The Impact of the Uncertainty in Bank Lending Standards*

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This version: August 29, 2025

Abstract

This paper examines the macroeconomic consequences of credit uncertainty using a structural vector autoregression model with stochastic volatility (SVAR-SV). Credit supply conditions in the U.S. is captured by the banks' reports on how credit standards for approving loans have change over time (Bank Lending Standards). The empirical analysis shows that the volatility of macroeconomic and financial variables rises in response to an increase in the credit uncertainty shock. The economic activity falls and credit growth and related interest rates decrease persistently. Moreover, credit volatility shocks explain around 10% of the FEV of endogenous variables. A dissagregated analysis shows that the effect of these shocks are mainly explained by their effects on the corporate business sector.

*I am indebted to Bulent Guler, Christian Matthes, Laura Liu, Rupal Kamdar, Rong Fan, Hyeyun Cho and seminar participants at Indiana University for their useful comments and suggestions. The author acknowledges the Indiana University Pervasive Technology Institute for providing HPC resources that have contributed to the research results reported within this paper. All remaining errors and omissions are my entirely responsibility.

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1 Introduction

After the Great Recession, uncertainty gained the interest of many studies in the attempt to explain severe drops in real activity. In this respect, one strand of the literature studies the role of the uncertainty originated in the real sector (e.g., Bloom, 2009; Bachmann, Elstner and Sims, 2013), while other studies evaluate how financial frictions could amplify the propagation of these uncertainty shocks (e.g., Gilchrist, Sim and Zakrajšek, 2014; Arellano, Bai and Kehoe, 2019). Other studies, however, focus the analysis on uncertainty shocks originated in financial markets (e.g., Bollerslev, Tauchen and Zhou, 2009; Ludvigson, Ma and Ng, 2021).[1] This paper examines how the uncertainty on bank lending standards affects the real economy by using a flexible empirical macroeconomic approach where uncertainty is captured by the average volatility of structural shocks and it affects the economy through a volatility-in-mean mechanism (Mumtaz and Zanetti, 2013; Mumtaz and Theodoridis, 2020).

But what is uncertainty and how it can be measured? Knight (1921) defined uncertainty as peoples' inability to forecast the likelihood of events happening in the future. It is not surprising that with this broad definition in mind, there is no a unique and perfect measure of uncertainty. Instead, the literature has relayed on a wide range of proxies, such as the volatility of macroeconomic and financial variables, since when a data series is more volatile, it is harder to forecast (Bloom, 2014). Other common measures of uncertainty include forecasters' disagreement, volatility of forecast errors in a large number of macroeconomic and financial variables, mentions of the word *'uncertainty'* in the news, etc. These proxies of uncertainty are then used in different empirical models suggesting that uncertainty rises sharply in recessions, decreasing output, consumption, investment, employment and trade (Bloom, 2014; Castelnuovo, Lim and Pellegrino, 2017).

Given the observed importance of credit markets during the Great Recession (Mian, Rao and Sufi, 2013; Guerrieri and Lorenzoni, 2017), the goal of this paper is to quantify the importance of uncertainty about the borrowing capacity of households and businesses in the U.S. Unlike previous literature that measures uncertainty based on externally calculated indicators such as the VIX index or a composite volatility index of financial variables, in this paper financial uncertainty is measured as the average volatility of structural shocks to bank lending standards. In particular, I use a measure of banks reporting tighter standards across different loan categories calculated from the Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS).

Bank lending *'standards'* refer to any of the various non-price lending terms specified in a typical bank loan or line of credit, such as collaterals, loan limits, etc. Lown and Morgan (2006) showed that the series reported by the SLOOS survey makes a reasonable indicator for the full vector of non-price lending conditions used by more than 80 of the largest banks in the U.S. In this regard, the main objective of this study is to evaluate the importance of uncertainty about bank lending

[1]For example, Ludvigson et al. (2021), using a small-scale structural VAR with a novel identification approach that imposes economic assumptions directly on the behavior of the shocks, find that macroeconomic uncertainty in recessions is often an endogenous response to output shocks, while uncertainty about financial markets is a likely source of exogenous and persistent output fluctuations.

standards in explaining fluctuations in macroeconomic variables and other financial variables.

To address this task, I use an structural vector autoregression (SVAR) model where the variance of endogenous variable shocks varies over time via a stochastic volatility specification and allows a dynamic interaction between the time-varying volatility and the level of endogenous variables. Using U.S. data the results show that bank lending standards uncertainty shocks rise the volatility of endogenous variables, persistently decrease credit growth and interest rates, and moderately decrease GDP growth in the short-run. It is also shown that lending standards volatility shocks are responsible for about 10% of the forecast error variance to the level of the endogenous variables. These contributions are comparable to the monetary policy volatility shocks that are an important source of the evolution of real GDP growth.

The database used in the econometric analysis allows me to disaggregate the results and evaluate how credit uncertainty shocks affect households and firms separately. Households lending growth contracts in response to an increase in volatility shocks of bank lending standards, however, there is little response on interest rates and no change in real GDP growth when these shocks hit the economy. On the other hand, GDP growth falls and businesses lending growth and rates respond strongly to an increase in the variance of shocks to credit standards on business loans. The composition of the debt portfolio and the response of monetary policy can explain these differences.

Related literature. This paper is related to the literature that studies the link between credit or financial markets and the business cycle. In a seminal work, Jordà, Schularick and Taylor (2013) collect long-run historical data for advanced economies and show that credit growth has the potential to predict financial crises, and conditional on facing a recession, stronger previous credit growth predicts deeper recessions. Gilchrist and Zakrajšek (2012) use firm level data to build an index of credit spread from which the excess bond premium component can be extracted. Innovations to the excess bond premium can be interpreted as a proxy for credit supply and are shown to cause significant contractions in consumption, investment, and output. In this line, Mumtaz, Pinter and Theodoridis (2018) propose different empirical macroeconomic models to identify and estimate the impact of innovations in credit supply in the U.S. and find that shocks that raise spreads by 10 basis points reduce GDP growth and inflation by 1 percent after one year, and explain about 13 percent of the FEV of GDP growth. Similar to these studies, I use the bank lending standards as an indicator of credit supply conditions and evaluate how its structural innovations affect key macroeconomic and financial variables.

This paper is also related to the studies that measure and quantify the link of credit and uncertainty in the economy. Arellano et al. (2019) develop a model with heterogeneous firms that face default risk and time-varying volatility shocks. Firms hire labor and take debt to pay for them before they receive the revenues from their sales. When making decisions, firms face a trade-off between the expected return from hiring workers and the risk of default. Fluctuations in the volatility of idiosyncratic productivity shocks lead to important contractions in economy activity as well as tightening in financial conditions, similar to those observed during the Great Recession

2007-2009. On the empirical side, Alessandri and Mumtaz (2019) study how the response of the U.S. economy to uncertainty shocks depends on aggregate financial conditions. Using a nonlinear VAR where aggregate uncertainty is captured by the volatility of structural shocks and a financial distress indicator that allows the parameters to differ across endogenous thresholds, the authors find that during normal times uncertainty shocks have little impact on output, but when financial markets are in distress, their impact on output is six times larger. Chatterjee, Gunawan and Kohn (n.d.) quantify and estimate credit uncertainty in an univariate stochastic volatility regression of credit growth in the U.S., and incorporate it as an exogenous variation in the volatility of credit available for financing working capital requirements in a standard RBC model. When the collateral constraint binds, unexpected changes in credit uncertainty generates a precautionary response that generates a simultaneous decline un output, consumption, investment, real wages and hours. In contrast to these studies, the framework used in this paper allows me to estimate credit uncertainty endogenously that is calculated by the average volatility of the structural shock of bank lending standards, and instead of using financial markets as amplifiers of uncertainty shocks, quantify the effect of uncertainty originated in the financial sector.

