News Shock to Credit Supply and Business Cycles

Tim Zhang*

March 20, 2026

Abstract

This paper identifies a news shock to bank credit supply, examining how economic agents respond to anticipated changes in banks' lending standards. Using a structural Bayesian VAR, I find that such shock triggers a temporary economic boom, followed by a normal credit crunch when the anticipated credit tightening materializes, which is consistent with preemptive borrowing behavior. Evidence from Euro area confirms that these patterns operate similarly across advanced economies. The news shock remains distinct compared with well-established macroeconomic shocks, indicating that it is itself an important driver of business cycles. Responses vary sharply across loan categories: long-term real estate loan rises, while short-term commercial and consumer loans decline, suggesting that borrowers prefer to lock in favorable terms on longer-term debt ahead of expected tightening. Counterfactual policy analysis demonstrates that responses to the news shock are a self-stabilizing cycle without changes in policy rates, and monetary tightening during credit-news-driven booms can amplify subsequent contractions.

*Tim (Qian) Zhang is at Kellogg School of Management, Northwestern University. Email: timq.zhang@kellogg.northwestern.edu. I appreciate discussions with Nicolas Crouzet, Diego Känzig, Dalton Zhang, Zhou Ren and feedbacks from Kellogg Finance Brownbags. All errors are on my own.

1 Introduction

The macroeconomic impact of financial markets has long been an important topic to business cycles, especially after the 2008 global financial crisis (GFC). Among various roles in financial systems, credit supply plays a central role in shaping macroeconomic dynamics. Episodes of financial turmoil, from GFC to the recent pandemics, have demonstrated that changes in credit availability can rapidly amplify economic fluctuations. As a result, a growing body of work has focused on measuring credit supply shocks and quantifying their propagation effects on general macroeconomic conditions such as output, investment, and inflation (e.g., see Broadbent et al. (2024), Bassett et al. (2014), Gilchrist and Zakrajšek (2012), etc.). In these literature, credit supply shocks are typically modeled as unexpected shifts in bank lending standards or credit conditions, either tightening or loosening, and literature often find a typical credit crunch: a sudden decline in credit supplies is followed by responses of typical recessions.

While a credit-crunch narrative is intuitive to understand, it overlooks a critical dimension when considering credit supplies: agents may forward-look or anticipate future changes in credit supply and adjust their behavior in advance. In reality, credit tightening does not always come immediately. Regulators or financial institutions may explicitly signal future changes in credit conditions. Such signals take the form of forward guidance, official regulatory announcements, or shifts in supervisory tone communicated through financial speeches or reports. For example, announcements of future changes in capital requirements may cause banks to begin preparing for reduced credit capacity ahead of the formal regulation date. One typical example is the Basel III, an international framework that sets minimum liquidity requirements for banks which implicitly reduces lending. It was initially announced in 2010 but formally implemented at major countries in 2012.

Domestically, the Dodd-Frank Stress Tests is another example, which was initially announced as a part of the Dodd-Frank Act, and officially taken in effect in around 2013. The test requires large banks to maintain capital ratios that would remain adequate under severely adverse scenarios. In anticipation of these requirements, banks may respond by tightening lending standards, slowing loan growth, or reducing exposure to higher-risk borrowers in order to improve their projected capital positions. As such, the stress test regime can be viewed as a signal of anticipated credit tightening. On the micro-level, banks' internal assessments of future credit risks or macroeconomic conditions might be disclosed by their earnings calls or public communications, meaning that even in the absence of current tightening, such forward-looking statements serve as credible signals of future constraints.

Another component of future credit tightening news comes from broader macroeconomic and monetary developments. For example, signals such as rising interest rates, a shift in

central bank tone, deteriorating financial conditions, or weakening growth prospects may lead economic agents to expect that lending standards will tighten in the future. In this sense, the credit supply news shock may reflect belief revisions shaped by a combination of macro-financial context. However, as I will show later, the correlation between shock series from credit supply news and from monetary/macroeconomic news remains low and insignificant. It implies that the identified credit supply news shock reflects mostly about anticipated credit supply conditions.

While the concept of credit supply news is intuitive, little empirical work has explicitly identified and quantified its macroeconomic effects, which is what this paper aims to uncover. Specifically, I disentangle the 'news' component from credit supplies and identify a credit supply news shock as a shock about future credit tightening that does not alter current lending standards. To measure credit supply conditions, I use the series Credit Supply Indicator (CSI) from Cavallo et al. (2024b), which is an exogenous measurement of credit supplies and is derived from the changes of banks' lending standards overtime. I cumulate CSI series to approximate a lending standard level. As for identification strategies, I use a Bayesian VAR framework and a widely-used identification strategy, which is commonly implemented for TFP news, to identify the credit supply news shock. Specifically, the new shock is identified by maximizing share of the forecast error variance of lending standard levels. Additionally, I impose a zero at-impact restriction to ensure that the news shock does not have influences to lending standard level at the beginning, i.e., a pure 'news' effect.

The key finding is that credit supply news shocks, while signaling future credit tightening, generate a short-run boom in macroeconomic conditions such as output, hours, and inflation. Such temporary-boom responses last for about 6 - 10 quarters and the economy moves to bust periods when credit conditions are tightened. It also generates in the short run a mild decline in GZ spread, a strong increase in core loans outstanding of banks, as well as a mild rise in interest rate. One explanation to support these results is that forward-looking borrowers increase borrowing today to lock in favorable conditions before credit tightening actually occurs, which is what I call *preemptive borrowing*. The importance of credit supply news shock to business cycles is revealed from the forecast error decomposition, from which it shows that the news shock contributes about 20 percentage of output volatility in the median run. Further, the historical decomposition indicates that news shock contributes much to output gaps during GFC and pandemic periods. The identified news shock is closely related to actual news heard from Michigan Survey of Consumers, where I find that the news shock has negative correlation with unfavorable credit-related news heard, which further supports the short-run boom and that the identified structural shock reflects tightening expectations.

Beyond baseline results, I make three important extensions. First, I ask the question on whether the preemptive borrowing has any heterogeneities across different loan categories.

To answer this question, I further split core loans outstanding in three major categories and find that long-term loans such as real estate loans increase more strongly in response to the news shock, while short-term loans such as commercial and consumer loans remain subdued or even decrease. This pattern uncovers that borrowers attempt to lock in favorable longer-term financing conditions ahead of expected tightening, while short-term loan outstanding declines due to increased uncertainty or rollover risk. Together, these results provide strong evidence on the priority of preemptive borrowing when the news shock hits.

Second, I examine evidence from Euro area. I utilize the Bank Lending Survey conducted by European Central Bank and apply similar methods. The results imply that anticipated credit tightening yields similar patterns as in the baseline, while the effect of credit supply news shock is more persistent. Such evidence further supports the baseline temporary boom that is shared across different areas triggered by the news shock.

Third, I investigate whether monetary policy should respond to credit supply news shocks. The credit news shock should generate a self-stablizing cycle: news of future credit tightening triggers a short-run boom, but when the anticipated tightening materializes, the economy smoothly transitions into recession as agents have already adjusted their behavior. This raises the question: should central bank make any intervention? To address this, I implement a counterfactual monetary policy rule where the Federal Reserve pegs the interest rate, preventing any endogenous response to macroeconomic conditions including credit supply news shocks. The results present two interesting conclusions. First, the self-stablizing cycle is verified under interest rate peg. Second, current intervention, i.e., the rise of interest rate, amplifies boom-bust cycles: it further pushes up the tightness of lending standard, and it amplifies the bust periods when credit condition is already tightened. These results support a policy approach emphasizing strategic restraint rather than activist stabilization during credit-news-driven cycles.

In summary, this paper presents a unified narrative: when borrowers anticipate credit tightening, they perform rushes to borrow when lending conditions are still favorable today, leading to a temporary expansion to avoid future constraints. Understanding this mechanism is important understand short term macroeconomic fluctuations. It suggests that financial market participants do not only respond passively to credit supply shocks: they might reallocate and rush to preemptive borrowing based on expectations, generating dynamics that differ remarkably from standard credit contraction scenarios.

The findings also have direct implications for both monetary and macro-prudential policies. The temporary expansion from a credit tightening news may distort real-time signals used by policymakers. In particular, central banks may mistakenly interpret the short-run boom as a sign of overheating, prompting premature policy rate increases, which would amplify the bust when credit is tightened. These dynamics highlight the importance of

monitoring forward-looking indicators of credit supply, such as bank guidance, supervisory tone, or market-based signals, rather than relying solely on contemporaneous credit conditions. More broadly, the results suggest that financial regulation and monetary policy should account for anticipatory responses to expected credit frictions, which helps examine credit-induced macroeconomic fluctuations.

Related Literature. This paper contributes to several strands of literature at the intersection of macroeconomics and finance. First, it relates to a bunch of research on credit supply shocks and macro-financial linkages. A large body of work has studied the effects of credit tightening on real activity (e.g., Broadbent et al. (2024), Cavallo et al. (2024a), Altavilla et al. (2019), Bassett et al. (2014) and Gilchrist and Zakrajšek (2012)), typically focusing on surprise or realized credit tightenings. These studies find that unexpected credit supply shocks induce busts and reduce output, investment, and employment. In contrast, this paper further decomposes the unexpected credit supply shocks into an unexpected and a news component, showing that anticipated credit tightening can generate the opposite pattern in the short run. This complements and extends the empirical literature by emphasizing how expectations about future financial constraints affect current macroeconomic dynamics.

This paper is also related to more recent literature which focuses on the sentiments in credit markets (e.g. Boeck and Zörner (2024) and López-Salido et al. (2017)). Specifically, Boeck and Zörner (2024) define optimistic and pessimistic credit regimes and find that in the optimistic regime, bad sentiment of credit conditions (higher credit spread) generates a strong growth in output and credit volume, meaning a persistent rise in levels. While results look a bit similar to my paper here, the explanations are quite different, that current result in this paper, as I will discuss later, seems to support more on rational expectations, or at least a mixture of rational and behavioral expectations rather than pure sentiments. Since I have not moved in to theoretical discussions, I cannot tell for now if the temporary expansion is generated by rational or irrational (like overreaction) beliefs.

Second, this paper builds on the growing literature on news shocks and anticipatory behavior in macroeconomic dynamics. Initially introduced in Beaudry and Portier (2006), news shocks, especially those on technology progresses, gain increasing attention in macroeconomic literature to explain business cycles. Literature like Kurmann and Sims (2021), Ben Zeev and Khan (2015), Francis et al. (2014), Barsky and Sims (2011) and others have shown that expectations of future productivity can stimulate economic activity before the realization of improved fundamentals. However, much less attention has been paid to the news from credit markets. This paper introduces a new class of forward-looking shocks on credit supplies, which capture beliefs about future credit conditions.

