. "LTV" represents the loan-to-value ratio on conventional single family mortgage loans obtained from the Federal Houshing Finance Agency. "CPI" and "FFR" represent the headline consumer price index and the effective Federal Funds rate respectively. Data are at the quarterly frequency. The LTV series is transfromed from the original data by the following steps: applying the seasonal adjustment, taking logarithm, calculating the year-to-year growth rate. The CPI series is the annualized quarterly growth rate of the original price index. The FFR is kept intact. The x-axis represents time, the y-axis represents (annualized) percentage points.

Figure 3: IRFs to a FFR Shock: Fixed-Parameter VAR, All Three Datasets



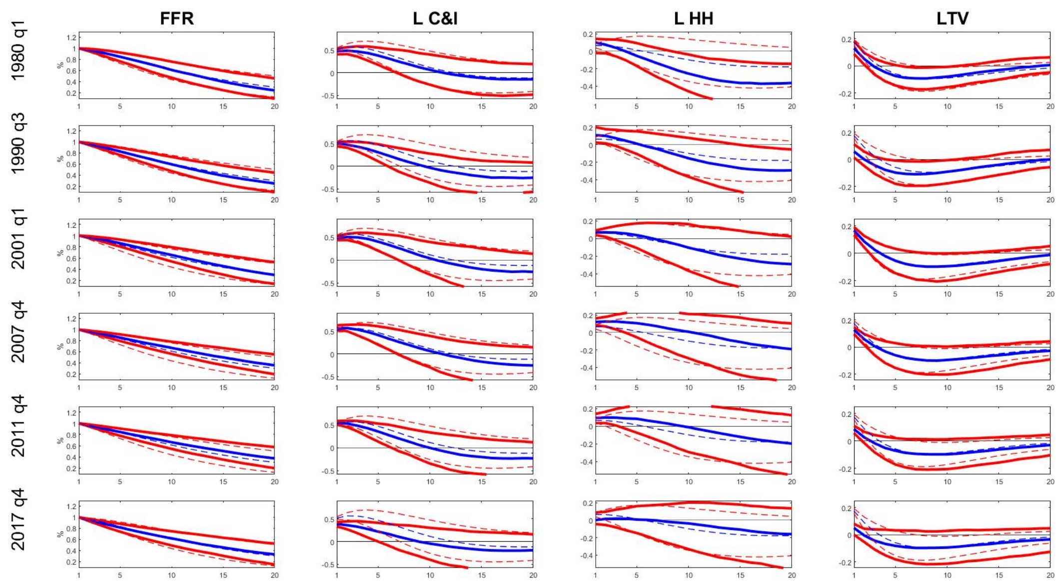
Notes: The row labels ("FFR", "L C&I", "L HH", and "LTV") represent the Federal Funds rate, loans or liabilities related to commercial and industrial (C&I) and real estate categories, and the loan-to-value ratio respectively. The column labels ("Call", "H8", and "Liability") indicate which dataset the impulse response functions (IRFs) on the corresponding row is based on, namely the Consolidated Reports of Conditions and Income, table H.8, or table Z.1 provided by the Board of Governors, respectively. The solid blue lines represent point estimates of IRFs for the fixed-parameter VAR with variables ordered as x = [FFR, L C&I, L HH, LTV]$'$. The shaded areas between dashed red lines display one standard deviation confidence bands obtained from the bootstrap method with 10,000 replications. The x-axis represents time in quarters. The y-axis represents (annualized) percentage points. The sample spans used to get the IRFs above run from 1976Q1 to 2011Q4 for all three datasets.

Figure 4a: IRFs to a FFR Shock: Dataset 1 (Call Report), Selected Dates



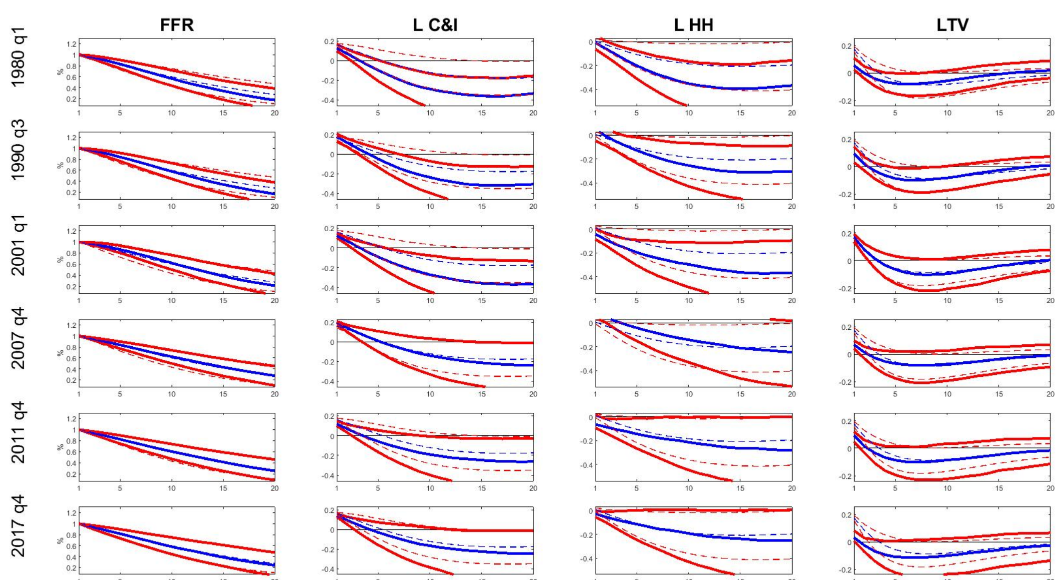
Notes: The row labels ("FFR", "L C&I", "L HH", and "LTV") represent the Federal Funds rate, loans or liabilities related to commercial and industrial (C&I) and real estate categories, and the loan-to-value ratio respectively. The column labels indicate which quarters the impulse response functions (IRFs) on the corresponding row are from. The solid blue lines represent the posterior medians of IRFs for the TVC-SV-VAR with variables ordered as $x =$ [FFR, L C&I, L HH, LTV]$'$. The areas between solid red lines display one standard deviation credible sets obtained from the posterior draws (500 effective draws after burn-in and thinning processes). The x-axis represents time in quarters. The y-axis represents (annualized) percentage points. The sample span used to get the time-varying IRFs above is the maximum sample length of the current dataset. The dashed (blue and red) lines represent the IRFs from the fix-parameter VAR using the maximum sample length of the current dataset.

Figure 4b: IRFs to a FFR Shock: Dataset 2 (H.8 Table), Selected Dates



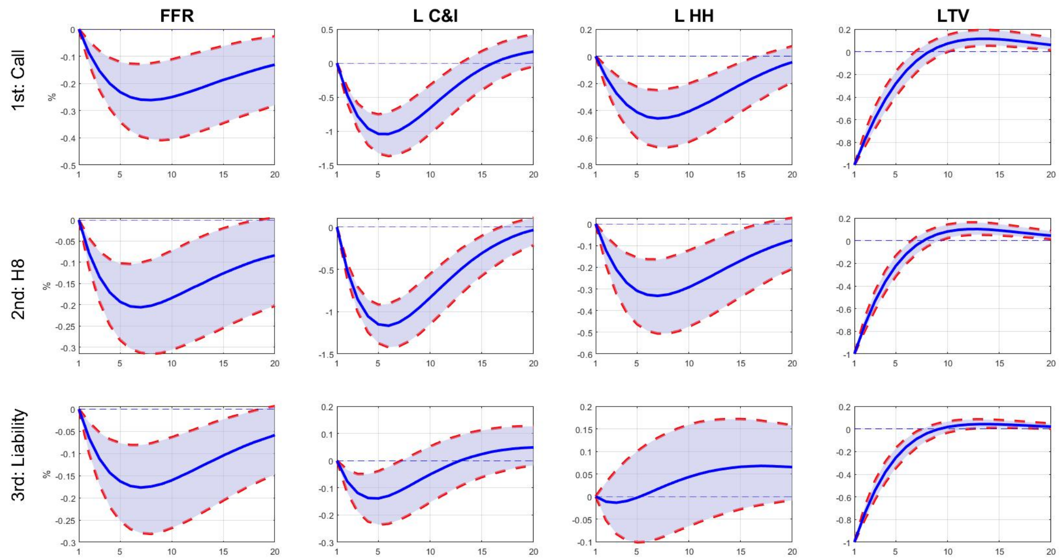
Notes: See explanations for Figure 4a.