2 Bank Lending Standards

The SLOOS survey is conducted by the Federal Reserve on a quarterly basis with the purpose of monitoring lending conditions in the banking sector. Around 80 U.S. commercial banks participate in each survey, answering questions about seven categories of core loans: (i) commercial and industrial, (ii) commercial real state, (iii) residential mortgages to purchase homes, (iii) home equity lines of credit, (iv) credit cards, (v) auto, and (vi) other consumer loans. Questions about changes in lending standards follow the following style: *"Over the past three months, how have your bank's credit standards for approving loans of type X changed?"*. The answers are then categorized into a discrete variable I^S_{ikt}, where

$$I^S_{ikt} = \begin{cases} -1, & \text{if bank } i \text{ reported } \textit{easing} \text{ standards on loan category } k \text{ in quarter } t, \\ 0, & \text{if bank } i \text{ reported no change in standards on loan category } k \text{ in quarter } t, \\ 1, & \text{if bank } i \text{ reported } \textit{tightening} \text{ standards on loan category } k \text{ in quarter } t. \end{cases}$$

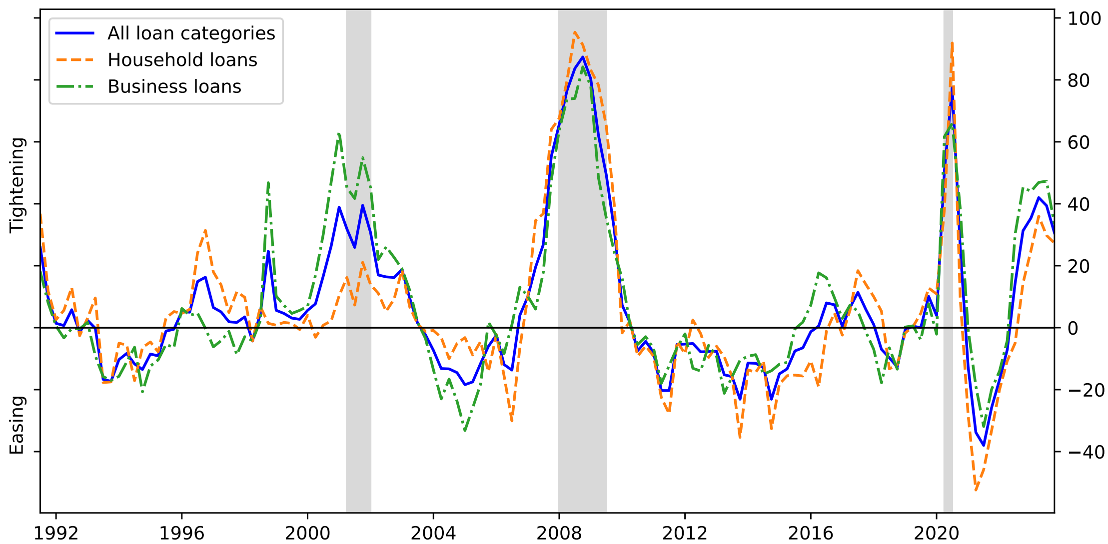
Glancy, Kurtzman and Zarutskie (2020) show how to aggregate the bank-level responses averaging over the N banks responding to that question in one specific quarter:

$$\Delta S_{kt} = 100\left(\sum_{i=1}^{N} \omega_{i,k,t-1} \times I^S_{ikt}\right),$$

where $\omega_{i,k,t-1}$ is a weight that measures the outstanding balance of loan type k for bank i as a fraction of the total outstanding loans of all responding banks.[2] The resulting weighted scheme

[2]These weights are calculated using the Call Reports data.

Figure 1: Bank Lending Standards



Note: Net percentage of domestic banks tightening standards across loan categories, weighted by banks' outstanding loan balances by category. The shaded vertical bars represent the NBER-dated recessions.
Source: Federal Reserve Board's DDP.

measures the fraction of loans held by banks reporting tighter standards, net of the fraction of loans in banks reporting easier standards.

To describe patterns in banking conditions more broadly, aggregating across subcategories of loan types is needed. This is done by taking a weighted average of the underlying portfolio-weighted series, where the weights are outstanding loans for the various subcategories in the Call Reports. Aggregate series for changes in standards for business loans, household loans, and all loans, are released to the public through the Federal Reserve Board's DDP.[3] These variables are useful to capture the significant influence that the largest lenders have on aggregate credit supply and can reflect the credit conditions for the typical borrower, especially in markets where the largest banks account for the majority of all lending.

Figure 1 shows the measures of bank lending standards reported in the Federal Reserve Board's DDP. The solid blue line represents the aggregate measure of standards for all loan categories. The dashed orange line represents the bank lending standards for all household loan categories. The dash-dotted green line is the corresponding one for all business loan categories. The weighted net share of banks reporting tighter standards rises during the last three recessions and declines toward the end or shortly after those recessions ended. Lending standards are otherwise eased in normal times, with some exceptions, such as in late 2023, when the Federal Reserve began raising interest rates to fight against high inflation rates. I use this variable as a measure of bank credit conditions, similar to Lown and Morgan (2006), Bassett, Chosak, Driscoll and Zakrajšek (2014), and Chen, Higgins and Zha (2021).

[3]Business loans is a weighted average of commercial and industrial and commercial and real state loans. Household loans is a weighted average of residential real state and consumer loans.

3 Econometric Model

To estimate the effects of uncertainty in bank credit conditions, I use a structural VAR model with stochastic volatility to estimate the time-varying volatility of shocks and assess how macroeconomic and financial variables respond to a volatility shock in bank lending standards.

The model builds on Mumtaz and Theodoridis (2020), where the observation equation is given by:

$$Y_t = c + \sum_{j=1}^{P} \beta_j Y_{t-j} + \sum_{k=1}^{K} b_k \tilde{h}_{t-k} + \Omega_t^{1/2} e_t, \quad e_t \sim \mathbb{N}(0, I_N), \tag{1}$$

where Y_t is the vector of N endogenous variables and $\tilde{h}_t$ is the vector of log stochastic volatilities (i.e., the log volatility of the N structural shocks in the VAR). The covariance matrix of the VAR residuals is time-varying and can be written as:

$$\Omega_t = A^{-1} H_t A^{-1'},$$
$$H_t = \operatorname{diag}\left(\exp \tilde{h}_t\right),$$

where H_t holds the stochastic volatility of the orthogonalized shocks on the main diagonal. The structure of the matrix A is chosen to model the contemporaneous relationship among the reduced-form shocks. The transition equation for the stochastic volatilities is given by the following VAR model:

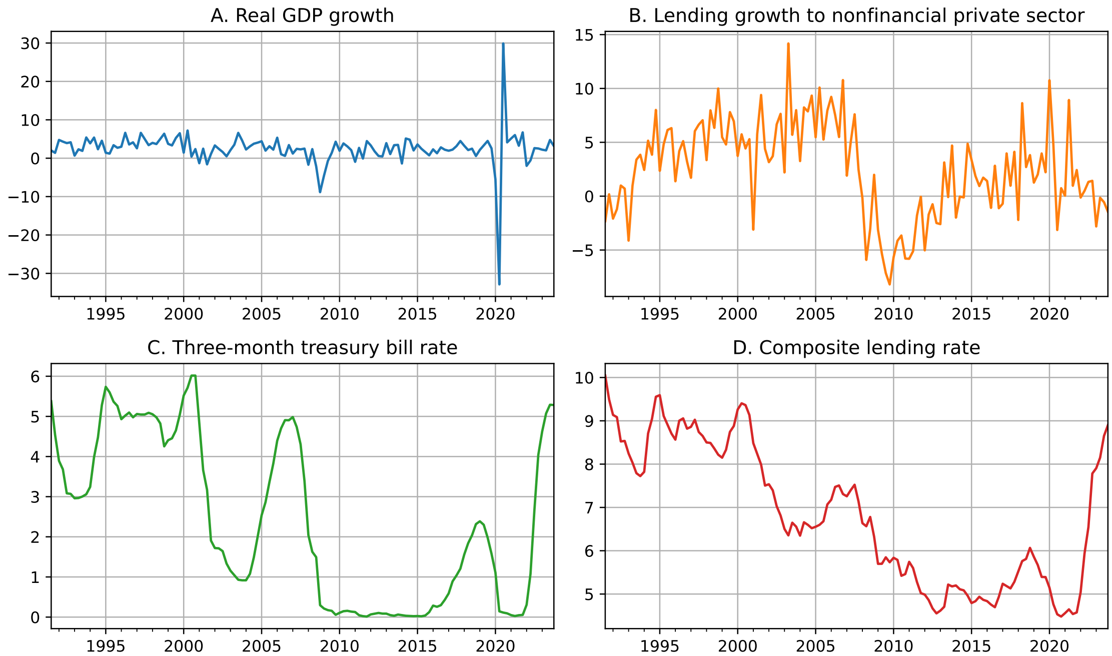
$$\tilde{h}_t = \alpha + \theta \tilde{h}_{t-1} + Q^{1/2} \eta_t, \quad \eta_t \sim \mathbb{N}(0, I_N), \mathbb{E}(e_t, \eta_t) = 0, \tag{2}$$

where log variances are allowed to depend on their first lag ($\tilde{h}_{t-1}$) and the covariance matrix Q is assumed diagonal.

The econometric model characterized by equations (1) and (2) features three characteristics similar to the related literature (e.g., Kim, Shephard and Chib, 1998; Cogley and Sargent, 2005; Mumtaz and Surico, 2018). First, the volatility of the structural shocks $\tilde{h}_t$ have a direct impact on the endogenous variables Y_t (i.e., the *volatility-in-mean* mechanism). Second, θ is not diagonal, allowing the feedback from lagged volatilities to the vector of stochastic volatilities $\tilde{h}_t$, a phenomenon that may be important during recessions. Third, equation (2) makes the simplifying assumption that shocks to the volatility equation η_t and the observation equation e_t are uncorrelated, and Q is a diagonal matrix. Then, an innovation in an element of η_t can be interpreted as a shock to the volatility of the structural shock of interest. When these assumptions hold, the structure of the matrix A in the covariance matrix Ω_t determines the interpretation of structural shocks and hence their volatility $\tilde{h}_t$.[4] Therefore, the structure of the econometric model is capable of identifying both innovations to the level and to the volatility using standard identification schemes that are applied to the contemporaneous relationships among the levels of the reduced form shocks.

[4] When these assumptions are relaxed, further identifying restrictions are required to distinguish among the volatility shocks and to separate the innovations to the level from the innovations to the volatility.

Figure 2: Data



4 Estimation and Identification

4.1 Data

I estimate the model using data for the United States running from 1991Q3 - 2023Q4 including the following variables: (i) real GDP growth, (ii) real growth of total loan volumes to households and non-financial corporate businesses, (iii) net percentage of loans held by domestic banks tightening standards across all loan categories, (iv) the three-month Treasury Bill rate, and (v) a composite lending rate.[5] Figure 1 shows the aggregated and disaggregated bank lending standards variables. Figure 2 shows the remaining variables used in the baseline specification.

The growth rates are annualized and the analysis period includes the last 3 U.S. recessions including the Great Recession (2007-2009) and the 2020 Great Lockdown. The lending growth series is calculated from the outstanding amounts of loans granted by financial intermediaries to households and nonprofit organizations, and non-financial corporate businesses. Figure A1 shows the composition of loans for the group of households and businesses reported by the Federal Reserve in the Financial Accounts for the United States (Z.1).

As a fraction of all household loans, mortgages (long-term debt) represent more than 60 percent of total household outstanding debt in the United States, followed by shorter-term debt such as consumer credit that includes motor vehicle loans, student loans, revolving debt, etc. On the other hand, the composition of corporate business debt is mainly driven by short-term loans, especially

[5]The sample is restricted to the credit standards variable that is public available since 1991. The Appendix provides details on data sources and construction.

after the Great Recession where the debt composition of long-term loans, such as commercial mortgages, fell. The calculated total amount of loans use in the analysis does not include security or foreign debt.

4.2 Model specification and identification

The nonlinear state-space model characterized by equations (1) and (2) is estimated using a Gibbs sampling algorithm to approximate the posterior distribution, similar to Cogley and Sargent (2005) and Mumtaz and Theodoridis (2020). In summary, the algorithm proceeds in the following steps:

1. The prior distributions for the VAR coefficients (equations (1) and (2)) shrink the coefficient matrix towards an AR specification and are normal distributed with moments implemented via dummy observations. A training sample is used to compute the prior distributions for the matrices A and $H_{t=0}$.

2. Equation (1) is a VAR model with heteroskedastic disturbances, conditional on $\tilde{h}_t$ and A draws. The VAR representation is rewritten as a state-space model and a Kalman filter algorithm is used to draw from the conditional distribution of $\Gamma = vec([c; \beta_j; b_k])$.

3. Given $\tilde{h}_t$ and Γ, the elements of the matrix A can be drawn using a series of linear regression models with a GLS transformation amongst the elements of the residual matrix $\Omega_t^{1/2} e_t$.

4. Given the VAR coefficients and the parameters of the transition equation, the model has a multivariate non-linear state-space representation. A particle Gibbs with ancestor sampling is used to draw the posterior of $\tilde{h}_t$ following Lindsten, Jordan and Schön (2014) and Andrieu, Doucet and Holenstein (2010).

5. Conditional in the draw for $\tilde{h}_t$, the conditional posterior of the parameters in the transition equation $\Theta = vec([\alpha; \theta])$ is normal and can be drawn using standard results for linear regressions.