More recent work, e.g. Görtz et al. (2022), starts to focus on the effect of TFP news shock

with financial frictions. Specifically, they find that credit supply conditions are an important transmission channel for TFP news shock, and that a shock that maximizes the median-run forecast error variance of Excess Bond Premium (EBP) would replicate the patterns of TFP news shocks. Such perspective treats credit conditions primarily as a passive transmission mechanism. In contrast, this paper takes a distinct view by treating expectations about credit supply conditions themselves as the fundamental shock. Rather than transmitting external news, the identified credit supply news shock originates from belief revisions about future lending standards. Such arguments greatly extend the arguments in Görtz et al. (2022) and emphasize an active role of credit supplies other than mere propagation channel to real economies. To further support the distinction between TFP news shock and credit supply news shock, in Sensitivity Analyses I identify the TFP news shock and calculate correlations of two shocks series, which are low and insignificant.

Outline. The remainder of the paper proceeds as follows. Section 2 introduces the empirical framework and identification strategy. Section 3 describes data sources and estimation methods. Section 4 presents the baseline results as well as corresponding sensitivity analyses. Section 5 provides three extensions from baseline results to discuss potential mechanisms. Section 6 concludes.

2 Methodology and Identification

In this section, I briefly introduce the econometric model used to identify news shocks of bank credit supplies. I follow the identification strategy in spirit of the max-share approach by Uhlig (2004) and the zero at-impact restriction of news shock from Barsky and Sims (2011), which is a common set of approaches to identify news shocks in macroeconomic literature.

A Framework of VAR Model. I start by considering a standard VAR model,

$$\boldsymbol{Y}_t = \boldsymbol{C} + \sum_{l=1}^{p} \boldsymbol{B}_l \boldsymbol{Y}_{t-l} + \boldsymbol{u}_t, \boldsymbol{u}_t = \boldsymbol{S}\boldsymbol{\varepsilon}_t$$

where $\boldsymbol{Y}_t$ denotes a $n \times 1$ vector of quarterly endogenous variables, p is the corresponding lag order. $\boldsymbol{u}_t$ is the vector of reduced form errors, $\boldsymbol{\varepsilon}_t$ is the vector of structural shocks and $\boldsymbol{S}$ is the at-impact structural matrix. These vectors satisfy $\mathbb{E}[\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t'] = \boldsymbol{I}_n, \mathbb{E}[\boldsymbol{u}_t\boldsymbol{u}_t'] = \boldsymbol{S}\boldsymbol{S}' = \boldsymbol{\Sigma}_u$ where $\boldsymbol{\Sigma}_u$ is the covariance matrix from reduced-form shocks. A more condense way to express the VAR framework is to denote $\boldsymbol{B}(L) = \boldsymbol{I} + \boldsymbol{B}_1 L + \boldsymbol{B}_2 L^2 + ...$ as a matrix lag

polynomial, and then the moving average representation is expressed as

$$\boldsymbol{Y}_t = \boldsymbol{B}(L)\boldsymbol{S}\boldsymbol{\varepsilon}_t = \boldsymbol{\Phi}(L, \boldsymbol{S})\boldsymbol{\varepsilon}_t$$

where each component of $\boldsymbol{\Phi}(L, \boldsymbol{S})$ is the corresponding Impulse Response (IRF) matrix to some horizon given certain structural at-impact $\boldsymbol{S}$. The Forecast Error and Forecast Error Variance (FEV) of $\boldsymbol{Y}_t$ at some horizon h is then

$$\begin{aligned}
\boldsymbol{Y}_{t+h} - \mathbb{E}_{t-1}[\boldsymbol{Y}_{t+h}] &= \sum_{l=0}^{h} \boldsymbol{B}_l \boldsymbol{S} \boldsymbol{\varepsilon}_{t+h-l} = \sum_{l=0}^{h} \boldsymbol{\Phi}_l(\boldsymbol{S}) \boldsymbol{\varepsilon}_{t+h-l} \\
\mathrm{FEV}(h) &= \sum_{l=0}^{h} \boldsymbol{B}_l \boldsymbol{\Sigma}_u \boldsymbol{B}_l' = \sum_{l=0}^{h} \boldsymbol{\Phi}_l(\boldsymbol{S}) \boldsymbol{\Phi}_l(\boldsymbol{S})'
\end{aligned}$$

where $\boldsymbol{B}_l$ and $\boldsymbol{\Phi}_l$ are lag l of the coefficient matrix and IRF polynomials.

Identification of News Shock. The main identification issue for any structural VAR models is to find a proper at-impact structural matrix $\boldsymbol{S}$ that satisfies $\boldsymbol{S}\boldsymbol{S}' = \boldsymbol{\Sigma}_u$. One common approach to transform this issue is to obtain firstly the Cholesky decomposition of $\boldsymbol{\Sigma}_u = \tilde{\boldsymbol{S}}\tilde{\boldsymbol{S}}'$, and then look for an orthonormal rotation matrix $\boldsymbol{Q}$ to recover the target at-impact structural matrix $\boldsymbol{S} = \tilde{\boldsymbol{S}}\boldsymbol{Q}$.

The approach I adopt to identify news shock is to find a shock that explains the maximum share of FEV for a target variable at a certain horizon, conditional on that such shock has no at-impact influence to the target variable. To implement this, consider the share of FEV of variable i from shock j at horizon h as

$$\Omega_{i,j}(h) = \frac{\boldsymbol{e}_i' \left(\sum_{l=0}^{h} \boldsymbol{B}_l \tilde{\boldsymbol{S}} \boldsymbol{Q} \boldsymbol{e}_j \boldsymbol{e}_j' \boldsymbol{Q}' \tilde{\boldsymbol{S}}' \boldsymbol{B}_l' \right) \boldsymbol{e}_i}{\boldsymbol{e}_i' \left(\sum_{l=0}^{h} \boldsymbol{B}_l \boldsymbol{\Sigma}_u \boldsymbol{B}_l' \right) \boldsymbol{e}_i} = \frac{\sum_{l=0}^{h} \boldsymbol{\Phi}_{i,l}(\tilde{\boldsymbol{S}}) \boldsymbol{q}_j \boldsymbol{q}_j' \boldsymbol{\Phi}_{i,l}'(\tilde{\boldsymbol{S}})}{\sum_{l=0}^{h} \boldsymbol{B}_{i,l} \boldsymbol{\Sigma}_u \boldsymbol{B}_{i,l}'}$$

where $\boldsymbol{e}_i$ is a column vector with all entries zero except the ith position, $\boldsymbol{\Phi}_{i,l}, \boldsymbol{B}_{i,l}$ are ith row of $\boldsymbol{\Phi}_l$ and $\boldsymbol{B}_l$, and $\boldsymbol{q}_j$ is the jth column of matrix $\boldsymbol{Q}$. If the target variable is at ith position, the news shock positioned at j is then to find such $\boldsymbol{q}_j$ vector that solves the following maximization problem with some fixed horizon H,

$$\max_{\boldsymbol{q}_j} \ \Omega_{i,j}(H), \ \text{s.t.} \ \boldsymbol{q}_j'\boldsymbol{q}_j = 1, (\tilde{\boldsymbol{S}}\boldsymbol{q}_j)_i = 0$$

where the first restriction ensures the vector $\boldsymbol{q}_j$ belongs to orthonormal matrix $\boldsymbol{Q}$, and the second restriction ensures that shock j has no at-impact influence to target variable i. The second restriction is more flexible than the one in Barsky and Sims (2011), as it does not

require the target variable be placed at the first position.

There are mainly two sets of choices when identifying news shocks in the previous literature. The first set is to decide whether to cumulate FEV share in the objective function of maximization problem[1], and the second set is to decide whether to impose zero at-impact restrictions to the target variables (if not, it is often called max-share methods). Almost each approach from two choice sets was implemented before[2]. I follow the strategy from Görtz et al. (2022) with two reasons. First, I derive the credit supply surprise shock, which is discussed later, to compare with previous credit supply shocks, where zero at-impact restriction is helpful to disentangle surprise and news shocks. Second, as suggested in Kurmann and Sims (2021), focusing on a long forecast horizon only would reduce potential biases by cyclical mismeasurements. In Appendix C.1, I show that major results are robust to other specifications.

Identification of Other Shocks. One other shock is the surprise shock. It is defined as the shock that explains the maximum share of at-impact FEV (variance then) of target variable i, conditional on that its corresponding $\boldsymbol{Q}$ column is orthogonal to that of the news shock. The goal for surprise shock is to explain as much the at-impact variations as possible. In the context of bank credit supplies, both surprise and news shock focus on the Lending Standard variable. Let $\boldsymbol{q}_{news}$ be the obtained vector for news shock, then the surprise shock to variable i solves the following problem,

$$\max_{\boldsymbol{q}_{surp}} \ \Omega_{i,surp}(0) \text{ s.t. } \boldsymbol{q}_{surp}'\boldsymbol{q}_{surp} = 1, \boldsymbol{q}_{surp}'\boldsymbol{q}_{news} = 0$$

In the special case when $i = 1$ and first two shocks to identify are news and surprise shock, the second restriction in news shock is equivalent to $\boldsymbol{q}_j(1) = 0$, given the property of Cholesky matrix $\tilde{\boldsymbol{S}}$. The vector for surprise shock is equivalent to assign $\boldsymbol{q}_{surp}$ as $\boldsymbol{e}_1$. In Section 5, two more shocks are identified, namely TFP news shock and max-MP shock. The approach is similar to news and surprise shocks, except that shocks ordered behind are identified in a more restricted vector space. In Appendix B.1, I show details of the implementation on the identification strategy. While the surprise shock is not the focus of this paper, one potential concern is that the order of two shocks to be identified might make a difference. To address this concern, in Appendix C.1 I show that when identifying the surprise shock first, results

[1]That is, the maximization problem targets on the FEV share of a given variable up to some horizon H, $\max_{\boldsymbol{q}_j} \sum_{h=0}^{H} \Omega_{i,j}(h)$, subject to certain restrictions.

[2]For example, Barsky and Sims (2011) use cumulative FEV and zero at-impact restrictions to identify TFP news shocks; Känzig and Williamson (2024), Kurmann and Sims (2021) and Francis et al. (2014) implement max-share FEV at certain horizon but no zero at-impact restrictions to identify energy shocks, TFP news shocks and technology shocks; Görtz et al. (2022) use max-share FEV at certain horizon and zero at-impact restrictions to identify TFP news shocks under financial frictions.

remain robust.

3 Data and Estimation

3.1 Data Sources

In this section, I describe the data sources I use in major models. More details of data sources and construction are described in Appendix A.1.