Figure 4c: IRFs to a FFR Shock: Dataset 3 (Liabilities), Selected Dates



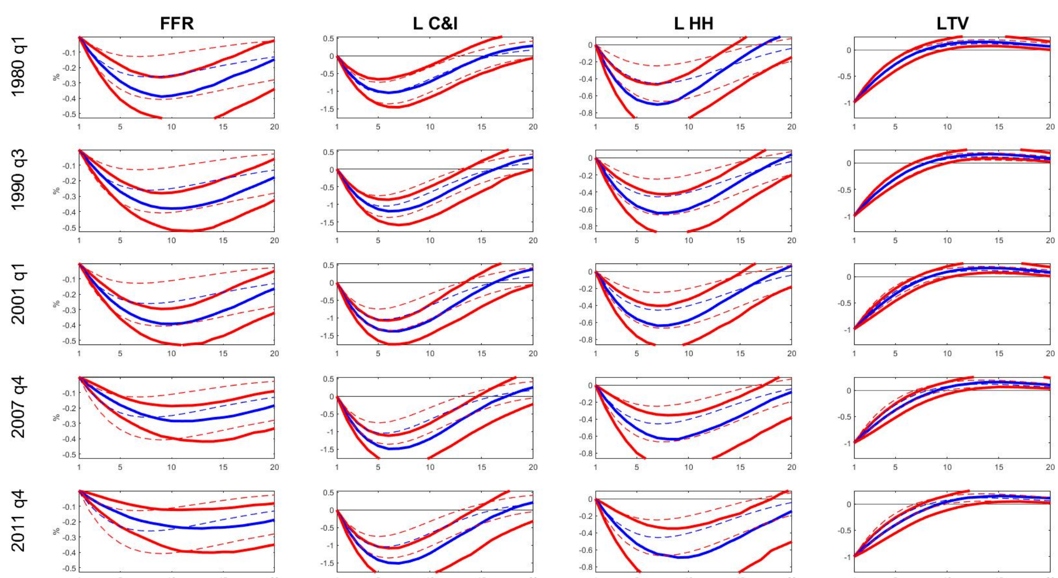
Notes: See explanations for Figure 4a.

Figure 5: IRFs to a LTV Shock: Fixed-Parameter VAR, All Three Datasets



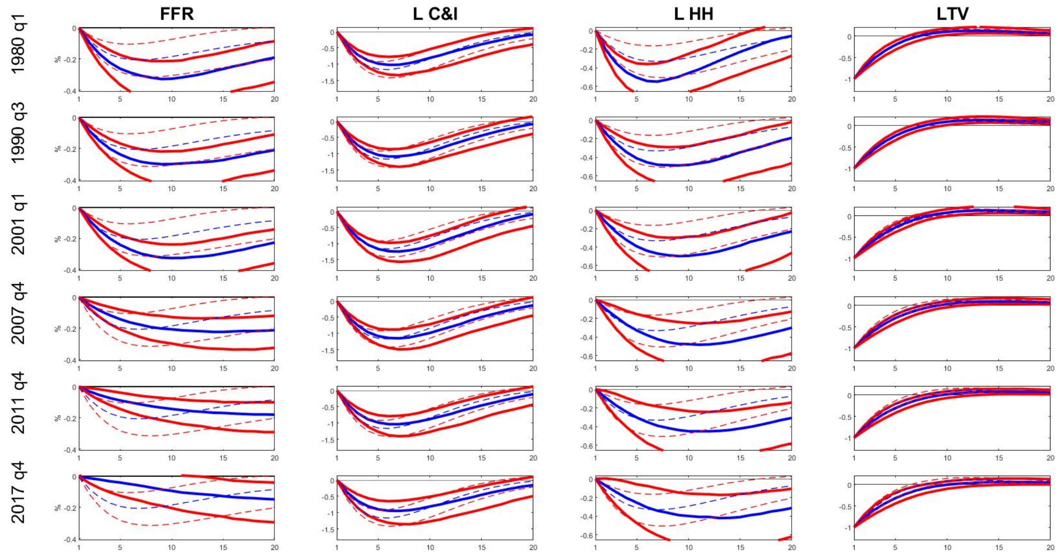
Notes: See explanations for Figure 3.

Figure 6a: IRFs to a LTV Shock: Dataset 1 (Call Report), Selected Dates



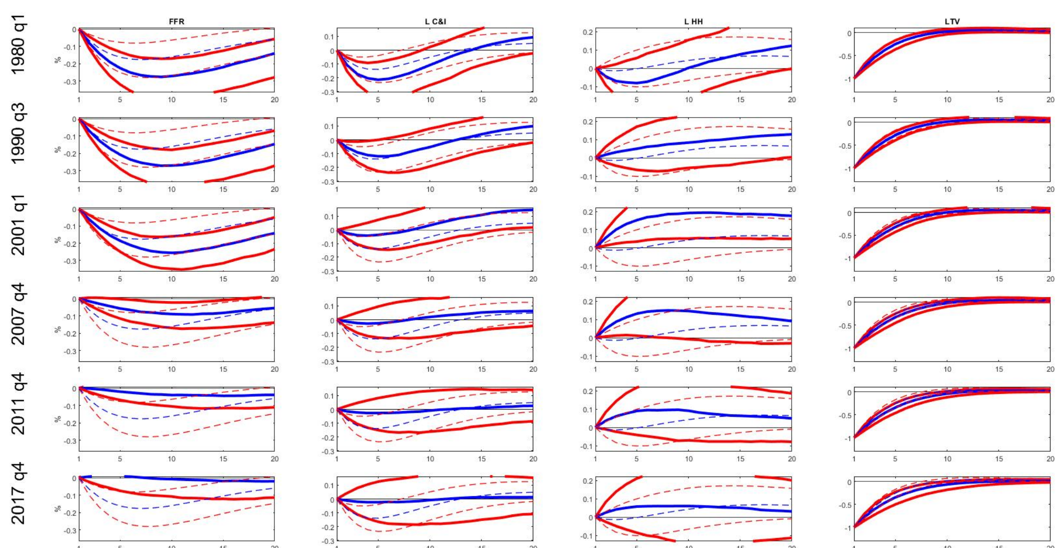
Notes: See explanations for Figure 4a.

Figure 6b: IRFs to a FFR Shock: Dataset 2 (H.8 Table), Selected Dates



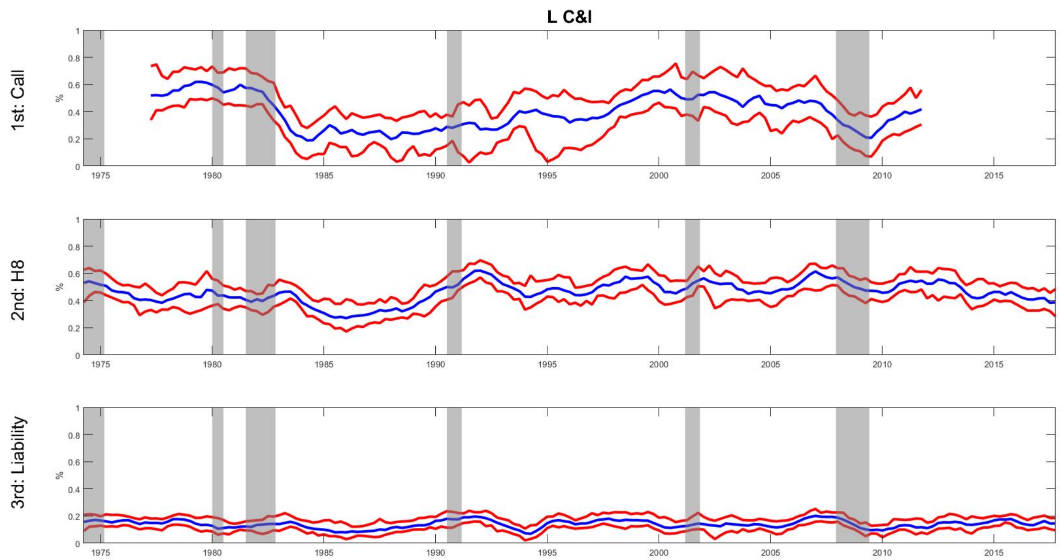
Notes: See explanations for Figure 4a.

Figure 6c: IRFs to a FFR Shock: Dataset 3 (Liabilities), Selected Dates



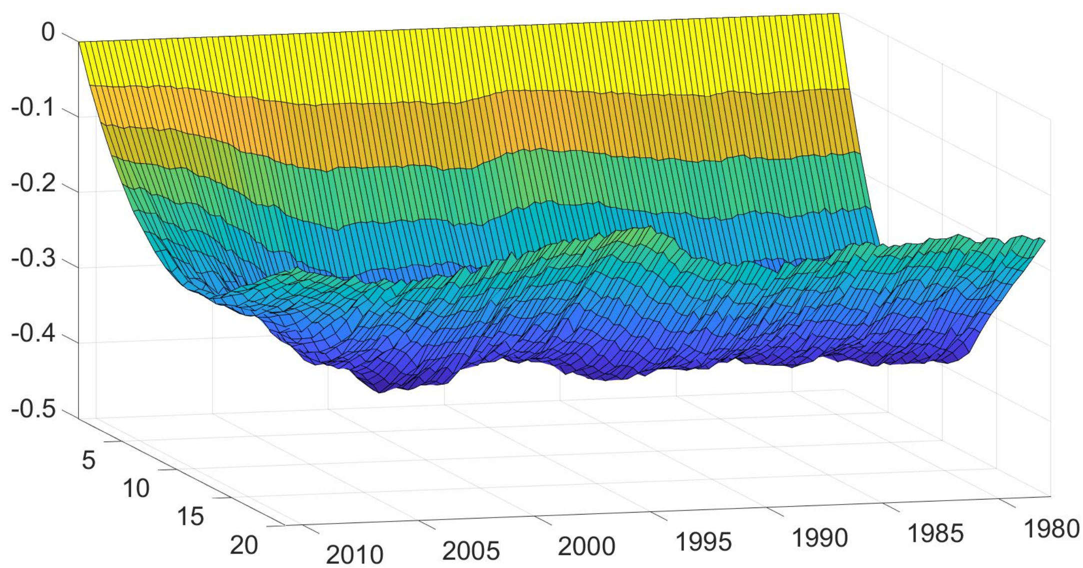
Notes: See explanations for Figure 4a.