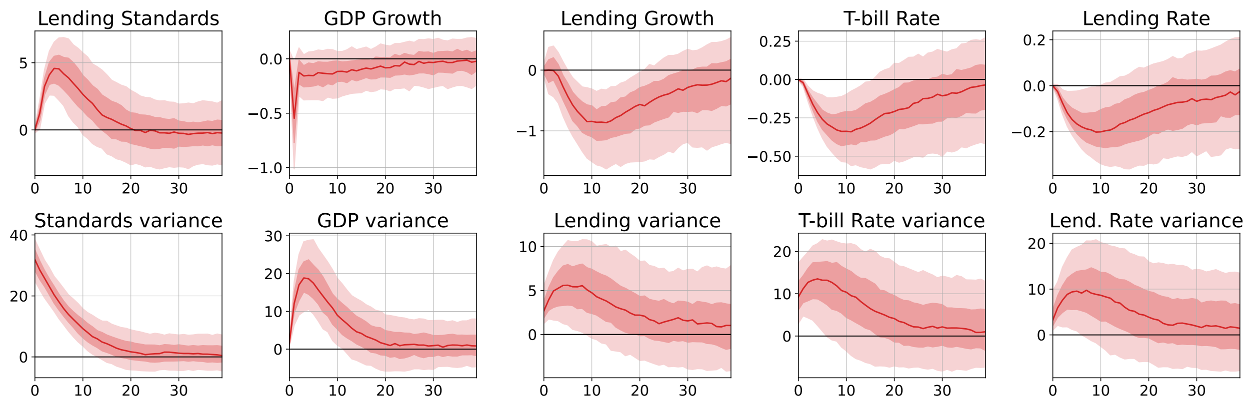
The IRFs of Y_t to a stochastic volatility shock are calculated via Monte-Carlo integration (Koop, Pesaran and Potter, 1996)

$$GIRF_t = \mathbb{E}\left[\, Y_{t+k} \,|\, \delta, \Psi_t, Y_{t-1} \,\right] - \mathbb{E}\left[\, Y_{t+k} \,|\, \Psi_t, Y_{t-1} \,\right],$$

where δ is the identified shock and Ψ_t denotes the parameters and state variables of the model. These strategy can also be used to compute the forecast error variance conditional on a particular shock, and then the contribution of each shock to the total forecast error variance can be calculated.

Identification. Similar to Mumtaz et al. (2018); Caldara and Herbst (2019); and other empirical studies that aimed to identify credit supply shocks, I use contemporaneous sign restrictions to identify the bank lending shock. In particular, I assume that tight bank credit conditions increases

Figure 3: Impulse responses to 1 standard deviation increase in the variance of bank lending standards



Notes: The solid line is the median. The light shaded area is the 84% error band while the dark shaded area is the 68% error band. The top row presents the response of the endogenous variables in levels. The second row shows the response of the unconditional volatilities in percentages.

bank lending standards on impact and leads to a fall in the volume of loans and an increase in the lending rate. The identification strategy is implemented by placing restrictions on the column of the A^{-1} matrix corresponding to the equation for the bank lending standards variable. If the endogenous variables follow the following ordering: bank lending standards, real GDP growth, real growth of loans to the non-financial sector, three-month Treasury Bill rate, and composite lending rate; the structure for A^{-1} is:

$$A^{-1} = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 & 0 \\ a_{31}^{(-)} & a_{32} & 1 & 0 & 0 \\ a_{41} & a_{42} & a_{43} & 1 & 0 \\ a_{51}^{(+)} & a_{52} & a_{53} & a_{54} & 1 \end{pmatrix},$$

where the superscript $(-)$ (or $+$) denotes the fact that this element is restricted to be less (or more) than zero. The sign restrictions are imposed via rejection sampling.

Since the frequency of the variables is quarterly, I will set the lag length in the VAR model to 3 and use 2 lags of the stochastic volatilities in the observation equation.

5 Results

5.1 Impulse response to a Bank Lending Standards volatility shock

Figure 3 shows the impulse responses to a one standard deviation increase in the variance of bank lending standards shock. The response of the standards volatility is short-lived and dissipates after 12 quarters. Bank lending standards rise in response to this shock, reaching a peak of 4.5 at the

Table 1: Median estimates for the FEVD of levels and volatility of endogenous variables

Variable	Horizon	Decomposition of level FEV		Decomposition of volatility FEV	
		All volat. shocks	Standards	All volat. shocks	Standards
Credit Standards	4 quarters	61.17	12.87	98.60	83.25
	20 quarters	82.05	16.50	88.55	49.56
	40 quarters	74.91	13.34	77.14	32.60
GDP growth	4 quarters	28.71	5.92	98.64	4.66
	20 quarters	46.64	9.44	90.00	10.25
	40 quarters	50.65	10.18	82.32	11.02
Lending growth	4 quarters	28.64	1.79	98.18	6.59
	20 quarters	67.69	14.76	85.40	12.79
	40 quarters	66.03	11.52	72.07	11.52
T-bill rate	4 quarters	51.38	12.69	98.58	8.73
	20 quarters	82.31	17.71	89.82	14.68
	40 quarters	70.55	11.84	80.47	13.19
Lending	4 quarters	37.82	12.36	98.70	4.23
rate	20 quarters	80.64	17.96	90.94	10.36
	40 quarters	69.71	11.57	82.89	10.39

end of one year. GDP growth falls by 0.5% the quarter after the shock was realized, but recovers quickly after that. The response of the aggregate lending growth, 3-month Treasury bill and the lending rate is much more persistent. The lending growth and the 3-month Treasury bill fall by 0.8% and 0.34 percentage points after about 10 quarters the shock was realized, respectively. The composite lending rate decreases in response to the standards volatility shock, but less than the 3-month Treasury bill reaching a trough of 0.2 percentage points after 10 quartes. Although these last two interest rates follow the same trajectory, the difference in their magnitudes account for the increase in the spread of interest rates observed during periods of tight credit conditions (e.g., Gambetti and Musso, 2017; Caldara and Herbst, 2019).

The second row of the figure presents the response of the unconditional volatility to this shock. It is evident that the volatility of all endogenous variables rises in response to this shock. An increase of 30 percent in bank lending standards variance rises the variance of the GDP growth in 18 percent after four quarters. The variance of the lending growth, the 3-month Treasury bill rate, and the composite lending rate rise in around 5, 13, and 9 percent at the same time time horizon. It is important to note that although the variance shock of bank lending standards has a short-lived impact on the level of GDP growth, its effect on the variance of GDP growth is more persistent and dissipates after 10 quarters.

5.2 Variance decomposition

The impulse response function results suggest that bank lending standard uncertainty may have important effects on the macroeconomy and the financial sector. Table 1 shows the median estimates for the forecast error variance decomposition (FEVD) of the level and volatility of the endogenous variables in the VAR. Columns 3 and 4 show the contribution of all volatility shocks and the lending standards volatility shock to the FEV of the level of variables. All volatility shocks explain more than 1/4 of future movements in GDP growth. However, lending standards volatility shocks only make a modest contribution to GDP growth FEV (around 6 percent and 10 percent after 4 and 40 quarters, respectively). One possible explanation is the rapid monetary policy response to these shocks that is reflected in the 3-month Treasury bill rate FEV of around 13 percent at the end of one year.

Columns 5 and 6 show the contribution of all volatility shocks and the lending standards volatility shock to the FEV of volatility of variables. The contribution of lending standards volatility shocks is also modest, but appears to be more important in the long-run. For instance, the total contribution to the FEV of GDP growth volatility is equal to 5 percent after 4 quarters, and is equal to 11 percent after 40 quarters.