Bank Lending Standard. The core time series is the measurement of bank credit supplies. In this paper, I use the cumulative version of Credit Supply Indicator (CSI) from Cavallo et al. (2024b) to proxy for banks' lending standard and credit supply conditions overtime, which is in spirit of Bassett et al. (2014). The series of CSI is derived from the Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS) conducted by Federal Reserve Board, which is a quarterly survey asking senior loan officers from selected banks on their recent lending practices[3]. In the survey, loan officers answer a set of questions related to lending standards,

"Over the past three months, how have your bank's credit standards for approving loans of type X changed?"

Answers vary from 5 categories. For the first question, answers are [1] eased considerably; [2] eased somewhat; [3] about unchanged; [4] tightened somewhat; and [5] tightened considerably. To derive some aggregate changes of bank lending standards, previous literature, e.g., Kurtzman et al. (2020), firstly map five categories into three dummies around zero,

$$I_{it}^{B}[k] = \begin{cases} -1 & \text{if bank } i \text{ reported easing standards on loan category } k \text{ in quarter } t \\ 0 & \text{if bank } i \text{ reported no change on loan category } k \text{ in quarter } t \\ 1 & \text{if bank } i \text{ reported tightening standards on loan category } k \text{ in quarter } t \end{cases}$$

where i indexes for bank and k indexes for loan type. Kurtzman et al. (2020) then aggregate such bank- and loan-level response by taking the weighted averages of certain loan outstanding across respondent banks, and further taking the weighted averages across aggregate loan

[3]According to the survey description, respondents to the survey include up to 80 large domestic banks and 24 U.S. branches and agencies of foreign banks. Most measurements of credit supplies based on this survey, however, only focus on respondents from domestically chartered commercial banks. (See Kurtzman et al. (2020) and Bassett et al. (2014))

outstanding of different loan types among respondent banks to obtain an aggregate Bank Lending Standard Index ΔB_t, to proxy for bank credit supplies[4],

$$\Delta B_t[k] = 100 \times \sum_i \omega_{i,t-1}[k] I_{it}^B[k], \ \Delta B_t = \sum_k \omega_{t-1}[k] \Delta B_t[k]$$

which measures the net percentage share of banks reporting tighter lending standards compared to the last quarter in an aggregate sense. As argued by Cavallo et al. (2024b) and Bassett et al. (2014), the measurement by simply taking weighted averages from SLOOS survey responses is endogenous and might be influenced by macroeconomic, financial or demand-side factors that simultaneously affect supply and demand of loans. One key challenge is to disentangle the component of borrowers' demand for credit. In order to address this identification challenge, Cavallo et al. (2024b) use the index ΔB_t by Kurtzman et al. (2020) and follows the strategy in Bassett et al. (2014) to run regressions and extract residuals as the weighted net share of banks reporting tighter standards, after *adjusting for macroeconomic, financial, demand-side, and bank-specific factors*, or CSI, which I denote as $\Delta \tilde{B}_t$[5].

Figure 1 presents the CSI series $\Delta \tilde{B}_t$ and the original bank lending standard index ΔB_t. Both series have the unit as percentage, and a higher value means a net tighter lending standard. The CSI index, compared to the original lending standard index, is less volatile, but both co-move in general overtime. As argued by Cavallo et al. (2024b) and Cavallo et al. (2024a), the CSI measurement is powerful to measure changes in the supply of bank credit and credit supply shocks. I take one step further from the CSI series and consider its cumulative version, $\tilde{B}_t = \sum_{s=0}^{t} \Delta \tilde{B}_s$, to proxy for the aggregate *level* of bank lending standard[6]. It is for sure not representing the 'true' bank lending standard level, as each net percentage change of lending standard $\Delta \tilde{B}_t$ does not track the response of specific banks. While it may not perfectly reflect the genuine level of lending standards, it serves as an informative proxy for the evolving stance of credit supply conditions over time, abstracting from cyclical demand-side fluctuations. In Appendix C.1, I show that using the raw CSI series yields robust results.

[4]The formula here is slightly different from the ones in Kurtzman et al. (2020) but just for the illustration of aggregation ideas. In their paper, each loan type has subcategories based on firm sizes from the questions in SLOOS survey. For example, C&I loans have those for large and middle-market firms and small firms.

[5]As a summary, two recent papers Cavallo et al. (2024b) and Kurtzman et al. (2020) basically extend the approach by Bassett et al. (2014) in two different angles, when measuring bank credit supplies from SLOOS survey data. Kurtzman et al. (2020) mainly extend the sample period to construct the aggregate net percentage share of banks reporting tighter standards, and Cavallo et al. (2024b) take over the series by Kurtzman et al. (2020) and extend the approach of running regressions to extract supply-side changes of lending standards by modifying original regression components. Details of how the index is constructed and how regressions are implemented can be found in Kurtzman et al. (2020) and Cavallo et al. (2024b).

[6]One may wonder if it is possible to replicate the calculation of lending standard and CSI series. The key issue here is that the respondent banks are confidential and only accessible to internal federal system.

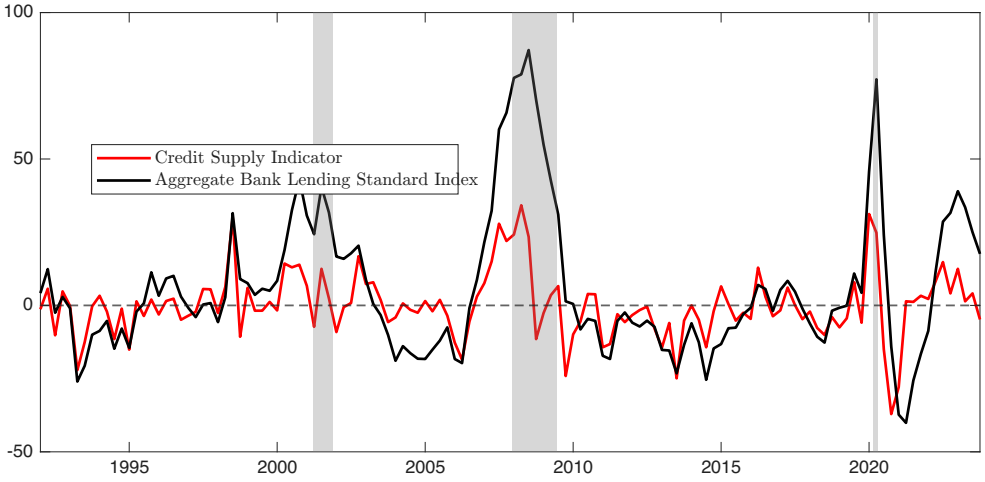


Figure 1: Lending Standard Measurements

Macroeconomic and Financial Factors. As for macroeconomic variables used in major models, I include real output, inflation (log-difference of GDP deflator), hours worked and effective federal fund rate to measure the overall economy-wide responses to news shock to credit supplies. As suggested in Barsky and Sims (2011), I also include the Index of Consumer Sentiment, a forward-looking variable which is helpful to identify news shocks. It measures how confident consumers are to short- and median-run economic conditions.

As for financial variables and particularly those related to bank credit supplies, I include GZ Spread, Core Loans outstanding in domestically chartered commercial (DCC) banks, Loan Demand Index and S&P 500 Index. The GZ spread is calculated by Gilchrist and Zakrajšek (2012), and it is a powerful measurement for default risk and credit conditions. Core loans outstanding is calculated from data of H.8 releases in Federal Reserve Board based on the FR 2644 reporting form, and it's one key measurement to credit outcomes. Loan Demand Index is another series calculated by Kurtzman et al. (2020) and Cavallo et al. (2024b), and it is based on one other question from SLOOS survey and aggregated in a similar way to Banking Lending Standard Index, measuring mainly the percentage changes of aggregate loan demand compared to previous quarter from respondent banks in SLOOS survey. The S&P 500 Index is included as another forward looking variable to help identify news shocks.

The sample period for baseline models are quarterly from 1992:I to 2023:IV, unless otherwise stated. Both the starting and ending period correspond to the availability of CSI series from Cavallo et al. (2024b). While there are several previous literature on credit supply shocks choosing the pre-Covid sample (see Broadbent et al. (2024) and Cavallo et al. (2024a)), some of them have shown that including the Covid period obtains similar results to

Without knowing respondent information, it is not possible for replication.

pre-Covid sample. There are two additional reasons I include the Covid period from 2020:I. First, the sample to 2023:IV greatly captures the latest monetary tightening cycle between 2021 and 2023, which is an important period also to credit tightenings and thus credit news shocks. The sample to 2023:IV also includes an important event for credit supplies - the bankruptcy of Silicon Valley Bank, which might help identify news shocks. Second, a longer sample helps capture any component of expectation or forward guidance, which is also significant for news shock identification. In Appendix C.1, I show that the results from pre-Covid sample is consistent to baseline results, and results using alternative variable measures are also robust to baseline results.

3.2 Estimation Method

In this section, I briefly describe the methods to estimate VAR model and relevant inferences. I use the framework of Bayesian VAR model with Minnesota priors and the Normal-Inverse Wishart prior distribution. Firstly introduced in Doan et al. (1984), Minnesota prior has been proved powerful and informative to macroeconomic research. One key parameter in Minnesota prior is the shrinkage parameter λ, which decides how concentrated the prior of coefficients is. I follow the approach by Giannone et al. (2015) who treat λ as a hyper-parameter and derive its posterior distribution, after which I implement Markov chain Monte Carlo (MCMC) method and obtain posterior draws for statistical inference. Variables are entered in log-level forms (times 100) except those that are already in percentage (e.g. lending standard), and those that are already stationary.

I choose the lag order for VAR model as $p = 2$ for baseline models unless otherwise stated. The order is determined by Bayesian Information Criterion (BIC) from the 6-variable baseline model and it is a common choice for quarterly VAR models. I set the forecast horizon for news shock as $H = 20$ in quarters, thus 5-year horizon. It is shorter than the horizon from previous literature on news shocks (TFP news shocks mainly), with the reason that unlike TFP news, credit market anticipations and reactions to news shocks should be quicker and have shorter horizon. In Appendix C.1, I show that major results are robust to lag orders and horizon choices. More details of the estimation methods can be found in Appendix B.2.

4 Baseline Results

4.1 Baseline Models

In this section, I present several preliminary results based on the discussions before. The baseline models include a 6-variable 'toy' VAR model and a 10-variable full VAR model.

Six-Variable Model. As a starting point, I present a basic 6-variable VAR model, which includes the Lending Standard for banks, Real Output, Inflation, Hours Worked, GZ Spread and Effective Federal Fund Rate. The first variable is the key measurement for bank credit supply conditions, the middle three variables capture the dynamics of real economy-wide variables, GZ Spread controls for general credit conditions and Effective Federal Fund Rate controls for monetary stances. Figure 2 presents the IRFs from surprise shocks to credit supplies, and Figure 3 presents IRFs from news shocks. The blue shadow area correspond to 68% confidence bands from 10,000 posterior MCMC replications and black lines correspond to median responses. The x axis corresponds to the horizons up to $h = 20$ quarters from the time when shock hits, and the y axis corresponds to percentage changes from equilibrium.