Figure 7: The Business Loan Puzzle Over Time (95% Credible Sets)



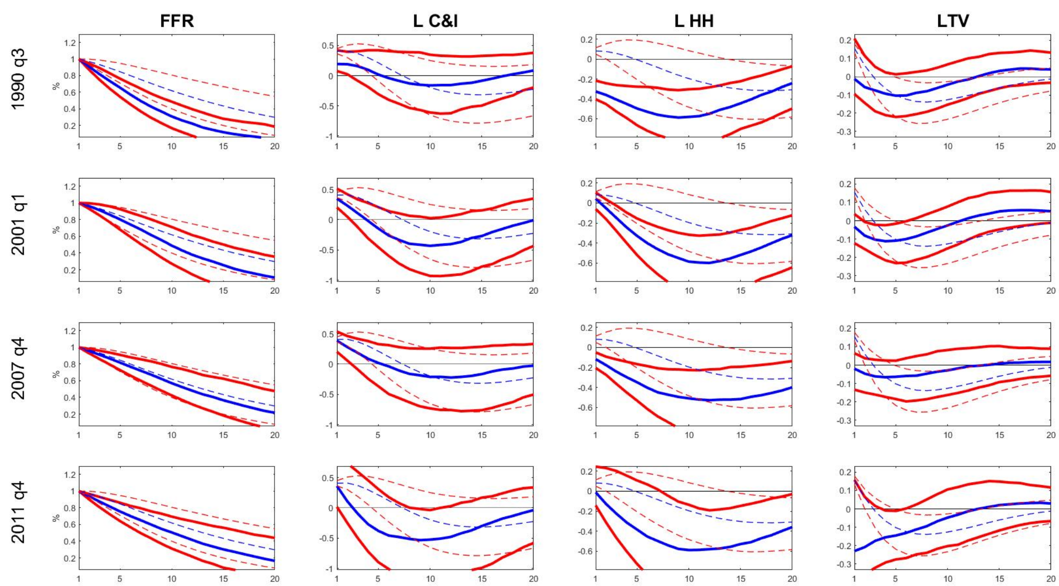
Notes: The figure displays the business loan puzzle across time for all three datasets under the benchmark specification of the model. The business loan puzzle is defined in the main text following Den Haan et al. (2007), which states the puzzling increase in the commercial and industrial (C&I) credit quantities under a monetary contraction. In the plot, the puzzle is measured by the on-impact responses of the C&I loans or liabilities to a one standard deviation increase in the Federal Funds rate. The associated bands represent 95% credible sets obtained from the posterior draws (500 effective draws after burn-in and thinning processes). The row label "L C&I" represents loans or liabilities related to the C&I category. The column labels ("Call", "H8", "Liability") indicate which dataset the impulse response tunnel on the corresponding row is based on, namely the Consolidated Reports of Conditions and Income, table H.8, or table Z.1 provided by the Board of Governors, respectively. The x-axis represents time, the y-axis represents (annualized) percentage point. The impulse response tunnel for dataset "Call" only runs from 1976Q1 to 2011Q4 due to limited data availability.

Figure 8: The Responses of (Shadow) Federal Funds rate to LTV Contraction Over Time



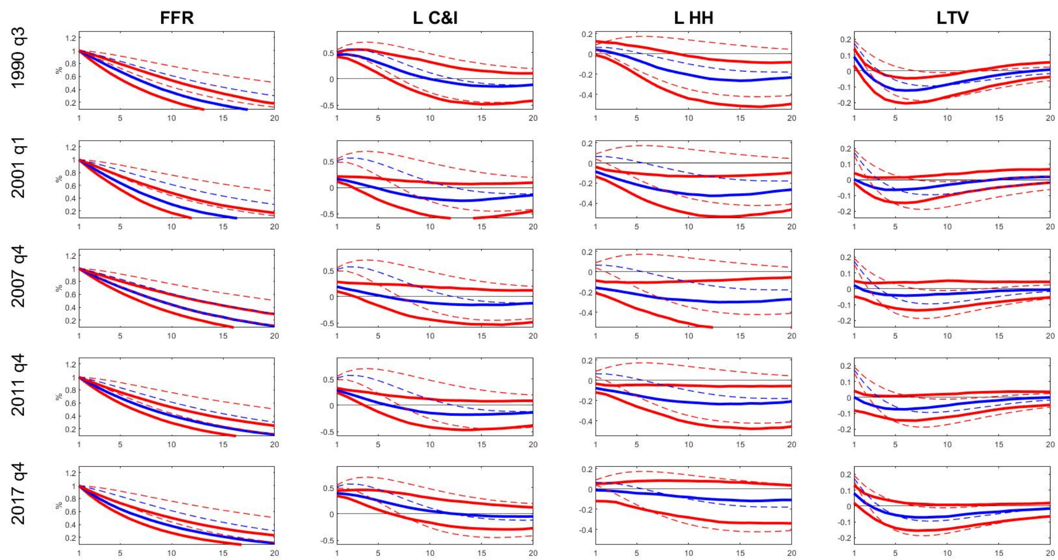
Notes: The figure plots the impulse response function (IRF) surface under negative LTV ratio shocks (one standard deviation negative shock on each date for all dates) from the dataset "Call". The IRFs are from the model under the benchmark specification. The three-dimensional surface is composed of median impulse responses from 1976Q1 to 2011Q4 in quarterly frequency. The x-axis and y-axis represent the timeline and the forecast horizon of IRFs with its maximum being 20 quarters respectively. The z-axis measures the magnitude of the response in the annualized percentage rate.

Figure 9a: IRFs to a FFR Shock: Dataset 1 (Call Report), Training Sample Prior



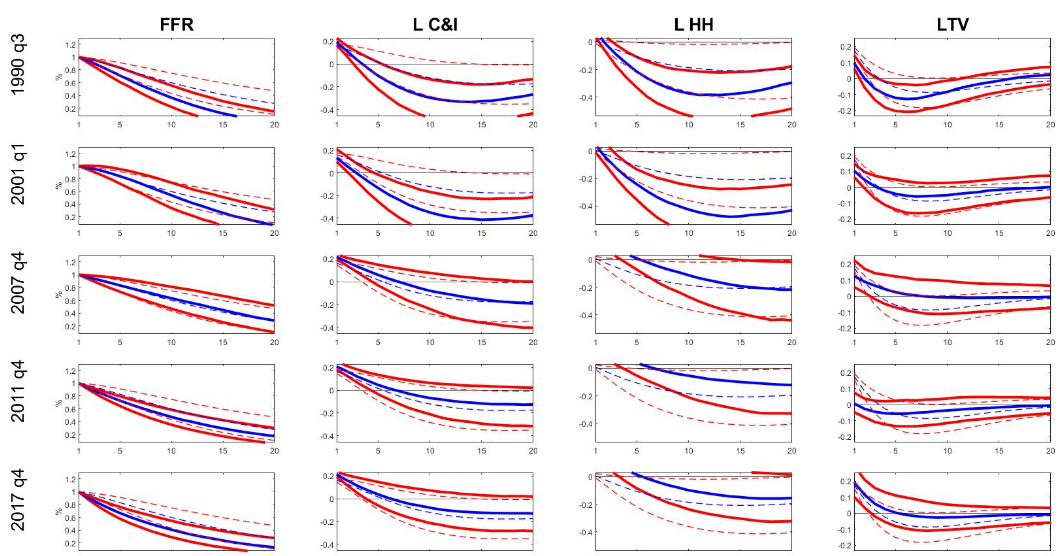
Notes: The figure shows results from the model using the training sample prior (calculated with data from the first forty quarters), which is the only difference with the benchmark specification of the model. The row labels ("FFR", "L C&I", "L HH", and "LTV") represent the Federal Funds rate, loans or liabilities related to commercial and industrial (C&I) and real estate categories, and the loan-to-value ratio respectively. The column labels indicate which quarters the impulse response functions (IRFs) on the corresponding row are from. The solid blue lines represent the posterior medians of IRFs for the TVC-SV-VAR with variables ordered as $x = [\text{FFR, L C\&I, L HH, LTV}]'$. The areas between solid red lines display one standard deviation credible sets obtained from the posterior draws (500 effective draws after burn-in and thinning processes). The x-axis represents time in quarters. The y-axis represents (annualized) percentage points. The sample span used to get the time-varying IRFs above is the maximum sample length of the current dataset. The dashed (blue and red) lines represent the IRFs from the fix-parameter VAR using the maximum sample length of the current dataset.