Relative to other volatility shocks, bank lending standards volatility shocks contribution to the FEV of levels of GDP growth, lending growth, and lending rate is similar to the monetary policy (3-month Treasury bill rate) volatility shocks (see table B2 in the appendix). In fact, these last volatility shocks explain more than 25% of future movements in bank lending standards over the 4-quarter horizon. Similar to previous studies, it turns out that the linkage between bank lending standards and monetary policy is important for understanding the effects of credit supply shocks on the economy.

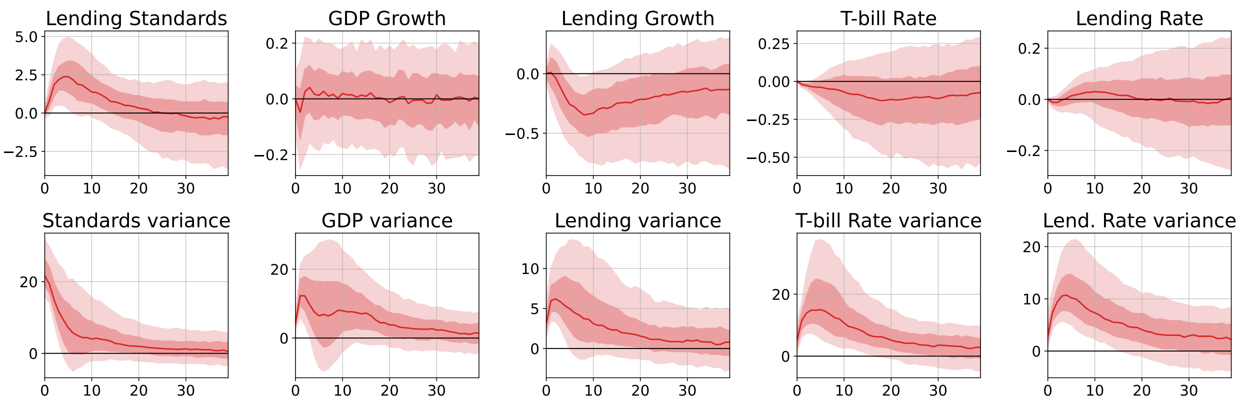
5.3 Disaggregated analysis

By construction, the previous analysis can be disaggregated to assess the extent to which the effect of bank lending standards differs for households and firms. In this section, I include specific variables for each subgroup and estimate the effects of volatility on credit standards for households and businesses separately. For the analysis of households I include the following variables: bank lending standards for household loans, real GDP growth, real growth of total loans volumes to households and nonprofit organizations, 3-month Treasury bill rate and a households' composite lending rate. In the case of businesses, the variables included are: bank lending standards for business loans, real GDP growth, real growth of total loans volumes to non-financial corporate businesses, 3-month Treasury bill rate and a business' composite lending rate. See figure A2 in the appendix for the disaggregated data for households and businesses.

Households. Figure 4 shows the responses of the endogenous variables to a one standard deviation increase in the variance of bank lending standards on households loans. Similar to the aggregate case analyzed before, the variance of endogenous variables increases in response to an increase in lending standards. However, there are two differences that are worth noting with respect to the response of the variables in levels.

First, lending standards on households loans increase in response to a shock in lending standards variance. At the same time, this shock also reduces the level of credit growth, which decreases by 0.4% over a 9-quarter horizon. These results align with the estimates for the aggregate variables.

Figure 4: Impulse responses to 1 standard deviation increase in the variance of bank lending standards on household loans



Notes: The solid line is the median. The light shaded area is the 84% error band while the dark shaded area is the 68% error band. The top row presents the response of the endogenous variables in levels. The second row shows the response of the unconditional volatilities in percentages.

However, in contrast to the estimates discussed in the model with aggregate data, the GDP growth is not affected at all by these type of credit shocks. Moreover, the 3-month Treasury bill and composite lending rates fall slightly (statistically not significant) the first two quarters after the shock was realized.

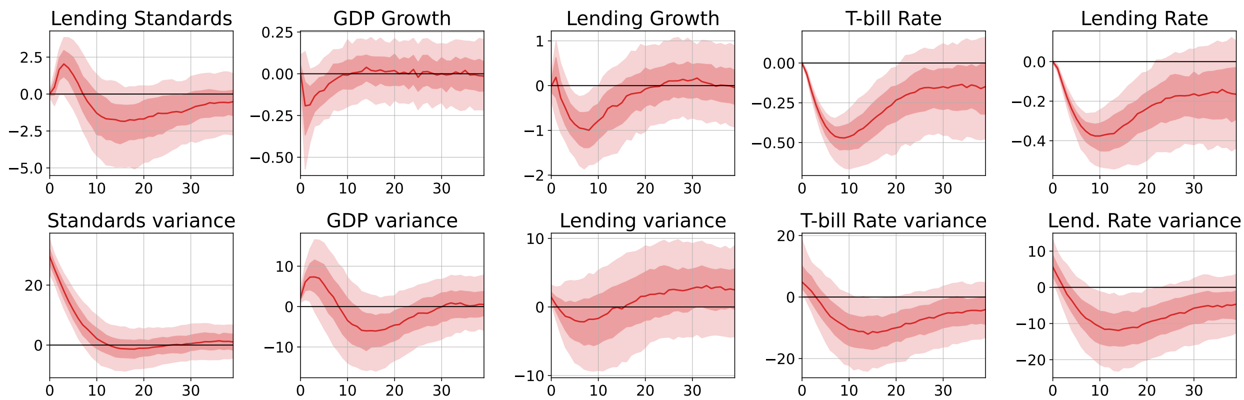
The almost non-response of real GDP growth and interest rates to this credit uncertainty shock may be due to the fact that, as discussed above, the majority of household debt is concentrated in mortgages (long-term debt) and changes in this level of debt does not necessarily translate into lower consumption, especially in the short-run. In the econometric model, monetary policy does not respond strongly to these shocks, which do not alter the evolution of real GDP much.[6]

Businesses. Figure 5 shows the responses of the endogenous variables to a one standard deviation increase in the variance of bank lending standards on business loans. The variance of endogenous variables rises in response to an increase in lending standards. Compared to the case of households, the response of the level of endogenous variables are aligned with the estimates using aggregate variables.

Lending standards on business loans increase in response to a shock in lending standards variance, and the level of lending growth decreases by 0.9% over a 9-quarter horizon, similar to the results presented in section 5.1. The response of monetary policy is more aggressive for the business sector, compared to the case with aggregate variables, and the 3-month Treasury bill and composite lending rate fall by 0.5 and 0.4 percentage points after 10 quarters, respectively. With this significant and persistent response of interest rates and lending growth against this uncertainty credit shock, the GDP growth decreases by 0.24% and recovers quickly after 9 quarters the shock hits the economy.

[6]Table C1 in the appendix shows that volatility shocks of household lending standards explain less than 9 percent of the FEV of all the endogenous variables in levels.

Figure 5: Impulse responses to 1 standard deviation increase in the variance of bank lending standards on business loans



Notes: The solid line is the median. The light shaded area is the 84% error band while the dark shaded area is the 68% error band. The top row presents the response of the endogenous variables in levels. The second row shows the response of the unconditional volatilities in percentages.

The fact that most corporate business debt is made up of short-term debt and that most business operations are driven by their access to credit markets, credit shocks could affect investment spending and, therefore, affect real GDP growth. Due to the importance of short-term debt in financing business operations, the monetary policy reaction is stronger and more important than in the case of households.[7]

6 Conclusion

This paper combines data about bank lending standards from the SLOOS and a SVAR model with stochastic volatility to estimate how credit uncertainty shocks affect macro and financial variables in the U.S. The chosen specification has the advantage of identifying the time-varying variance of structural shocks using standard identification schemes.