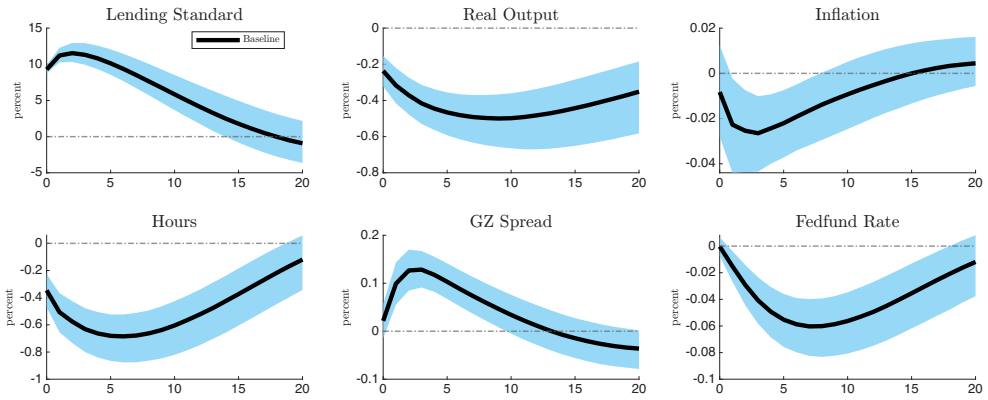


Figure 2: IRF of variables to a credit supply surprise shock

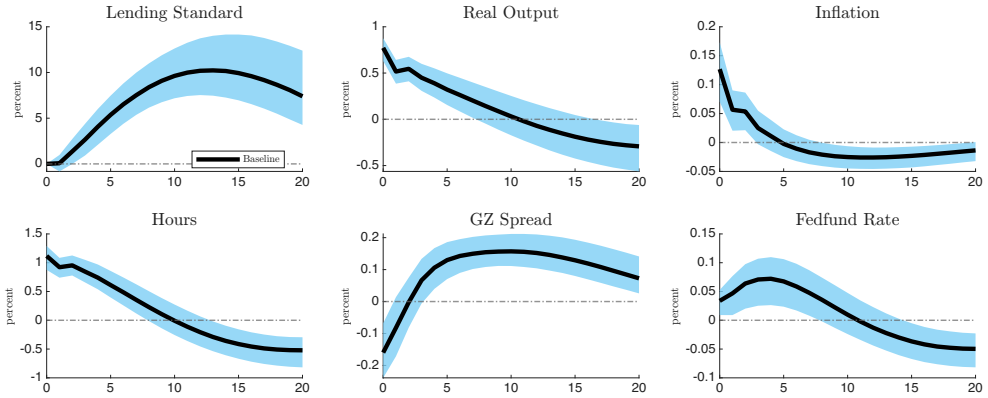


Figure 3: IRF of variables to a credit supply news shock

A surprise shock to bank lending standards/credit supplies generates a classic credit crunch and recession of economies. As a transitory shock, the response of lending standard increases at impact, and gradually goes back to zero. The macroeconomic variables show a clear recession response, even at impact: real output and hours worked drop at impact

and slowly recover, and price level shows a slight deflation before its recovery, indicating a normal demand-driven price changes. The GZ spread responds a gradual increase before going back to zero, which implies a reactive but delayed response to a transitory credit supply shrinkage. The federal fund rate responds by a clear easing. Such responses are consistent with a bunch of previous literature studying credit supply shocks, e.g., Broadbent et al. (2024), Hviid and Schroeder (2024), Cavallo et al. (2024a), Boeck and Zörner (2024), Altavilla et al. (2019), Bassett et al. (2014) and Gilchrist and Zakrajšek (2012), all of which report negative responses to a general surprise shock to credit supplies.

The responses to a news shock of bank credit supplies is the target of this paper. Figure 3 presents quite different responses from those to a surprise shock. The bank lending standard shows a quite classic feature for news shocks, that it has no response to news shock at impact, but has a positive response in the median run. It provides a clear explanation to credit supply news shocks: when the shock hits, lending standard does not change at impact but the shock provides a news signal that there will be tightening in lending in the future; up to 5 years later, the news is "realized", the lending standard is tightened to and stay at a new and higher level. The response from lending standard is consistent to previous literature on news shocks which mainly targets on TFP or technology, e.g., Görtz et al. (2022), Kurmann and Sims (2021), Cascaldi-Garcia and Galvao (2021), Ben Zeev and Khan (2015) and Barsky and Sims (2011).

Responses from macroeconomic variables present quite different dynamics to news shocks than to surprise shocks. Real output has an at-impact surge of about 0.7 percentage when news shock hits, and gradually fades to zero in about 10 quarters. The at-impact rise is even stronger in absolute values compared to surprise shock. When the lending standard is tightened, it shows a normal credit crunch feature. I call such feature as a *temporary boom* - an initial expansion of economy when the news hits and a following bust when news is realized. Responses of other variables show similar temporary-boom features: inflation rises at-impact for about 0.12 percentage, then moves below zero before going back to zero; hours worked increases about 1 percentage at zero horizon and slowly to move below zero; GZ spread, unlike its response to surprise shock, responds negatively at-impact, implying an initial easing credit conditions or financial stress from firms. Responses from federal fund rate shows a monetary tightening in short horizons before it becomes easing.

Ten-Variable Model. In order to uncover more detailed dynamics found in the 6-variable VAR model, I add 4 more variables into the system. Two of them are closely related to loan conditions, as seen in Broadbent et al. (2024), Altavilla et al. (2019) and Bassett et al. (2014). They are namely the Core Loans outstanding for domestic banks, consisting of three major loan categories (C&I loans, real estate loans and consumer loans), and Loan Demand

Index, which measures the aggregate demand for loans. The rest two variables come from literature of news shocks (e.g. Görtz et al. (2022), Barsky et al. (2015), Barsky and Sims (2012), Barsky and Sims (2011) and Beaudry and Portier (2006)), namely S&P 500 Index and Index of Consumer Sentiment. Two variables both capture the median- to long-run expectations of the economy and thus help identify the news shocks to bank credit supplies.

Figure 4 and 5 present the IRF responses from two shocks in the 10-variable model. The first observation from these results is that variables in the 6-variable model remain robust when including the additional 4 variables, despite of slight differences, e.g., the responses of real output, GZ spread and federal fund rate are slightly dampened at impact, but roughly stay significant. The more noticeable difference is that inflation from surprise shocks becomes muted and insignificant, which is actually consistent to results in Bassett et al. (2014) and Boeck and Zörner (2024) that inflation has no significant responses to surprise shocks of credit supplies when core loans are included.

The second observation focuses on the added 4 variables. Under a surprise shock, core loan is generally muted in short term before a persistent and strong decline. The loan demand index also drops mildly, and when lending standards move back to zero in the median run, it rebounds quickly. For two expectational variables, both S&P 500 index and sentiment index present a normal response during recessions. In contrast, responses of 4 variables to news shock further support the temporary-boom story. The loan demand index rises on impact, while core loans increases with a moderate lag, implying a stronger borrowing incentive and more loan originations. Consumer sentiment also has a slight increase at-impact, although not significant.

Interestingly, the S&P 500 index does not respond a rise at impact. Together with the insignificant responses from consumer sentiment, they show a feature of forward-looking variables that internalize not just the short-term macroeconomic expansion but also the anticipated deterioration in credit conditions. The persistent decline in the S&P 500 index suggests that financial markets expect future tighter financing conditions, slower profit growth, or monetary tightening in response to inflation pressure. This behavior is in sharp contrast to the temporary boom observed in real activity variables like output and hours, reinforcing the notion that the news shock represents shifts in expectations rather than a contemporaneous change in fundamentals. Taken together, the divergence between responses from backward-looking and forward-looking variables paints a consistent picture: while economy expands in the short run, markets begin to price in the credit tightening and policy responses implied by the news, validating the temporary boom narrative and responses of forward-looking variables.