Figure 9b: IRFs to a FFR Shock: Dataset 2 (H.8 Table), Training Sample Prior



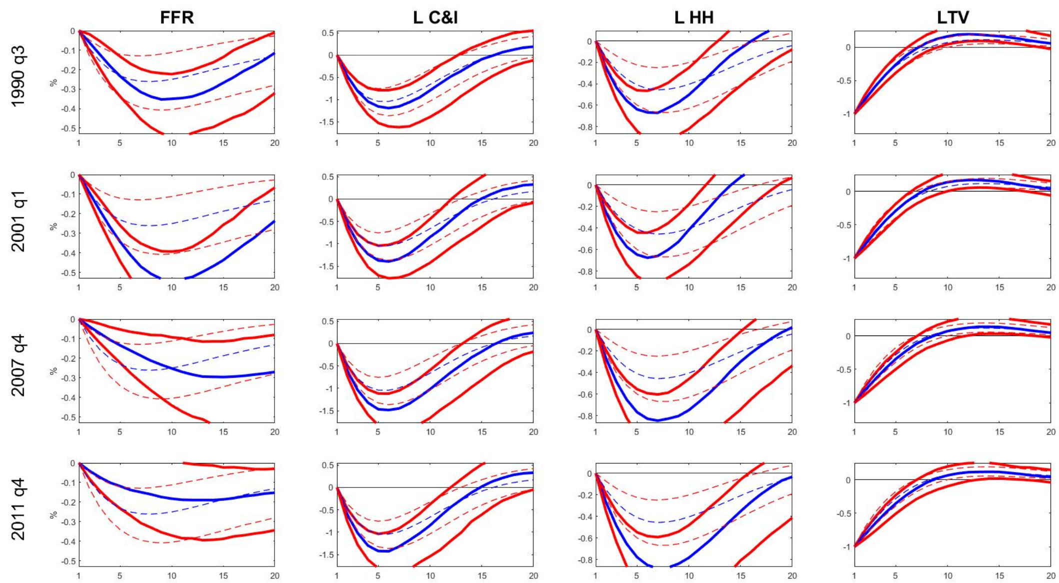
Notes: See explanations for Figure 9a.

Figure 9c: IRFs to a FFR Shock: Dataset 3 (Liabilities), Training Sample Prior



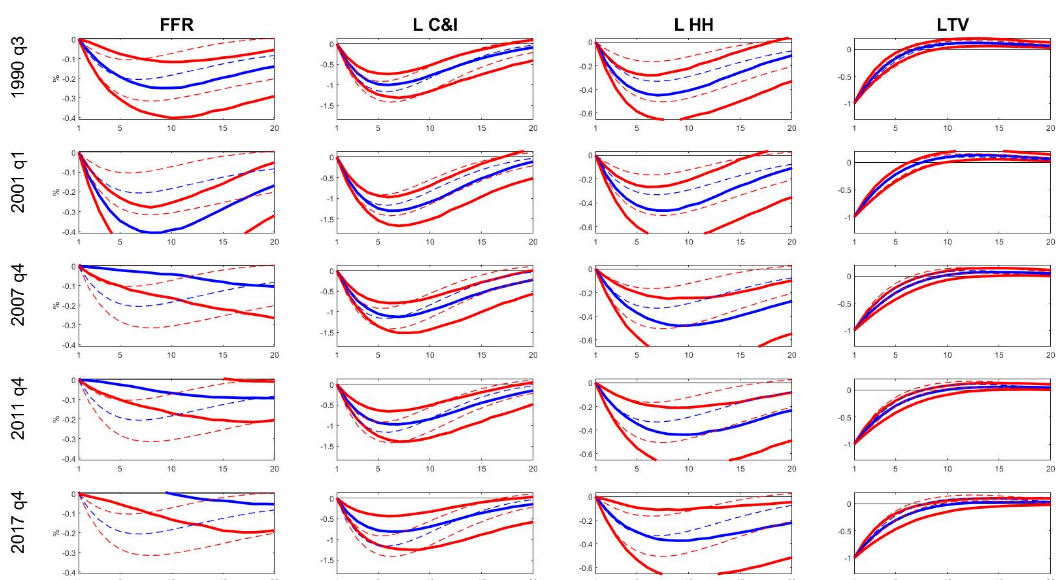
Notes: See explanations for Figure 9a.

Figure 10a: IRFs to a LTV Shock: Dataset 1 (Call Report), Training Sample Prior



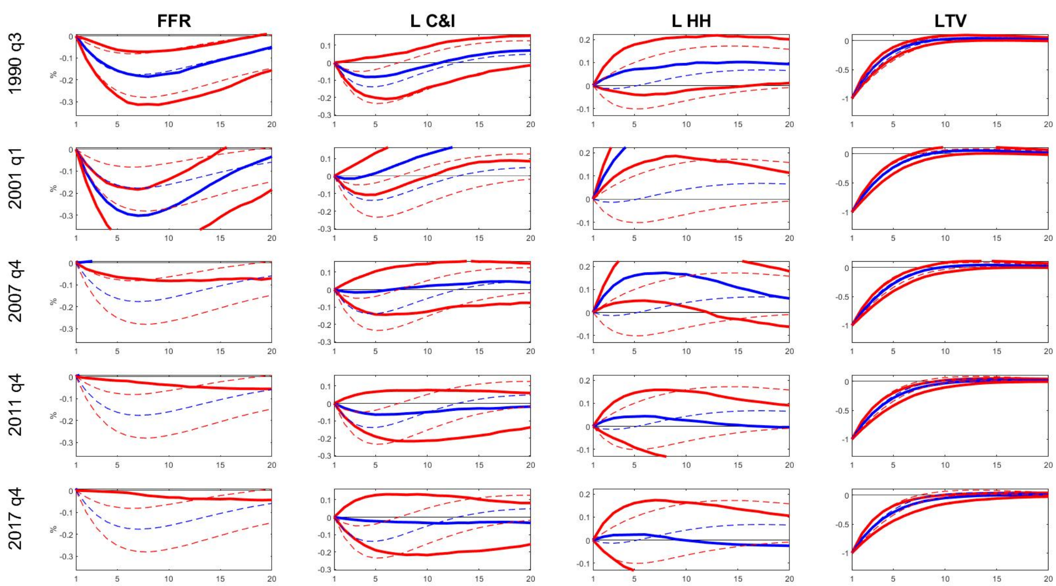
Notes: See explanations for Figure 9a.

Figure 10b: IRFs to a FFR Shock: Dataset 2 (H.8 Table), Training Sample Prior



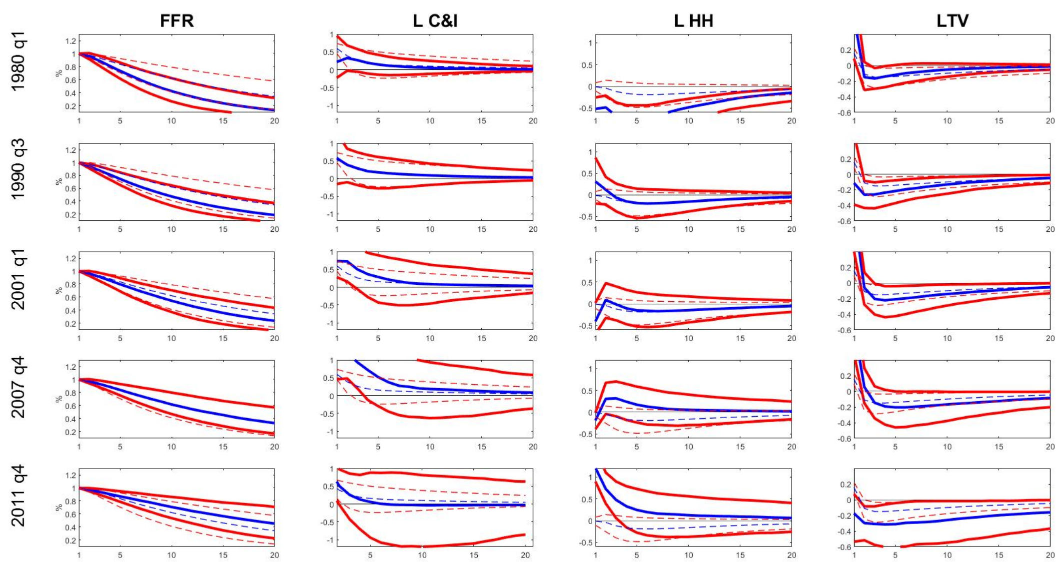
Notes: See explanations for Figure 9a.

Figure 10c: IRFs to a FFR Shock: Dataset 3 (Liabilities), Selected Dates



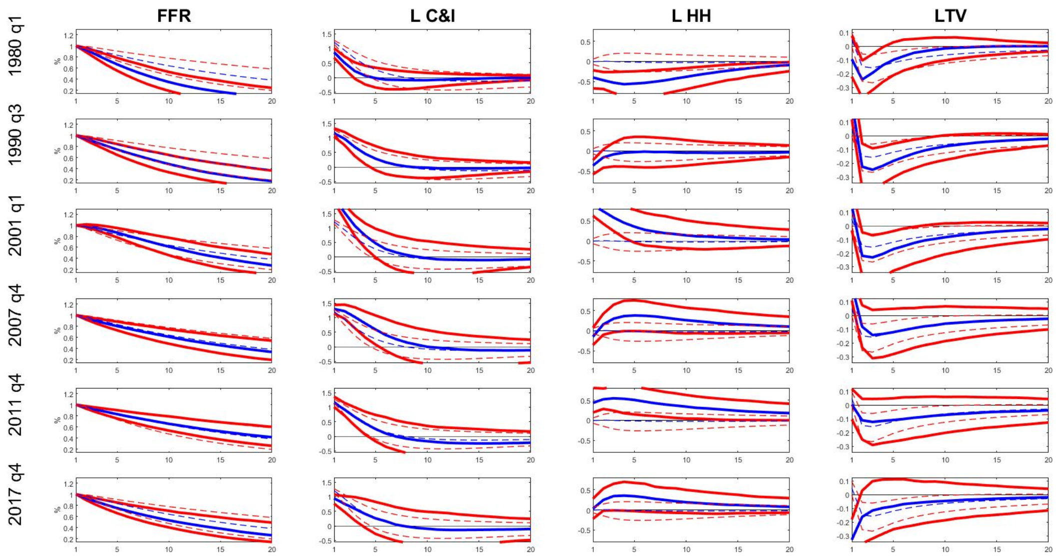
Notes: See explanations for Figure 9a.