Similar to previous studies that identify credit supply shocks in SVAR models, I use a contemporaneous sign restriction strategy in which I assume that tight bank credit conditions raise bank lending standards on impact and lead to a drop in loan volume and an increase in the lending rate. I find that these types of uncertainty shocks have a contractionary and short-lived effect on GDP growth, but their effects are more persistent on the evolution of credit growth and interest rates. Moreover, using the same empirical strategy for specific data on households and businesses separately, I find that shocks to the volatility of credit standards on business loans behave similarly to the aggregate results while the same volatility shocks to households do not have a significant effect on GDP growth or interest rates. The estimation results suggest a key role of monetary policy in mitigating credit uncertainty shocks.

[7] Table C2 in the appendix shows that volatility shocks of business lending standards explain more than 20 percent of the 3-month Treasury bill rate and the composite lending rate for businesses. This effect decreases over time suggesting the importance of these shocks for monetary policy and interest rates in the short-term.

References

Alessandri, P. and Mumtaz, H. (2019), 'Financial regimes and uncertainty shocks', *Journal of Monetary Economics* **101**, 31–46.

Andrieu, C., Doucet, A. and Holenstein, R. (2010), 'Particle Markov Chain Monte Carlo Methods', *Journal of the Royal Statistical Society Series B: Statistical Methodology* **72**(3), 269–342.

Arellano, C., Bai, Y. and Kehoe, P. J. (2019), 'Financial Frictions and Fluctuations in Volatility', *Journal of Political Economy* **127**(5), 2049–2103.

Bachmann, R., Elstner, S. and Sims, E. R. (2013), 'Uncertainty and Economic Activity: Evidence from Business Survey Data', *American Economic Journal: Macroeconomics* **5**(2), 217–249.

Bassett, W. F., Chosak, M. B., Driscoll, J. C. and Zakrajšek, E. (2014), 'Changes in bank lending standards and the macroeconomy', *Journal of Monetary Economics* **62**, 23–40.

Bloom, N. (2009), 'The Impact of Uncertainty Shocks', *Econometrica* **77**(3), 623–685.

Bloom, N. (2014), 'Fluctuations in Uncertainty', *Journal of Economic Perspectives* **28**(2), 153–176.

Bollerslev, T., Tauchen, G. and Zhou, H. (2009), 'Expected Stock Returns and Variance Risk Premia', *The Review of Financial Studies* **22**(11), 4463–4492.

Caldara, D. and Herbst, E. (2019), 'Monetary Policy, Real Activity, and Credit Spreads: Evidence from Bayesian Proxy SVARs', *American Economic Journal: Macroeconomics* **11**(1), 157–192.

Castelnuovo, E., Lim, G. and Pellegrino, G. (2017), 'A Short Review of the Recent Literature on Uncertainty', *Australian Economic Review* **50**(1), 68–78.

Chatterjee, P., Gunawan, D. and Kohn, R. (n.d.), 'The Interaction between Credit Constraints and Uncertainty Shocks', *Journal of Money, Credit and Banking* **n/a**(n/a).

Chen, K., Higgins, P. and Zha, T. (2021), 'Cyclical lending standards: A structural analysis', *Review of Economic Dynamics* **42**, 283–306.

Cogley, T. and Sargent, T. J. (2005), 'Drifts and volatilities: monetary policies and outcomes in the post WWII US', *Review of Economic Dynamics* **8**(2), 262–302.

Gambetti, L. and Musso, A. (2017), 'Loan Supply Shocks and the Business Cycle', *Journal of Applied Econometrics* **32**(4), 764–782.

Gilchrist, S., Sim, J. W. and Zakrajšek, E. (2014), 'Uncertainty, Financial Frictions, and Investment Dynamics'.

Gilchrist, S. and Zakrajšek, E. (2012), 'Credit Spreads and Business Cycle Fluctuations', *American Economic Review* **102**(4), 1692–1720.

Glancy, D., Kurtzman, R. and Zarutskie, R. (2020), 'An Aggregate View of Bank Lending Standards and Demand'.

Guerrieri, V. and Lorenzoni, G. (2017), 'Credit Crises, Precautionary Savings, and the Liquidity Trap*', *The Quarterly Journal of Economics* **132**(3), 1427–1467.

Jordà, Ò., Schularick, M. and Taylor, A. M. (2013), 'When Credit Bites Back', *Journal of Money, Credit and Banking* **45**(s2), 3–28.

Kim, S., Shephard, N. and Chib, S. (1998), 'Stochastic Volatility: Likelihood Inference and Comparison with ARCH Models', *The Review of Economic Studies* **65**(3), 361–393.

Knight, F. H. (1921), *Risk, Uncertainty, and Profit*, Houghton Mifflin Company: The Riverside Press Cambridge, Boston and New York.

Koop, G., Pesaran, M. and Potter, S. M. (1996), 'Impulse response analysis in nonlinear multivariate models', *Journal of Econometrics* **74**(1), 119–147.

Lindsten, F., Jordan, M. I. and Schön, T. B. (2014), 'Particle Gibbs with Ancestor Sampling', *Journal of Machine Learning Research* **15**(63), 2145–2184.

Lown, C. and Morgan, D. P. (2006), 'The Credit Cycle and the Business Cycle: New Findings Using the Loan Officer Opinion Survey', *Journal of Money, Credit and Banking* **38**(6), 1575–1597.

Ludvigson, S. C., Ma, S. and Ng, S. (2021), 'Uncertainty and Business Cycles: Exogenous Impulse or Endogenous Response?', *American Economic Journal: Macroeconomics* **13**(4), 369–410.

Mian, A., Rao, K. and Sufi, A. (2013), 'Household Balance Sheets, Consumption, and the Economic Slump*', *The Quarterly Journal of Economics* **128**(4), 1687–1726.

Mumtaz, H., Pinter, G. and Theodoridis, K. (2018), 'What do VARs tell us about the impact of a credit supply shock?', *International Economic Review* **59**(2), 625–646.

Mumtaz, H. and Surico, P. (2018), 'Policy uncertainty and aggregate fluctuations', *Journal of Applied Econometrics* **33**(3), 319–331.

Mumtaz, H. and Theodoridis, K. (2020), 'Dynamic effects of monetary policy shocks on macroeconomic volatility', *Journal of Monetary Economics* **114**, 262–282.

Mumtaz, H. and Zanetti, F. (2013), 'The Impact of the Volatility of Monetary Policy Shocks', *Journal of Money, Credit and Banking* **45**(4), 535–558.

Appendix A Data sources and definitions

- Macroeconomic and price index data: These data are obtained from FRED. Real Gross Domestic Product, Billions of Chained 2017 Dollars, Seasonally Adjusted (GDPC1). The real GDP growth is calculated as the annualized percentage growth in the real GDP. Consumer Price Index for All Urban Consumers: All Items, Index 2017=100, Seasonally Adjusted (CPIAUCSL). Three-month Treasury Bill secondary market rate (TB3MS).