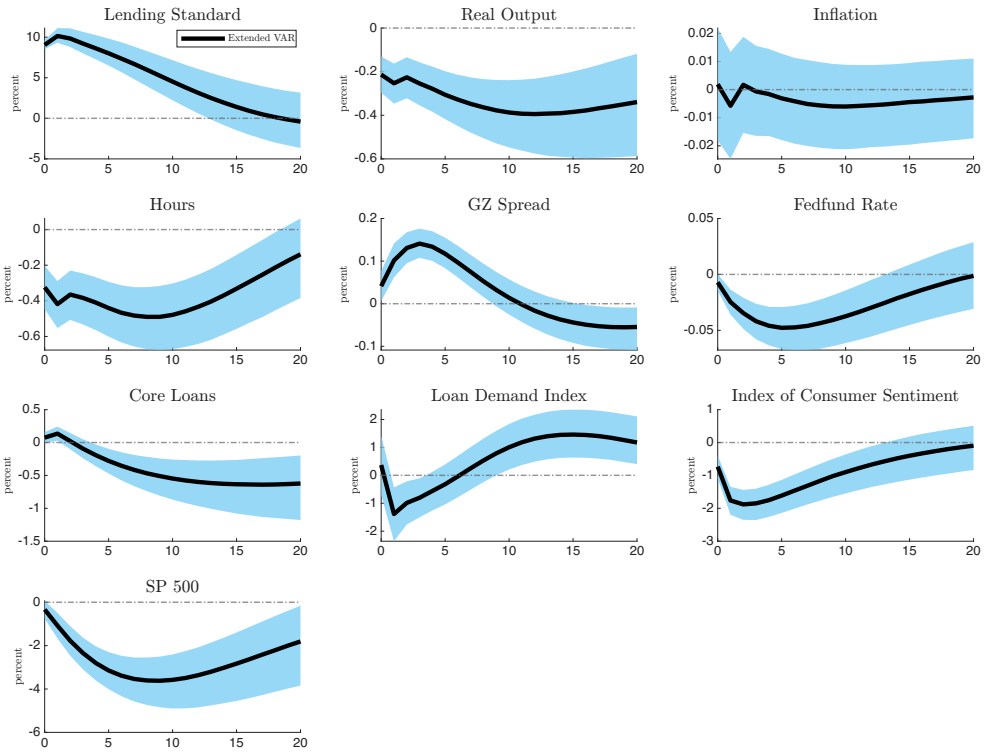


Figure 4: IRF of variables to a credit supply surprise shock, 10-variable model

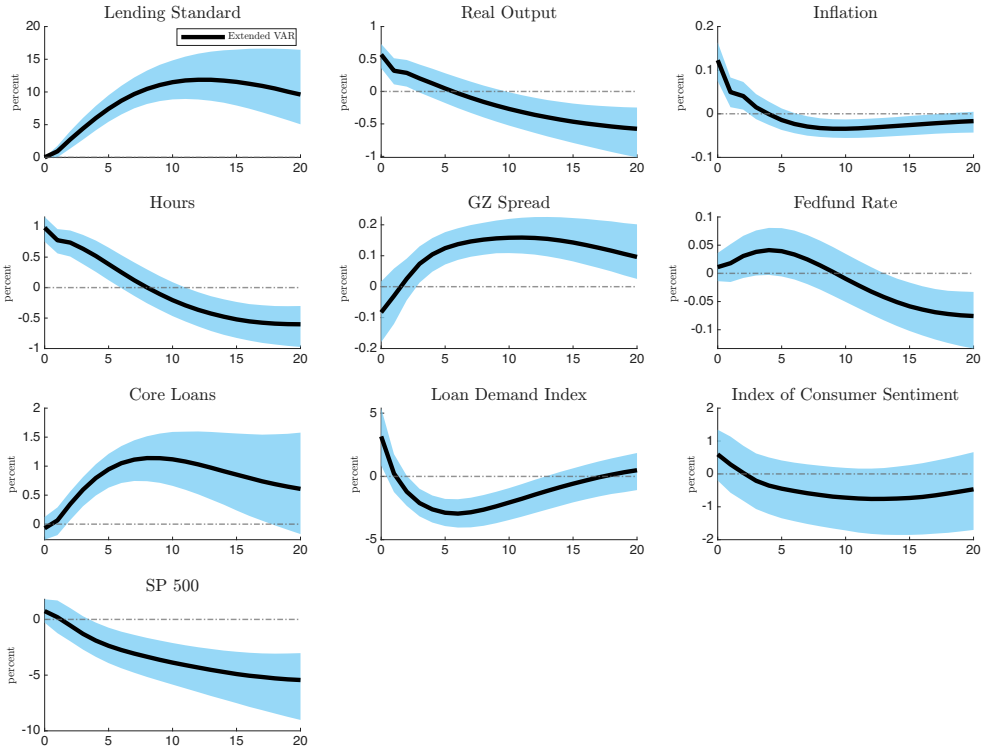


Figure 5: IRF of variables to a credit supply news shock, 10-variable model

4.2 Discussion of Results

A natural question coming from Section 4.1 is, what drives such temporary boom? In later sections, I will try to answer this question with more empirical results. At this stage, both version of models suggest that the temporary boom is a typical demand-driven outcome. The most clear evidence comes from the inflation rises in the short run. From these, I conjecture one explanation which aligns with forward-looking behavior by borrowers (firms or households): when agents receive news that credit conditions will tighten in the future, they may accelerate borrowing and investment decisions in the present. Such preemptive borrowing generates a short-lived expansion in economic activity, even in the absence of immediate changes in lending standards. Firms may bring forward production plans or investment, while households increase consumption, both contributing to the observed short-run rise in output, labor input and inflation. The rises in core loans outstanding and loan demands, as well as the easing in GZ spreads at impact support this interpretation. Overall, results suggest a demand-driven, expectation-based mechanism behind credit supply news shocks, which is quite distinct from the normal credit surprise contractions. These responses also reflect a classical narrative of rational expectations.

The channel of preemptive borrowing comes from the demand side of credits. Another channel might come from a lending expansion channel, that banks originate more loans following the credit tightening news. However, such narrative is not supported by baseline results. Specifically, impulse responses show no evidence of eased lending standards - a necessary condition for banks to proactively expand lending. Furthermore, banks facing future tightening constraints have no plausible incentive to increase loan originations, as this would worsen their balance sheets ahead of impending tightening. The absence of these credit supply-side markers, coupled with the surge in loan volumes, together suggests to preemptive borrowing by firms and households anticipating scarcer future credit.

One interesting result is that the federal funds rate rises mildly after the news shock. One concern is whether the responses are generated from a conventional monetary policy shock, and the lending standard follows to rise with a delay. However, baseline results do not support this narrative. First, the federal funds rate rises only after the initial boom, suggesting monetary policy is reacting to but not causing the temporary expansion. That is, the monetary tightening policy responds to a boom that is itself triggered by forward-looking behavior. Second, the decline of federal fund rate after about 10 quarters cannot trigger the bust responses from other variables. To address this concern more formally, in Sensitivity Analyses I compute the correlation between credit supply news shock and a monetary policy shock, which is low and insignificant.

The rise of policy rate might even reinforce the temporary boom-bust cycle, generating

additional forces to bust periods. It is because when central bank reacts to raise the rate, it not only pushes further the tightening of bank lending standards, but also drives to stabilize inflation and output. This sequence - anticipated credit tightening, temporary boom, monetary tightening - aligns with standard macro-financial dynamics. It reflects how private sector expectations can interact with credit supply conditions to produce cyclical patterns: the economy temporarily expands as agents act preemptively, and policymakers step in to curb potential overheating or inflationary pressures.

A noteworthy implication from the responses of federal funds rate is that the temporary boom triggered by a credit supply news shock may mislead monetary policymakers. Because output, hours worked, and inflation rise in the short run, the boom may resemble an overheating period driven by strong macro-fundamentals or excess demand. In response, central banks may tighten monetary policy, interpreting these developments as signs of persistent expansion. However, this reaction may be mis-calibrated if the underlying shock is anticipatory like the identified news shock, which itself generates a self-stabilizing cycle. In this case, a premature or excessive policy response may therefore amplify volatility, worsening the outcome in bust periods, and tightening into a phase when credit is already becoming less available. This will be discussed in more details from the counterfactual policy analyses in Section 5.

The muted responses in the short run for two forward-looking variables (S&P 500 index and index of consumer sentiment) are another interesting result. Together with the temporary boom results, they provide evidence of rational expectations. Specifically, asset prices immediately incorporate both the short-term boom (higher earnings from preemptive borrowing) and the long-term drag (future credit tightening raising discount rates), leading to around zero at-impact responses. Similarly, flat consumer sentiment suggests households anticipate tighter future credit conditions, offseting optimism from temporary income gains. Rational expectations also explain the temporary boom: firms and households rationally front-load activity to exploit favorable borrowing terms before constraints bind, without requiring behavioral frictions. The joint evidence thus underscores how credit supply news shocks propagate through fundamentally rational, intertemporally optimizing behavior.

Readers may find similarity between the identified credit supply news shock and the credit sentiment shock identified in Boeck and Zörner (2024) inspired by López-Salido et al. (2017). The sentiment shock is based on diagnostic expectations and a regime-dependent Threshold VAR model. The responses in the optimistic credit regime in their paper kind of resemble the responses to the news shock here: given a credit sentiment shock, the growth rate of economic activity rises and credit volume expands. However, there are two major differences. First, their results are reported in growth rates rather than levels, which suggests a persistent but not temporary boom in the levels of output and credit volume. Second, the

interpretation in an optimistic regime in their paper is that the economy remain calm or strong sentiment to future conditions, while my interpretation does not focus on behavioral reasons but front-loading actions when expecting future tightenings.

Another concern is whether the observed temporary boom is generated by the central bank information effect, as in Jarociński and Karadi (2020), where a rise in interest rates signals the Fed's private information about better future conditions, leading markets and the real economy to respond positively. Baseline results seem to partially support such narrative, since federal fund rate rises with a delay, and economies react with an expansion. However, the central bank information effect might not explain the bust periods in the median run. To address this more formally, in Sensitivity Analyses I again run correlations between two shocks and results suggest that the identified news shock is not a relabelled shock by the central bank's information set but reflects structural expectations of credit tightening.

4.3 Historical Importance

In this section, I present the historical importance of two shocks to bank credit supplies in the system of 10-variable VAR model. Specifically, I perform the forecast error variance decomposition (FEVD) and historical decomposition (HD) from two shocks to explain the their explaining power to variations in the variables of interest.

Forecast Error Variance Decomposition. Forecast Error Variance decomposition mainly examine the contributions of each shock to the volatility of target variables among different forecast horizons. News shocks have been proven to be one important driver to output, e.g., Görtz et al. (2022) and Barsky and Sims (2011) show that TFP news shocks explains about 40% to 60% of the variation of output. Figure 6 present the variance decomposition of surprise and news shocks to bank credit supplies. Stacked area represents the median FEVD contribution of each shock to each variable, from 10,000 posterior MCMC draws. The confidence bands of each FEVD share can be found in Appendix D. The x axis is the forecast horizon up to 20 quarters, the same to IRF horizons, and y axis is in percentage unit.

The decomposition results reveal a clear distinction between the role of credit supply surprise shocks and news shocks. Across most financial variables, credit supply surprise shocks dominate at short horizons, while news shocks gradually take over at medium horizons. For example, for bank lending standards and by construction, surprise shock explains the full variance at impact, and overtime its importance diminishes to about 30% when news shocks take over and account for nearly half of the FEV at the 20-quarter horizon. Similar logics can apply to GZ spread, core loans, loan demand index and S&P 500 index, which

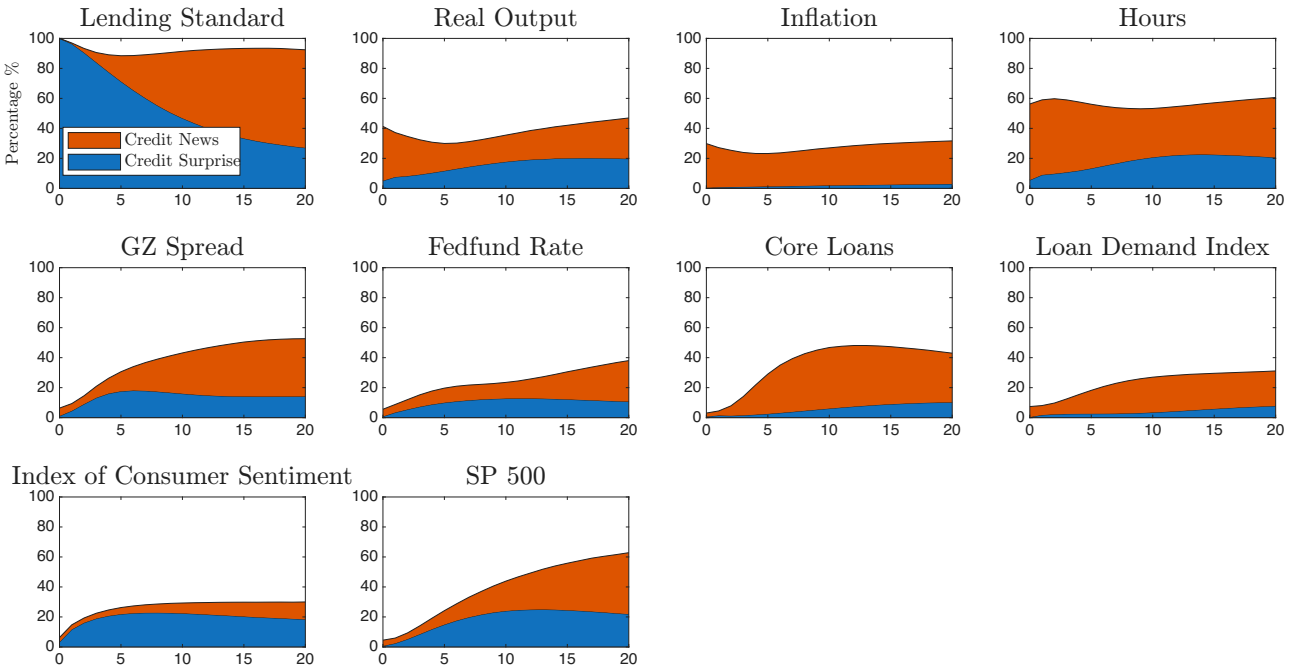


Figure 6: Variance decomposition to credit supply shocks

all present a sizable contribution of news shocks to their median-run variations, compared to the contribution of surprise shocks. A bigger FEVD share from news shocks also reflect a forward-looking financial sector that reacts not only to contemporaneous shocks but also to signals about the likely trajectory of credit supply in the quarters ahead.