Figure 11a: IRFs to a FFR Shock: Dataset 1 (Call Report), Quarterly Growth Data



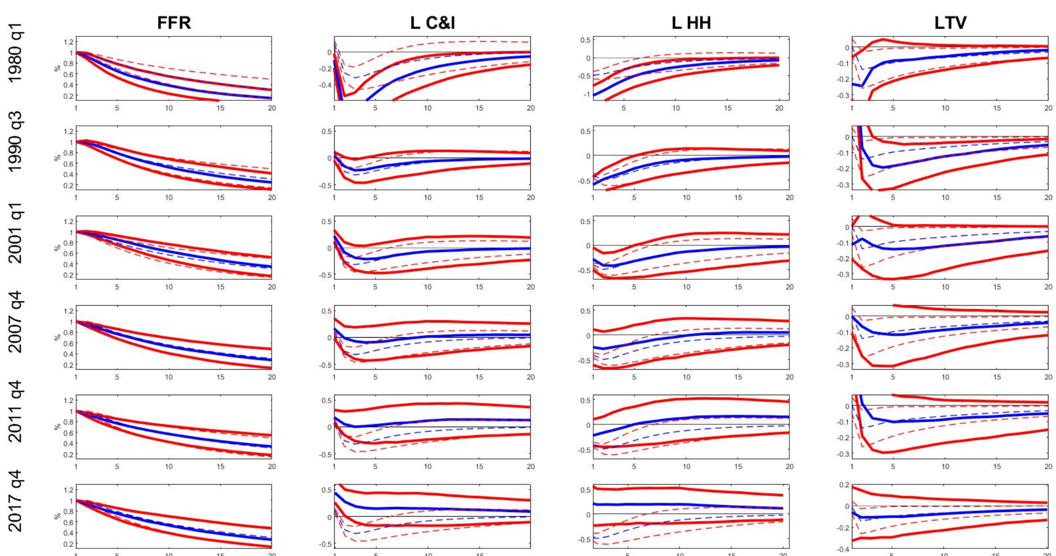
Notes: The figure shows results from the model using the annualized quarterly growth rate data for credit quantity variables, which is the only difference with the benchmark specification of the model. The row labels (“FFR”, “L C&I”, “L HH”, and “LTV”) represent the Federal Funds rate, loans or liabilities related to commercial and industrial (C&I) and real estate categories, and the loan-to-value ratio respectively. The column labels indicate which quarters the impulse response functions (IRFs) on the corresponding row are from. The solid blue lines represent the posterior medians of IRFs for the TVC-SV-VAR with variables ordered as $x = [\text{FFR, L C\&I, L HH, LTV}]'$. The areas between solid red lines display one standard deviation credible sets obtained from the posterior draws (500 effective draws after burn-in and thinning processes). The x-axis represents time in quarters. The y-axis represents (annualized) percentage points. The sample span used to get the time-varying IRFs above is the maximum sample length of the current dataset. The dashed (blue and red) lines represent the IRFs from the fix-parameter VAR using the maximum sample length of the current dataset.

Figure 11b: IRFs to a FFR Shock: Dataset 2 (H.8 Table), Quarterly Growth Data



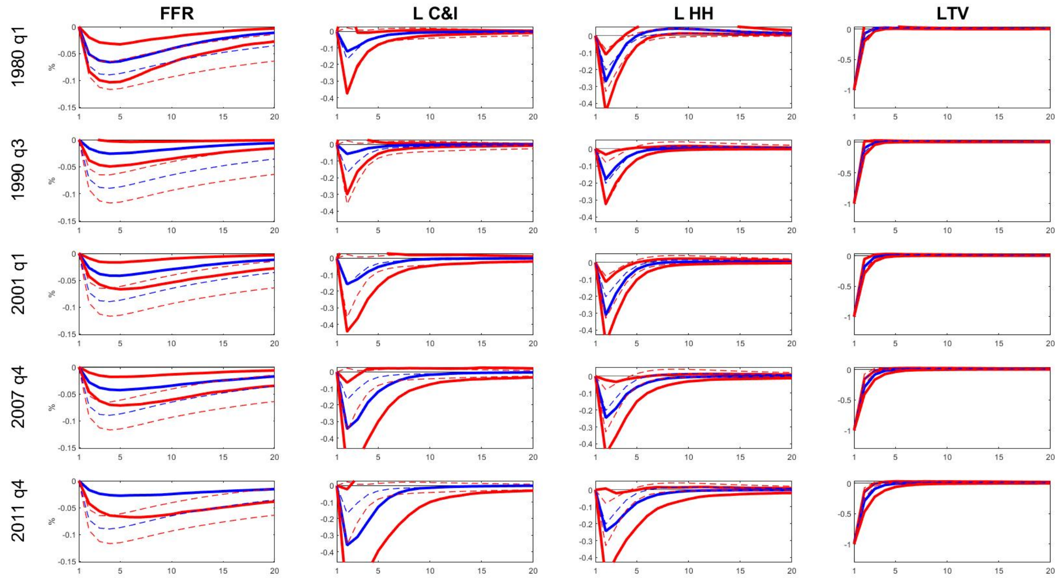
Notes: See explanations for Figure 11a.

Figure 11c: IRFs to a FFR Shock: Dataset 3 (Liabilities), Quarterly Growth Data



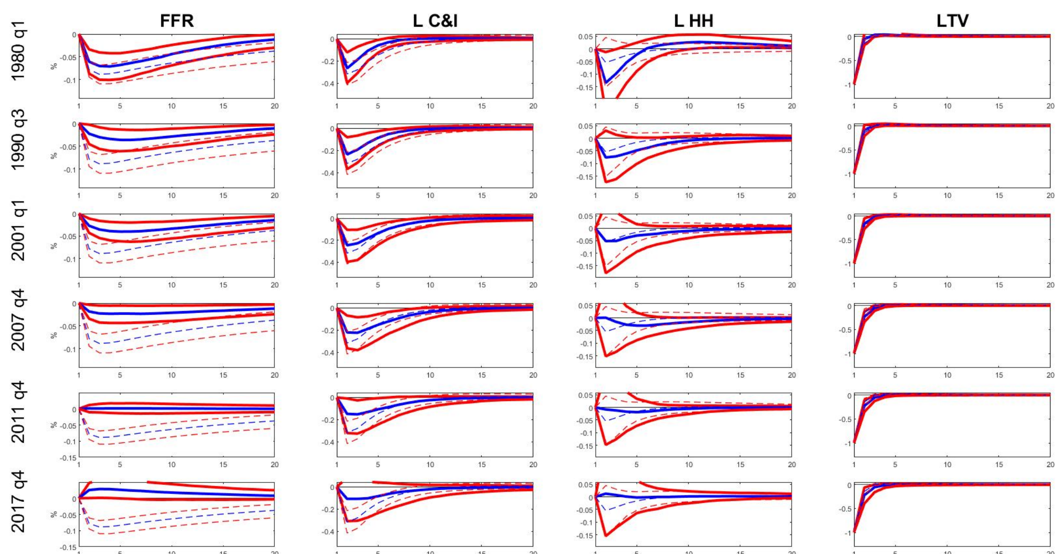
Notes: See explanations for Figure 11a.

Figure 12a: IRFs to a LTV Shock: Dataset 1 (Call Report), Quarterly Growth Data



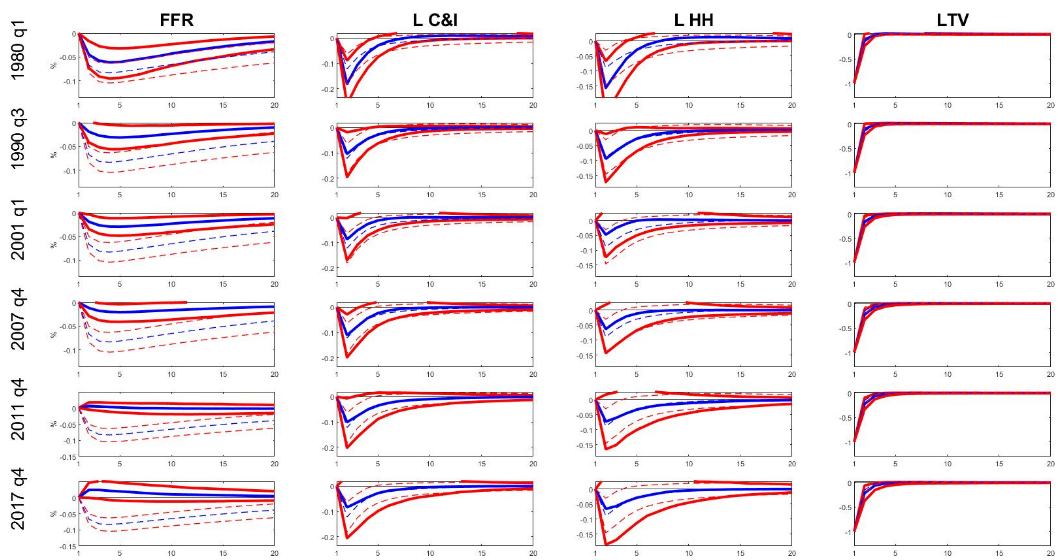
Notes: See explanations for Figure 11a.