- Bank lending standards: Senior Loan Officer Opinion Survey on Bank Lending Practices, Memo, Federal Reserve Board's Data Download Program. Net percentage of domestic banks tightening standards across loan categories, weighted by banks' outstanding loan balances by category (SUBLPDMOS_XWB_N.Q). Net percentage of domestic banks tightening standards on household loans, weighted by banks' outstanding loan balances by category (SUBLPDMHS_XWB_N.Q). Net percentage of domestic banks tightening standards on business loans, weighted by banks' outstanding loan balances by category (SUBLPDMBS_XWB_N.Q).

- Loans to non-financial private sector: This is constructed using the Federal Reserve Board's Financial Accounts of the United States - Z.1. The sum of nominal outstanding amounts of loans to households and nonprofit organizations that includes total mortgages (FL153165005.Q), consumer credit (FL153166000.Q), depository institution loans (FL153168005.Q), and other loans and advances (FL153169005.Q); and loans to nonfinancial corporate businesses that includes total mortgages (FL10 3165005.Q), depository institution loans (FL103168005.Q), and other loans and advances (FL1031690 05.Q). The nominal variables are then deflated using the CPI price index and the lending growth rate is calculated as the annualized percentage growth in the real outstanding amount of loans for the non-financial private sector.

- Composite lending rate: Constructed as a weighted average of interest rate charged on loans to households and nonprofit organizations and nonfinancial corporate businesses. The weights are derived using the amounts outstanding.

- Interest rate charged on loans to households: Weighted average of the 30-Year Fixed Rate Mortgage (FRED code MORTGAGE30US), the 48-month rate on loans for new autos, the commercial bank interest rate on credit card plans, and the 24-month rate on personal loans. These latter three are available from the Federal Reserve's Consumer Credit (G.19) with codes RIFLPBCIANM48_N.M, RIFSPBCICC_N.M, and RIFLPBCIPLM24_N.M, respectively. The series RIFSPBCICC_N.M is available from 1994 onward and is extended backward using the average growth rate of the rate on loans for new autos and the rate on personal loans at commercial banks. The amount of consumer credit category reported in the Financial Accounts of the United States - Z.1 is composed of revolving debt (25%), motor vehicle loans (30%), student loans (30%) and other loans (15%). I use the personal loan rate to approximate the interest rate charged on these last two categories and the depository institution loans and other loans and advances. The series are then averaged at the quarterly level and are aggregated using the amounts outstanding of each type of loan.

- Interest rate charged on loans to corporate businesses: Weighted average of the 30-Year Fixed Rate Mortgage (FRED code MORTGAGE30US) and the simple average between the bank prime loan rate (FRED code DPRIME) and the loan rate for all commercial and industry loans (FRED code EEANQ). The last two rates approximate the interest rate charged on short-term loans for businesses (depository institution loans and other loans and advances). The interest rate for all commercial and industry loans is only available from 1997Q2 to 2017Q2, and is extended backward and forward using the growth rate of the prime loan rate. The series are then averaged at the quarterly level and are aggregated using the amounts outstanding of each type of loan.

Figure A1 shows the composition of loans (weights) used in the calculation of the composite interest rate for households and businesses.

Figure A1: Composition of loans to non-financial private sector

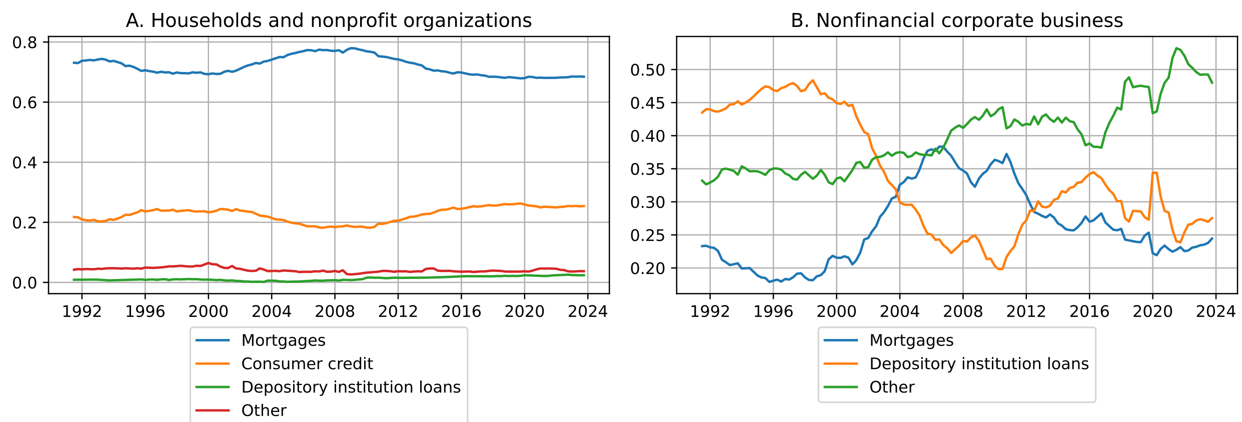
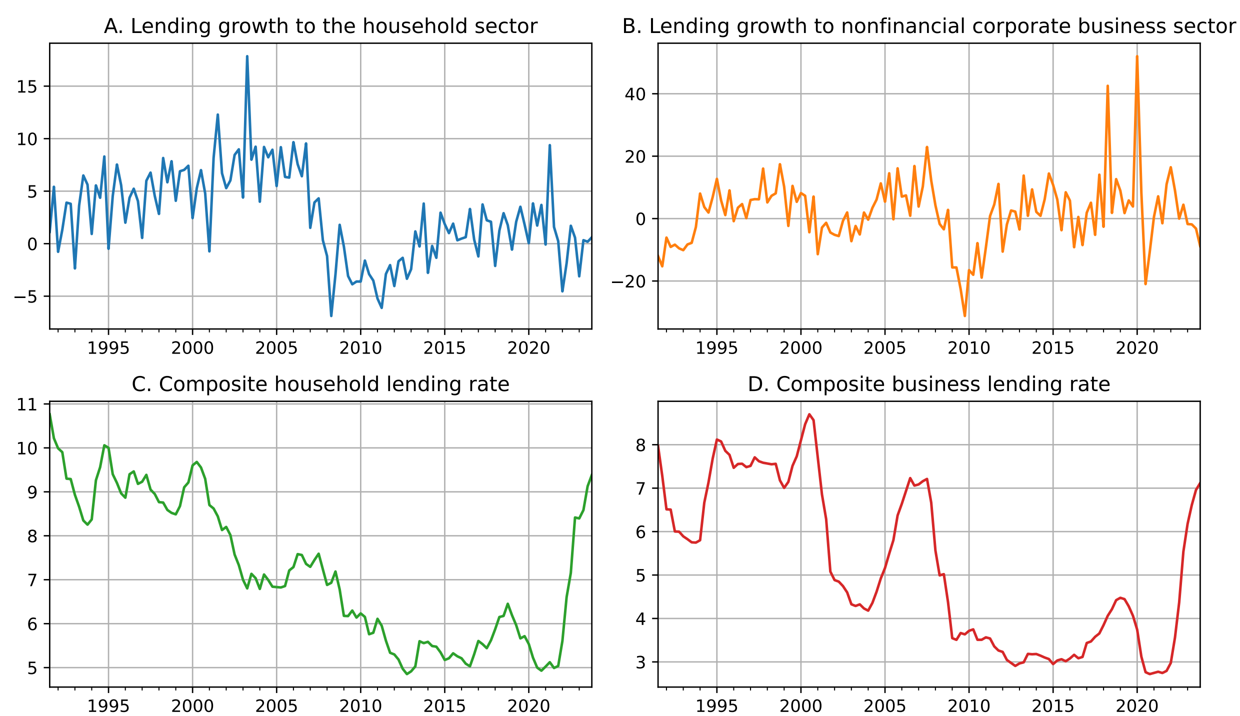


Figure A2: Disaggregated variables for households and firms



Appendix B Complementary econometric results

Table B1 shows the contribution of all shocks in levels and the bank lending standard level shock (in columns) to the FEV of the levels and volatility of endogenous variables. Table B2 shows the individual contribution of each volatility shock (in columns) to the FEV of the levels of endogenous variables. Table B3 shows the individual contribution of each volatility shock (in columns) to the FEV of the volatility of endogenous variables.