Macroeconomic variables, on the other hand, present some interesting features. The contribution of news shock to real output is already sizable at short horizons, accounting for around 35% of the variance at impact. As horizon goes up, the contribution first shrinks to about 20% at 6-quarter horizon, and then continues to slowly grow up later on. The 'cut'-point, namely the 6-quarter horizon, matches consistently to the time when bank lending standard reaches its higher level, i.e., standard is tightened, and the time when real output turns to negative response, as seen in Figure 5. This suggests that anticipated shifts in future credit availability - not just unexpected credit tightening - play an immediate and significant role in shaping real activity. When lending standards become tightened, uncertainty of news is partially resolved, its contribution to output correspondingly decreases.

Contributions of news shock for other macroeconomic variables present similar patterns. By contrast, the contribution to consumer sentiment from news shock is mild in median run, showing that consumers might not be as sensitive to news as a more direct exposure of credit supply crunches. It is consistent to the insignificant responses in Figure 5 and might reflect that news shock is too abstract or uncertain for households to fully internalize, leading to a comparatively smaller role in shaping sentiment variations.

Historical Decomposition. Historical decomposition mainly check how shocks contribute historically to each variable. For convenience, Figure 7 presents the stack HD plot of two shocks to only two major variables, bank lending standards and real output. Other HD results are listed in Appendix D. Similar to FEVD results, I plot the median share of each shock to each variable at each time period. I remove the deterministic trends and for I(1) variables, I plot their growth rates. The x axis presents time, and y axis presents percentages.

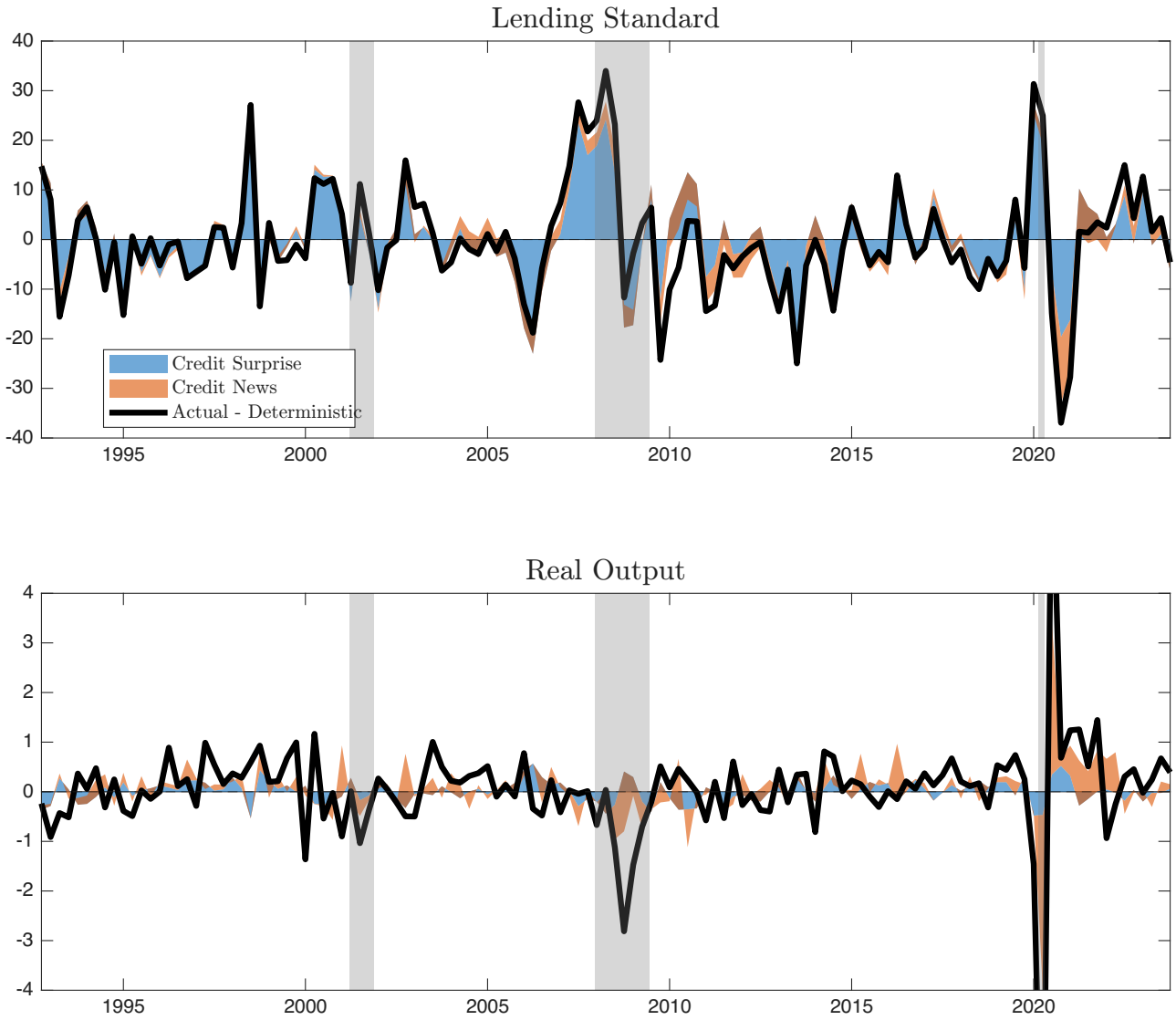


Figure 7: Historical decomposition to credit supply shocks

The historical decomposition for the bank lending standard reveals important dynamics about the roles of credit supply surprise and news shocks over time. Credit supply surprise shock appears to dominate the historical fluctuations of the lending standard throughout the entire sample, which is align with identification strategies. In contrast, credit supply news

shock contribute more persistently and gradually across episodes, and it has particularly sizable exposure in the post-GFC years.

As for real output, credit news shocks explain notable portions of fluctuations during key episodes in three recession periods across the sample. Also, the shocks contribute positively during periods such as the pre-GFC boom and the early post-COVID recovery. Throughout the sample, news shock turns out to be a more important driver to real output than surprise shocks, which presents a different scenario from HD in lending standards.

4.4 Relevance to News Heard

How is the identified credit supply news shock related to actual news heard from agents? Specifically, I ask two questions: first, what kind of news heard might explain the identified news shock, and second, how might the news shock predict the future awareness of news heard? One survey question in Michigan Consumer Survey allows me to link actual news heard from consumers to news shocks. The survey asks respondents the following question,

"*During the last few months, have you heard of any favorable or unfavorable changes in business conditions?*"

If the answer is yes, the follow up question is "*What did you hear?*", which provides several categories of favorable-unfavorable news pairs, e.g., price levels, credit access and stock performance, etc. Answers are aggregated as the fraction of survey respondents having heard news in each category. As argued in Barsky and Sims (2012), the term 'news' in the survey does not correspond to news shocks in a rational expectations sense. Rather, the wording of the survey questions - particularly the phrase "during the last few months" - indicates that respondents are reporting news about current or very recent macroeconomic developments. These responses likely reflect perceptions of ongoing economic conditions rather than genuine forward-looking information or news about the future. Therefore, the survey-based "news heard" is better interpreted as retrospective or contemporaneous news exposure, rather than anticipatory signals that drive formal news shocks in the VAR. Such distinction is important to explain the later-on results. Other than the news heard from survey, the extracted news shock is obtained as the median structural shocks for each time period from the posterior 10,000 MCMC replications.

Explaining News Shock. To answer the first question, I perform regressions of median news shocks on selected categories of news, similar to regressions presented in Barsky and

Sims (2012), which has the form of

$$\text{News Shock}_t = \alpha + \sum_{k=1}^{K} \beta_k \times \text{News Heard Cateogory}_{k,t} + \boldsymbol{\gamma}' \boldsymbol{Z}_{t-1} + \epsilon_t$$

where $\boldsymbol{Z}_{t-1}$ is a set of lagged controls of macroeconomic and financial conditions, and it includes all variables in the 6-variable VAR model, in which real output and hours worked are taken the form of growth rate, and lending standard uses the raw CSI series to reflect changes. The inclusion of these controls will help test if the news shock is exogenous, and the one-quarter lag of these controls can avoid potential endogeneity issue. I do not include the lagged news shock in the regression since there is no evidence of autocorrelations from a simple autocorrelation test. Since Barsky and Sims (2012) does not include controls, I add in $\boldsymbol{Z}_{t-1}$ only in the full specification of regression. As variables in both sides of regressions are time series, I use Newey-West standard errors with the cut parameter as $T^{1/3}$. Table 1 presents stepwise regression results.

The regression results suggest that certain categories of subjective news heard by consumers are significantly related to the extracted credit news shocks, and coefficients present some interesting features. For example, the coefficient on "Unfavorable Tighter Credit" is negative across specifications and statistically significant in specifications (1), (4) and (5), suggesting that when more respondents report hearing about tighter credit conditions, it is associated with a more eased news shock or lending standard. On the other hand, the coefficient of "Favorable Easier Credit" remains positive across 5 regressions, although only specification (3) is weakly significant. Such results might look counterintuitive at a first glance, but this may reflect an important timing discrepancy: once the credit tightening becomes widely reported, it is already being realized rather than anticipated, thus it is less likely to have further news of future tightenings. Such result is consistent with the news shock capturing forward-looking revisions rather than current conditions.