Figure 12b: IRFs to a FFR Shock: Dataset 2 (H.8 Table), Quarterly Growth Data



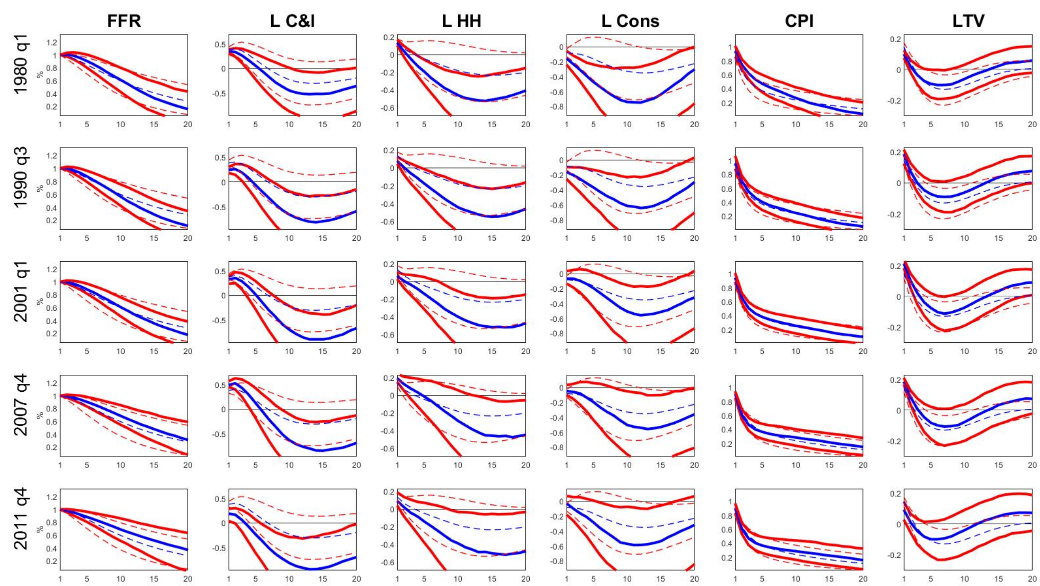
Notes: See explanations for Figure 11a.

Figure 12c: IRFs to a FFR Shock: Dataset 3 (Liabilities), Quarterly Growth Data



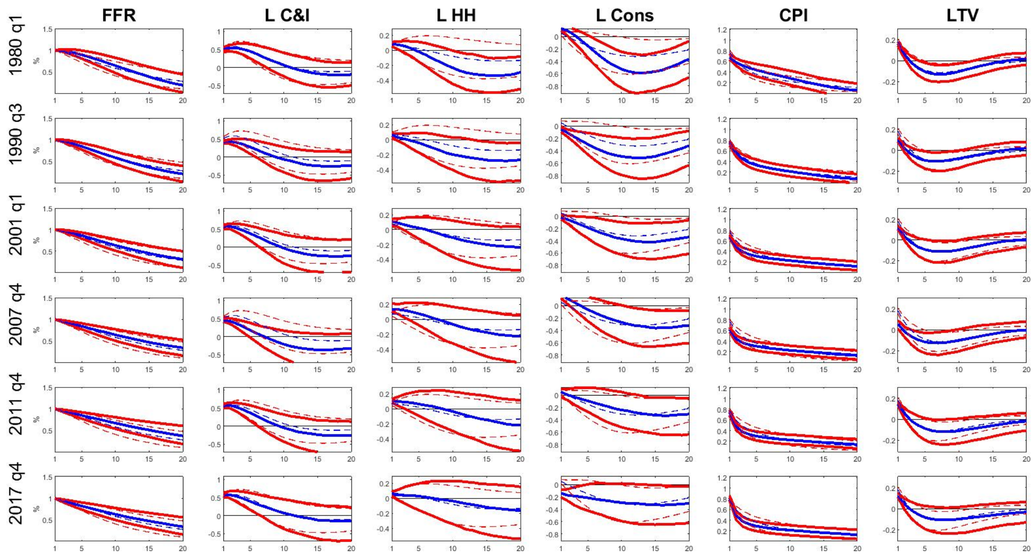
Notes: See explanations for Figure 11a.

Figure 13a: IRFs to a FFR Shock: Dataset 1 (Call Report), Additional Variables



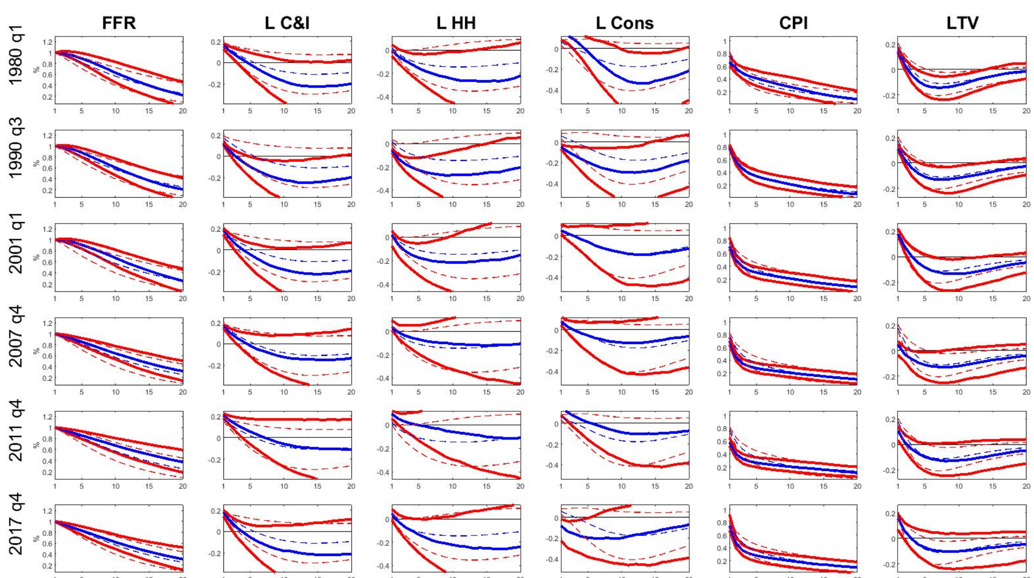
Notes: The figure shows results from the model including six variables, which is the only difference with the benchmark specification of the model. The row labels ("FFR", "L C&I", "L HH", "L Cons", "CPI", and "LTV") represent the Federal Funds rate, loans or liabilities related to commercial and industrial (C&I), real estate and consumer categories, the headline consumer price index, and the loan-to-value ratio respectively. The column labels indicate which quarters the impulse response functions (IRFs) on the corresponding row are from. The solid blue lines represent the posterior medians of IRFs for the TVC-SV-VAR with variables ordered as x = [FFR, L C&I, L HH, L Cons, CPI, LTV]$'$. The areas between solid red lines display one standard deviation credible sets obtained from the posterior draws (500 effective draws after burn-in and thinning processes). The x-axis represents time in quarters. The y-axis represents (annualized) percentage points. The sample span used to get the time-varying IRFs above is the maximum sample length of the current dataset. The dashed (blue and red) lines represent the IRFs from the fix-parameter VAR using the maximum sample length of the current dataset.

Figure 13b: IRFs to a FFR Shock: Dataset 2 (H.8 Table), Additional Variables



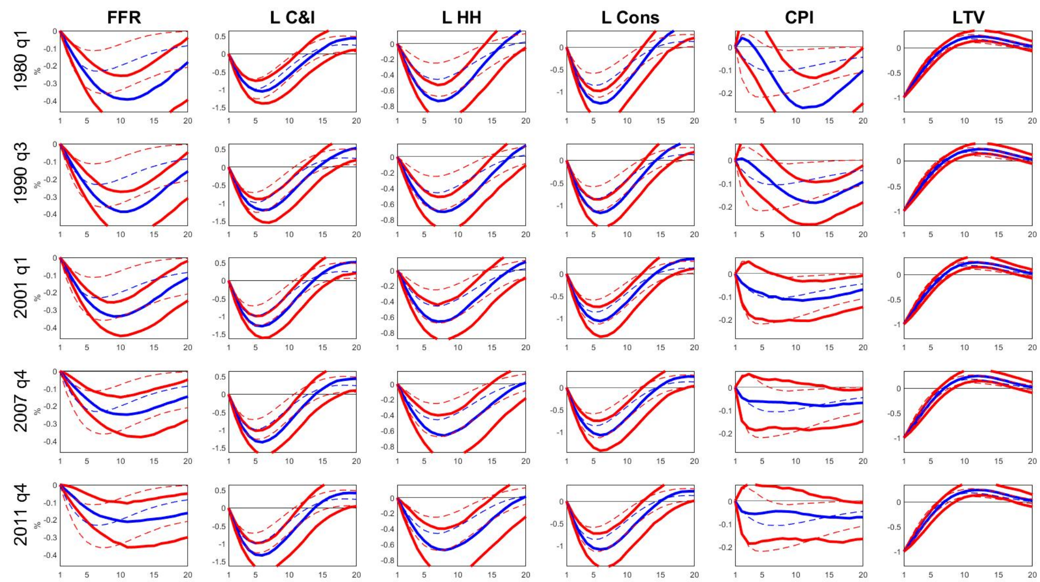
Notes: See explanations for Figure 13a.