Table B1: Median contribution of levels shocks to the FEV of levels and volatility of endogenous variables

Variable	Horizon	Decomposition of level FEV		Decomposition of volatility FEV	
		All level shocks	Standards	All level shocks	Standards
Credit Standards	4 quarters	38.83	33.72	1.40	0.21
	20 quarters	17.95	8.10	11.45	1.89
	40 quarters	25.09	7.22	22.86	3.68
GDP growth	4 quarters	71.29	1.66	1.36	0.24
	20 quarters	53.36	4.28	10.00	1.88
	40 quarters	49.35	6.04	17.68	3.35
Lending growth	4 quarters	71.36	3.11	1.82	0.28
	20 quarters	32.31	2.87	14.60	2.39
	40 quarters	33.97	4.67	27.93	4.51
T-bill rate	4 quarters	48.62	2.16	1.42	0.23
	20 quarters	17.69	2.55	10.18	1.64
	40 quarters	29.45	5.04	19.53	3.33
Lending	4 quarters	62.18	0.69	1.30	0.21
rate	20 quarters	19.36	2.08	9.06	1.42
	40 quarters	30.29	4.42	17.11	2.82

Table B2: Median contribution of each volatility shock to the FEV of levels of endogenous variables

Variable	Horizon	Standards	GDP growth	Lending growth	T-bill rate	Lend. rate
Credit Standards	4 quarters	12.87	8.27	0.98	29.04	1.32
	20 quarters	16.50	5.93	6.26	26.74	8.14
	40 quarters	13.34	6.34	8.68	19.58	11.12
GDP growth	4 quarters	5.92	4.46	1.90	6.54	3.03
	20 quarters	9.44	6.38	6.30	9.33	7.54
	40 quarters	10.18	7.46	7.86	9.85	9.14
Lending growth	4 quarters	1.79	7.92	1.19	8.89	2.35
	20 quarters	14.76	6.76	7.04	13.65	9.49
	40 quarters	11.52	7.17	9.14	11.20	11.69
T-bill rate	4 quarters	12.69	6.32	6.83	5.60	5.56
	20 quarters	17.71	6.95	11.43	10.27	10.19
	40 quarters	11.84	7.01	10.12	9.77	12.02
Lending	4 quarters	12.36	5.08	1.36	4.88	3.21
rate	20 quarters	17.96	5.85	5.83	13.64	11.36
	40 quarters	11.57	6.32	8.11	11.14	14.05

Table B3: Median contribution of each volatility shock to the FEV of the volatility of endogenous variables

Variable	Horizon	Standards	GDP growth	Lending growth	T-bill rate	Lend. rate
Credit Standards	4 quarters	83.25	1.97	1.57	3.27	2.12
	20 quarters	49.56	2.99	8.38	7.73	8.89
	40 quarters	32.60	4.62	9.53	8.64	11.04
GDP growth	4 quarters	4.66	87.79	1.02	0.69	1.28
	20 quarters	10.25	57.41	5.36	4.47	5.24
	40 quarters	11.02	44.66	6.62	6.22	7.18
Lending growth	4 quarters	6.59	2.43	53.54	22.32	2.73
	20 quarters	12.79	3.58	25.09	16.23	10.10
	40 quarters	11.52	5.20	16.49	13.38	11.81
T-bill rate	4 quarters	8.73	3.27	1.90	71.21	2.91
	20 quarters	14.68	3.19	6.57	37.02	11.98
	40 quarters	13.19	4.50	8.31	25.84	13.53
Lending rate	4 quarters	4.23	1.90	1.62	46.23	34.13
	20 quarters	10.36	2.24	7.59	24.31	30.95
	40 quarters	10.39	3.45	9.15	18.43	26.57

Appendix C Complementary results for disaggregated data

Table C1 shows the contribution of all volatility shocks and the volatility shock of bank lending standards on household loans (in columns) to the FEV of the levels and volatility of endogenous variables. Credit Standards, Lending growth and the composite lending rate are calculated for the household sector. Table C2 shows the contribution of all volatility shocks and the volatility shock of bank lending standards on business loans (in columns) to the FEV of the levels and volatility of endogenous variables. Credit Standards, Lending growth and the composite lending rate are calculated for the business sector.

Table C1: Median contribution of volatility shocks to the FEV of levels and volatility of endogenous variables (Households)

Variable	Horizon	Decomposition of level FEV		Decomposition of volatility FEV	
		All level shocks	Standards	All level shocks	Standards
Credit Standards	4 quarters	20.25	3.52	98.49	42.46
	20 quarters	59.95	8.12	87.94	25.87
	40 quarters	66.01	9.33	77.54	20.02
GDP growth	4 quarters	17.76	1.60	98.75	2.57
	20 quarters	35.54	5.78	90.62	7.00
	40 quarters	42.72	7.54	82.59	8.00
Lending growth	4 quarters	27.81	1.43	97.79	18.10
	20 quarters	59.69	6.98	85.46	15.30
	40 quarters	65.15	8.22	73.18	13.39
T-bill	4 quarters	45.25	1.33	98.57	13.32
	20 quarters	81.36	6.06	90.06	16.66
	40 quarters	75.56	8.38	80.24	15.69
Lending rate	4 quarters	16.27	1.12	98.34	12.31
	20 quarters	72.32	5.63	89.60	15.69
	40 quarters	74.90	7.60	81.06	13.72

Table C2: Median contribution of volatility shocks to the FEV of levels and volatility of endogenous variables (Businesses)

Variable	Horizon	Decomposition of level FEV		Decomposition of volatility FEV	
		All level shocks	Standards	All level shocks	Standards
Credit Standards	4 quarters	70.93	2.73	98.72	71.17
	20 quarters	84.01	7.69	90.60	27.80
	40 quarters	76.88	9.26	80.37	20.23
GDP growth	4 quarters	21.99	3.18	98.80	1.25
	20 quarters	39.94	6.41	91.31	5.11
	40 quarters	44.62	7.97	82.79	6.50
Lending growth	4 quarters	19.70	1.95	98.68	0.77
	20 quarters	53.33	7.43	90.73	4.32
	40 quarters	55.40	8.58	81.55	6.95
T-bill	4 quarters	60.24	45.12	98.60	1.69
	20 quarters	82.85	31.48	90.57	7.92
	40 quarters	72.51	14.72	81.57	9.39
Lending rate	4 quarters	43.19	28.20	98.46	1.93
	20 quarters	84.20	31.65	90.20	9.95
	40 quarters	75.55	14.70	81.68	10.67