Other than credit news, the most notable coefficient is from "Unfavorable Higher Price", which is consistently and significantly associated with positive news shocks across all specifications. More generally, most favorable news categories show positive coefficients and unfavorable news categories show negative coefficients, which are consistent with conclusions before and further support the temporary-boom narratives. Specifically, while higher prices are counted as unfavorable news to consumers in the survey, it can also be a positive signal of heating economies.

To summarize the findings from coefficients, while the regression does not aim to uncover causal relations, the coefficients support previous stories from both directions. For example, on the one hand, when the news shock hits, it contemporaneously generates re-

Table 1: Regressions of extracted news shocks

News Heard Category	(1)	(2)	(3)	(4)	(5)
Favorable Easier Credit	0.064	0.109	0.114*	0.082	0.119
	(0.052)	(0.071)	(0.068)	(0.067)	(0.075)
Unfavorable Tighter Credit	-0.058*	-0.039	-0.057	-0.065*	-0.075*
	(0.031)	(0.038)	(0.036)	(0.033)	(0.044)
Favorable Lower Price	-0.008	-0.015	-0.028	-0.036	-0.047
	(0.031)	(0.033)	(0.035)	(0.034)	(0.043)
Unfavorable Higher Price	0.035***	0.045***	0.045***	0.043***	0.055***
	(0.009)	(0.015)	(0.012)	(0.012)	(0.017)
Favorable Stock Market		0.085*	0.050	0.054	-0.008
		(0.051)	(0.038)	(0.040)	(0.048)
Unfavorable Stock Market		-0.014	-0.003	-0.0007	-0.018
		(0.020)	(0.021)	(0.019)	(0.028)
Favorable Employment			0.008	0.015	-0.0001
			(0.011)	(0.012)	(0.018)
Unfavorable Employment			-0.015*	-0.016	-0.037**
			(0.009)	(0.009)	(0.018)
Favorable Government Elections				-0.018	-0.014
				(0.016)	(0.014)
Unfavorable Government Elections				-0.010	-0.018
				(0.010)	(0.012)
Including $\boldsymbol{Z}_{t-1}$	No	No	No	No	Yes
Adjusted R^2, %	4.6	7.7	11.3	12.6	21.9
# of Obs	126	126	126	126	126

Note: Newey-West standard errors are in parentheses.
*,** ,*** indicate significance at 10%, 5% and 1% level.

ports of favorable economic news, supporting the temporary boom narrative. On the other hand, when agents report hearing unfavorable news about economic conditions, it may coincide with periods when information about future policy tightening is actually arriving in the economy. The former direction verifies the temporary boom narrative, and the latter direction validates the news shock capturing future credit conditions.

The adjusted R^2 rises gradually across the stepwise regressions from 4.6% to 12.6% without controls. Such increase reflects a moderate improvement in explanatory power as more subjective news variables are introduced. The lagged controls $\boldsymbol{Z}_{t-1}$, while not reported here, are all not significant at even 10% level, which greatly suggests the exogeneity of news shock. The adjusted R^2, when including controls, rises to 21.9%, which implies that adding controls generally improves the model specification.

As a simple robustness check, I include two lags of controls and find robust results. I

also run similar regressions on the extracted credit supply surprise shock, but unfortunately find almost no significant relationship between it and the news heard indicators. To conserve space I do not report here. Such results might be interpreted as the surprise shock capturing unanticipated, contemporaneous tightening.

Overall, the regression results reveal important patterns in what types of news heard by consumers explain movements in the extracted credit supply news shock. Most notable news heard is the news of higher price levels. The news heard about credit access also has non-trivial explaining power. The fact that many other news categories show little explanatory power demonstrates that the credit supply news shock captures specific news categories. The resulting coefficients support the interpretation that the news shock represents genuine expectations about future credit tightening that precede, rather than coincide with, widespread public awareness of credit conditions, and they further reinforce the temporary boom results found before.

Transmission of Credit News. The second question asks how the identified news shock might predict the future awareness of credit news among consumers. In other words, when do consumers become aware of credit easing/tightening after the news shock hits? This question helps to understand the transmission of news shock by which expectations about future credit conditions eventually become widely recognized and reported by the public. If the news shock truly captures forward-looking information on credit conditions, one should observe a predictable pattern when credit-related news becomes "heard" by consumers following the shock. To investigate this transmission, I consider the following regression in the style of Local Projection form:

$$\begin{aligned}\text{Credit News Heard}_{t+h} = \alpha + \beta_h \times \text{News Shock}_t \\ + \delta \times \text{Credit News Heard}_{t-1} + \boldsymbol{\gamma}' \boldsymbol{Z}_{t-1} + \epsilon_{t+h}\end{aligned}$$

where h is the horizon from 0 to 12, accounting for up to 3 years after the shock. The lagged news heard controls for the persistence of news heard, as argued by Barsky and Sims (2012), and the lagged $\boldsymbol{Z}_{t-1}$ controls the same set of variables in the previous subsection. Figure 8 presents the estimated $\hat{\beta}_h$, shown in black line, and (dashed) red lines present 90% and 95% confidence bands using Newey-West Standard Errors. The left subfigure uses the news heard on tighter credit, and right subfigure on easier credit.

The results demonstrate a clear sequence that aligns remarkably well with the VAR-based impulse responses. At initial several horizons, the news shock predicts that consumers hear more about favorable easier credit news while hearing less about unfavorable tighter

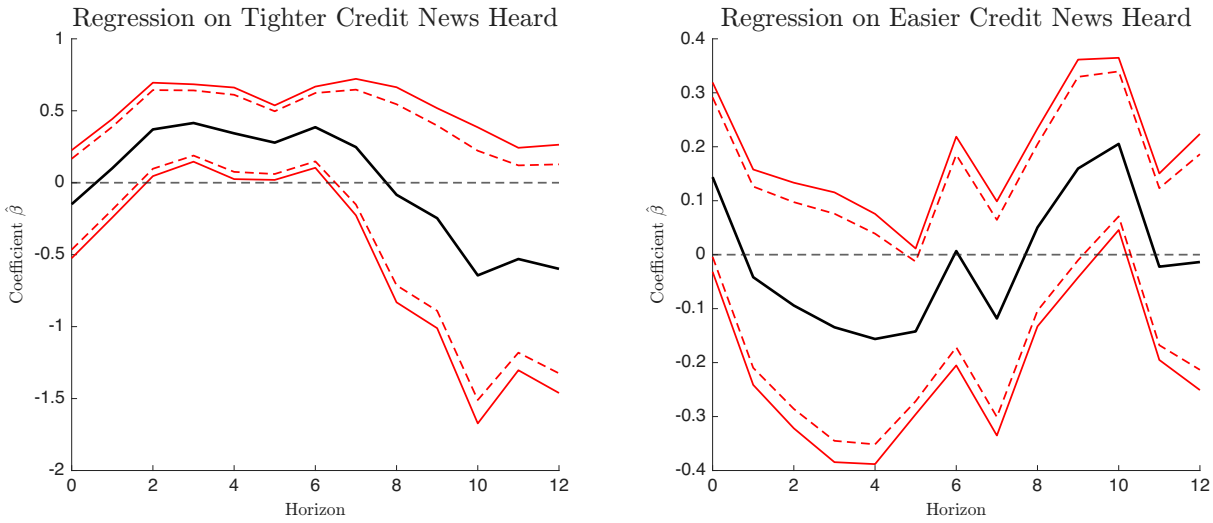


Figure 8: Regressions on credit news heard

credit news, which is consistent with the temporary boom phase identified in the previous VAR results. At median horizons around 2 to 6 quarters ahead, the news shock strongly predicts increased reports of unfavorable tighter credit news heard. The coefficient peaks around 0.4, and the persistently positive coefficients in the median run corresponds with the VAR results when the actual lending standards gradually become tightened. After the peak awareness of tightening, the predictive power gradually fades to zero and becomes insignificantly negative, which probably reflects that credit conditions stay at a tighter level or are just eased later on. The regression results on easier credit news heard present a quite similar flip-sign pattern, in the median run, although they are not as clear as those from tighter credit news heard.

As a simple robustness check, I include two lags of controls and news heard variables, yielding robust results. I also replace the news shock with credit supply surprise shock to re-run the regressions, but find almost no significant results, which might suggest that only persistent changes of lending standards/credit access induced by the new shock can be clearly perceived by public.

Overall, these findings present a complete cycle of the perceptions of credit conditions after the news shock: when the news shock hits, agents first perceive favorable credit news consistent with the temporary boom narrative, become aware of credit tightening after about half year to two years, and do not hear more in the long run when credit conditions stay at a tighter level or are finally eased. While such cycle is shorter than the ones in the VAR model, it still provides strong external validation that the identified news shock captures genuine forward-looking information on credit supply conditions.

4.5 Sensitivity Analyses

In this section, I perform various robustness checks to the baseline 10-variable VAR model and figures are reported in Appendix C.1. I also perform identical tests to 6-variable model but for convenience results are not reported. Also for convenience, I do not report results from surprise shocks unless otherwise stated, but they are robust in general. In several cases, two IRF results are presented, where for alternative results, dashed red lines correspond to median responses, and grey shadow area are corresponding 68% confidence bands. More details of additional variables used in this section are discussed in Appendix A.

Alternative Measures. To ensure that baseline results are robust to alternative measurements of variables used in the baseline model, I re-run the model by replacing certain variable with its alternative measure.

I start by considering other measures of bank credit supplies, and there are several candidates. The first one is the original bank lending standard index ΔB_t from which the CSI index is extracted. I use its cumulative version, similar to baseline, to represent a bank lending standard level. As argued by Broadbent et al. (2024), adding sufficient variables and original standard index in the VAR model is an macro-approach to address endogeneity issues of credit supply measures, while the micro-approach is to run granular regressions as in Cavallo et al. (2024b). Figure C.1 presents the result, which are generally similar to baseline versions, except that the shock is less persistent, i.e., the response from lending standard mean-reverts in the median run. Also, responses from core loans are kind of muted, showing that the macro-approach might not be as clean and explicit as the micro-approach from regressions. The second one is the close companion series of CSI in Cavallo et al. (2024b), namely the aggregate CSI series, and the result is in the red dashed line in Figure C.6, which is highly robust.

The third one is the GZ spread and Excess Bond Premium (EBP) series from Gilchrist and Zakrajšek (2012), both of which represent general credit supply conditions. Figure C.2 presents the result compared to the baseline confidence bands, in red and green dashed lines. It is interesting to see that while Gilchrist and Zakrajšek (2012) argues EBP is more proper to depict credit supply conditions, using GZ spread mostly generates baseline results, but EBP does not. Figure C.3 presents the corresponding confidence bands of responses generated from GZ spread and EBP, where EBP clearly shows less significance and wider confidence bands, potentially due to that EBP is noisier as a residual measure. However, both measures from Gilchrist and Zakrajšek (2012) are generally robust to baseline version.