Figure 13c: IRFs to a FFR Shock: Dataset 3 (Liabilities), Additional Variables



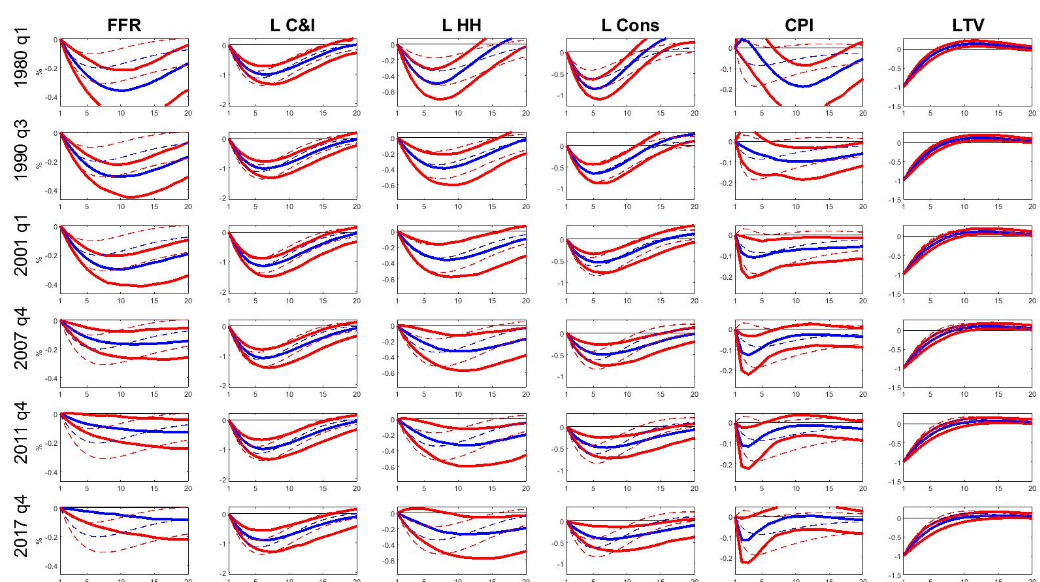
Notes: See explanations for Figure 13a.

Figure 14a: IRFs to a LTV Shock: Dataset 1 (Call Report), Additional Variables



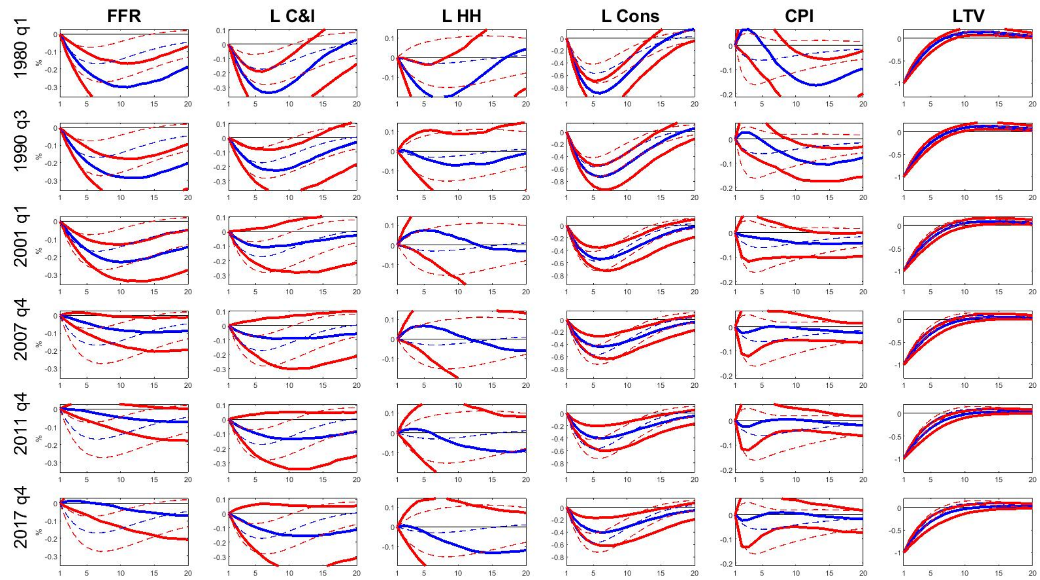
Notes: See explanations for Figure 13a.

Figure 14b: IRFs to a FFR Shock: Dataset 2 (H.8 Table), Additional Variables



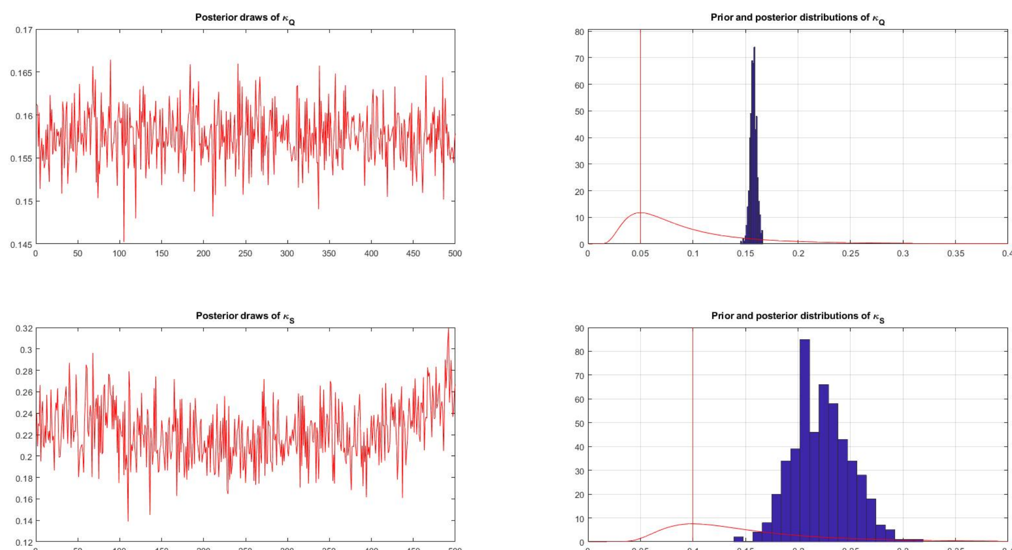
Notes: See explanations for Figure 13a.

Figure 14c: IRFs to a FFR Shock: Dataset 3 (Liabilities), Additional Variables



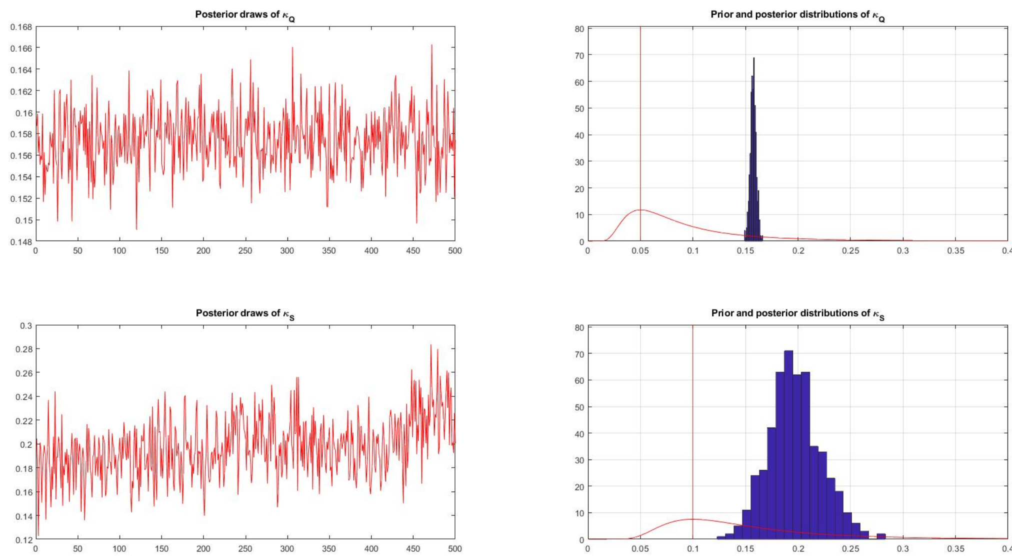
Notes: See explanations for Figure 13a.

Figure 15a: Posterior Distributions of Hyperparameters: Dataset 1 (Call Report), Benchmark Specification



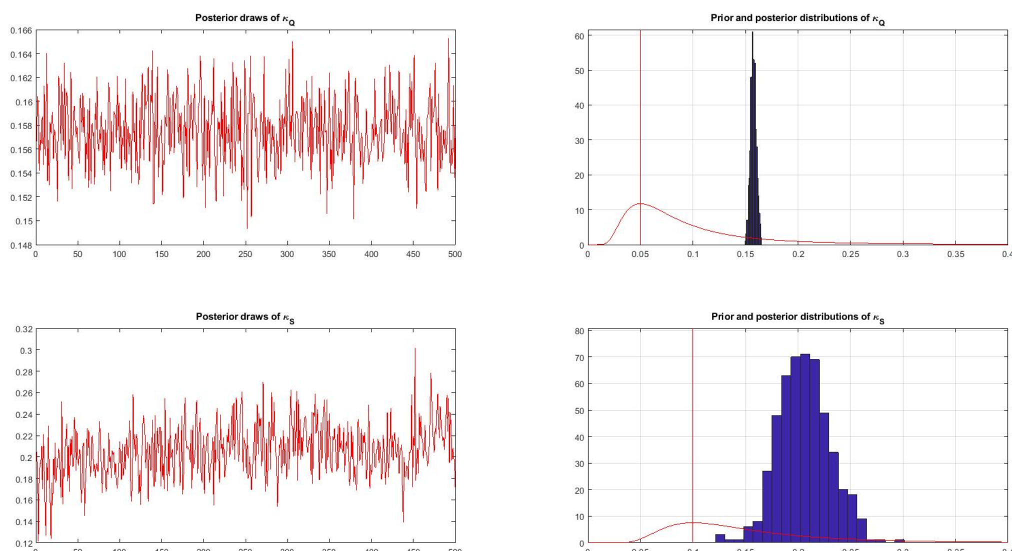
Notes: The figure shows the posterior draws of hyperparameters from the model with the benchmark specification. The left two panels plot draws for hyperparameters κ_Q and κ_S (κ_V in the main text). The right two panels plot the histograms of these draws with solid blue bars. Solid red curves plot the prior distributions of these two parameters as references. The vertical red lines represent the modes of these prior distributions.

Figure 15b: Posterior Distributions of Hyperparameters: Dataset 2 (H.8 Table), Benchmark Specification



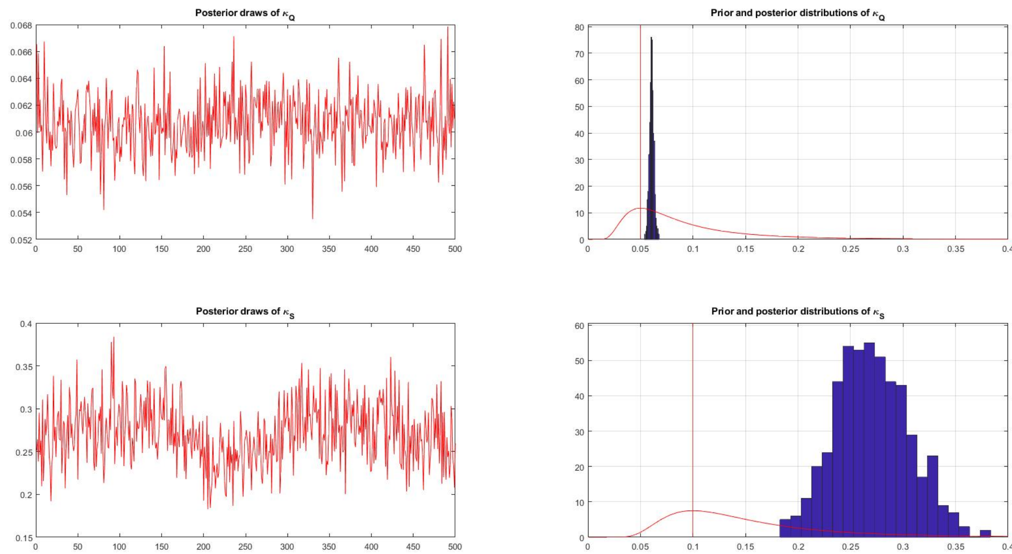
Notes: See explanations for Figure 15a.

Figure 15c: Posterior Distributions of Hyperparameters: Dataset 3 (Liabilities), Benchmark Specification



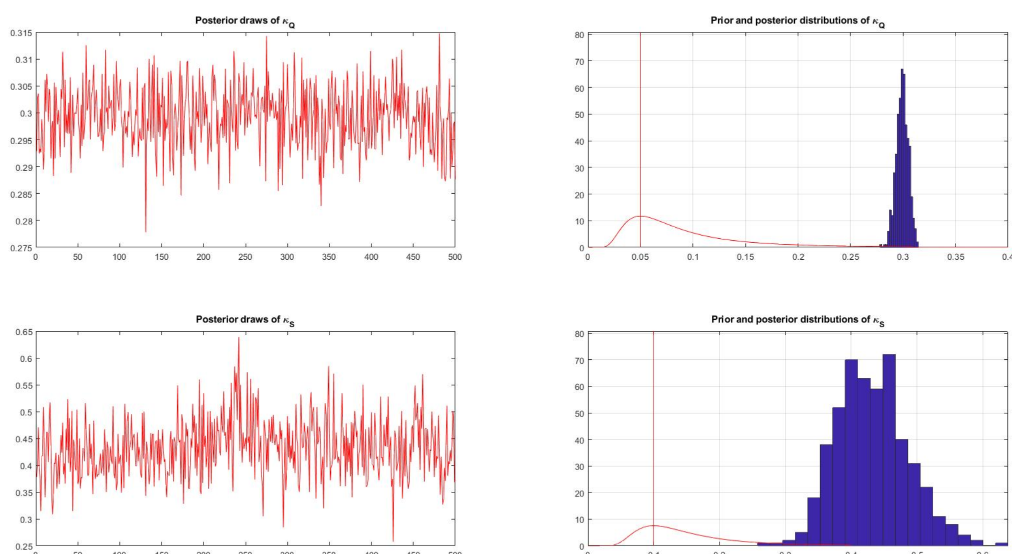
Notes: See explanations for Figure 15a.

Figure 16a: Posterior Distributions of Hyperparameters: Dataset 1 (Call Report), Training Sample Prior



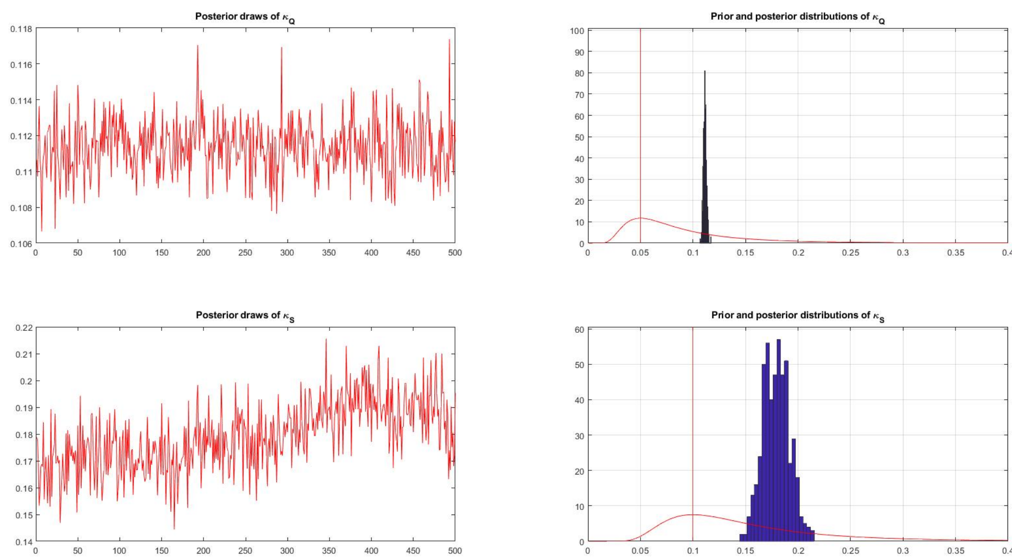
Notes: The figure shows the posterior draws of hyperparameters from the model using the training sample prior (calculated with data from the first forty quarters) which is the only difference with the benchmark specification of the model. The left two panels plot draws for hyperparameters κ_Q and κ_S (κ_V in the main text). The right two panels plot the histograms of these draws with solid blue bars. Solid red curves plot the prior distributions of these two parameters as references. The vertical red lines represent the modes of these prior distributions.

Figure 16b: Posterior Distributions of Hyperparameters: Dataset 1 (Call Report), Quarterly Growth Data



Notes: The figure shows the posterior draws of hyperparameters from the model using the annualized quarterly growth rate data for credit quantity variables, which is the only difference with the benchmark specification of the model. The left two panels plot draws for hyperparameters κ_Q and κ_S (κ_V in the main text). The right two panels plot the histograms of these draws with solid blue bars. Solid red curves plot the prior distributions of these two parameters as references. The vertical red lines represent the modes of these prior distributions.

Figure 16c: Posterior Distributions of Hyperparameters: Dataset 1 (Call Report), Additional Variables



Notes: The figure shows the posterior draws of hyperparameters from the model including six variables, which is the only difference with the benchmark specification of the model. The left two panels plot draws for hyperparameters κ_Q and κ_S (κ_V in the main text). The right two panels plot the histograms of these draws with solid blue bars. Solid red curves plot the prior distributions of these two parameters as references. The vertical red lines represent the modes of these prior distributions.

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