An alternative specification for GZ spread and EBP is to relax the zero at-impact restriction. Figure C.4 presents the result, which yields several observations. First, when

relaxing zero at-impact restriction, both GZ spread and EBP react a decrease at impact. Second, compared to responses from the max share EBP shock, the shock from GZ spread resembles much more closely, e.g., the temporary boom still holds, and lending standard rises in a similar manner, while responses from max share EBP shock is more delayed and dampened, but remains robust.

The max share EBP shock is exactly one shock that is identified by Görtz et al. (2022), in which results are similar to ones here, except that inflation here rises in the short run. As argued in Görtz et al. (2022), financial shocks are accompanied with inflation rises while TFP news shock is more likely to have deflation responses. Such distinction greatly distinguishes between the credit supply news shock and TFP news shock. One might consider that the inflation responses might come from different setting and sample periods between Görtz et al. (2022) and baseline here[7], so to further formally address the concern that the identified news shock overlaps with the TFP news shock, in Section 5 I run correlation between two shock and conclude that two shocks are quite distinct.

Lastly, I consider the CSI series $\Delta\tilde{B}_t$, instead of its cumulative version, and results are presented in Figure C.5. Similar to the result using EBP, the median results basically replicates the baseline version, but just confidence bands are noisier. Overall, four alternative measures verify that baseline results are not sensitive to other measures of credit supplies.

Alternative measures to other variables are tested one each time and results are presented in Figure C.6. Specifically, candidates include: non-farm real output (used in Barsky and Sims (2011)) for real output, PCE price index for inflation and price levels, 100 minus unemployment rate for employment level, EBP for credit supply and credit risk conditions, shadow federal fund rate by Wu and Xia (2016) for monetary stances which addresses the concern of Zero-Lower-Bound periods, core loans for all commercial banks instead of DCC banks to include U.S. branches of foreign banks, and E5Y used in Barsky and Sims (2012), another survey question response from Michigan Survey to present long term expectations of economy[8]. I do not find alternative measures for S&P 500 index and loan demand index since they are quite the representative measures and there are no proper alternatives. The figure implies that baseline results are robust across all alternative measures[9].

[7] I replicate the results in Görtz et al. (2022) using their original settings and find that response of inflation changes with sample periods. For example, using the original 1984:I to 2017:I generates rough deflation results, but using either 1992:I to 2019:IV or to 2023:IV gives clear inflation results.

[8] In the baseline model, I use the Index of Consumer Sentiment, which is a combination between sentiment of current conditions and expectations of future business conditions. E5Y is one component of Index of Consumer Sentiment. More details can be found in https://data.sca.isr.umich.edu/survey-info.php.

[9] One minor robustness check is adding consumption in the VAR model. The responses of consumption is highly similar to that of real output, so I do not include it in the baseline version.

Alternative Identifications. As discussed in Section 2, two other identification methods are commonly used, namely the one from Barsky and Sims (2011) which use cumulative FEV in the objective function, and the one from Francis et al. (2014) and Kurmann and Sims (2021) which use FEV at certain horizon but no zero at-impact restrictions. Figure C.7 and C.8 present the baseline results from news shock with these two alternative identification strategies, both of which are quite similar to baseline version. Another concern might come from the setting in Bayesian VAR and Minnesota prior. To address this, I estimate the baseline VAR model with a usual frequentist approach, presented in Figure C.9. The confidence bands are obtained via the bias-corrected bootstrap from Kilian (1998) and results are again similar to baseline version.

Loan-Specific Shocks. Other than the CSI series, Cavallo et al. (2024b) also provides credit supply indicators for each major loan category, which include C&I loans, consumer loans, commercial real estate loans and residential real estate loans. To examine whether loan-specific shocks generate similar results to baseline, I replace the aggregate shock with each loan-specific shock. Figure C.10 presents the result. While there are clear heterogeneity across responses of each shock, the overall dynamics are consistent with the baseline version. In particular, responses to the shock from commercial credit supplies seem to react more intensely than others. These findings suggest that the temporary boom effect is robust across loan-specific credit supply news shocks, confirming that anticipatory credit tightening can stimulate real economic responses regardless of loan type. This reinforces the interpretation that forward-looking adjustments in lending behavior are a key channel in driving near-term macroeconomic dynamics. In the extension Section 5.2, I will discuss more on the heterogeneous responses from each loan categories.

Comparison with Other Shocks. In order to address the concern that the credit supply news shock might overlap with some identified shocks in the previous literature, here I consider correlations with some well-established shocks. First, I consider two macroeconomic shocks which are TFP news shock from Kurmann and Sims (2021) and Main Business Cycle (MBC) shock from Angeletos et al. (2020). Second, I consider two monetary shocks, including the conventional monetary policy shock from Bauer and Swanson (2023) and Central Bank Information shock from Jarociński and Karadi (2020). Lastly, I consider two versions of financial shocks identified by Ottonello and Song (2024). These six shocks represent a general set of well-established shocks that capture business cycles and dynamics in credit markets.

For the first two groups of shocks, I follow identification strategies in each paper and replicate shock series in my context. For TFP news shock, I use the version in Kurmann

and Sims (2021) and target the max-share of FEV to TFP series at 20 quarter horizon[10]. For MBC shock, I use their output-targeting version at 4-quarter in time domain for replication[11]. For monetary policy shock from Bauer and Swanson (2023), I use their high-frequency surprises *mps* and adopt typical VAR-IV strategies. For Central Bank Information shock, I use their proposed sign restrictions on high-frequency surprises to FF4 and S&P 500 index[12]. The shock series from Ottonello and Song (2024) is directly from their published version[13] and I take quarterly summation. Specifically, authors provide a broad and purged version of financial shocks which are identified via high frequency surprises of earning calls from financial institutions. More details can be found in specific papers.

The resulting IRFs from replicated shocks (first two groups) are presented in Appendix C.1 from Figure C.11 to C.14. For each shock, I consider both the full sample (1992:I to 2023:IV) and pre-Covid sample (1992:I to 2019:IV) in order to examine whether pandemic periods might generate spurious correlations. For the first two groups of shocks, I simply replicate them in two samples. For two financial shocks, the broad financial shock is from 1998:IV and the purged version is from 2002:III, and both end up in 2020:III. I use the overlapping range from full sample and pre-Covid sample of credit supply news shock to calculate correlations.

The IRFs from replicated shocks basically mimic the results from previous literature, and they are generally different from the IRFs to credit supply news shock. For the monetary policy shock, it clearly performs better and generates more reasonable responses in pre-Covid sample, probably due to the aggregation of monetary surprises into quarter frequency and the drastic volatilities during Covid period. It is illustrated in Figure C.13. Central Bank information shock does not show much differences between two sample ranges.

To further validate the argument that credit supply news shock does not overlap with previous shocks, Table 2 presents the correlation between credit supply news shock and other

[10]Due to a shorter sample range, I choose the 20-quarter horizon other than 40 quarters. One may notice that the IRF from TFP news shock has some differences from the one in Kurmann and Sims (2021), which is due to the inclusion of Covid periods. In the Online Appendix of Känzig and Williamson (2024), authors discuss more details and compare their technology shocks with previous TFP news shocks. In particular, their results with longer sample periods are quite similar to results here. I do not consider the version by Barsky and Sims (2011) since Kurmann and Sims (2021) argue improvements from original strategies in terms of identification of TFP news shock.

[11]As argued in the paper, the business cycle of 6-32 quarters in frequency domain can be best approximated by 4 quarters in time domain with max-share method on specific variables. I choose the output-targeting version because my baseline specification does not include variable of unemployment rate.

[12]The baseline sample range in Jarociński and Karadi (2020) spans to 2016. For missing values of high-frequency surprises, I follow Känzig (2021) to censor them as zero. The baseline VAR estimation in Jarociński and Karadi (2020) limits the dynamics of high frequency variables, i.e., high frequency variables are not affected by their lagged version nor lagged low frequency macroeconomic variables. I adopt a more relaxed version that corresponds to a standard VAR framework for convenience of replications. As shown in their online appendix, such relaxed version of estimation yields robust results.

[13]Shock series are available at `https://financialshocks.com/`.

shocks. The way I construct the inference is that I generate 10,000 replications for each shock fixing the random seed, obtain correlations and find 99% ([0.5, 99.5]% quantile), 95% ([2.5, 97.5]% quantile) and 90% ([5, 95]% quantile) critical values. If value ranges include zero, I consider it as insignificant at a certain level. For two financial shocks, the replication draws are only from credit news shock itself.

A clear observation from these correlations is that major macroeconomic and monetary shocks are mostly not significant even at 10% level. The noticeable correlations are with (1) MBC shock in full sample, but in pre-Covid sample the correlation largely dampens, meaning potential spurious correlations induced by pandemic voltalities; (2) monetary policy shock in full sample, but as mentioned before, the monetary shock is not well identified in the full sample; (3) two financial shocks. Specifically, the purged financial shock, as argued by Ottonello and Song (2024), is constructed to correlate negatively with EBP to capture credit supply conditions.

The mildly significant but low correlation between the credit news shock and purged financial shock might suggest that bank earnings calls contain both current lending capacity information and forward-looking outlook about future bank-specific credit conditions. In other words, while Ottonello and Song (2024) generally link high frequency earning call surprises of banks with credit supply conditions, earning calls themselves usually contain important outlook information of banks and thus future credit supply conditions. In conclusion, these results suggest that the credit news shock is quite distinct from those well-established macroeconomic, monetary and other financial shocks.

Table 2: Comparison with other shocks

Shock Name	Relevant Literature	Correlation		Source
		Full Sample	Pre-Covid Sample	
Macroeconomic Shocks				
TFP News Shock	Kurmann and Sims (2021)	-0.032	-0.124	Author's replication
Main Business Cycle Shock	Angeletos et al. (2020)	0.372*	0.082	Author's replication
Monetary Shocks				
Monetary Policy Shock	Bauer and Swanson (2023)	-0.381	-0.164	Author's replication
Central Bank Information Shock	Jarociński and Karadi (2020)	0.059	0.100	Author's replication
Financial Shocks				
Broad Financial Shock	Ottonello and Song (2024)	0.161*	0.192*	Original paper's data
Purged Financial Shock	Ottonello and Song (2024)	0.312**	0.309*	Original paper's data

Information Efficiency. The full baseline model consists of 10 variables, which is a median-scale VAR model. In order to examine whether the model spans over sufficient information and address potential concerns on fundamental representation of VAR systems,

I consider a Factor-Augmented VAR (FA-VAR) model. Factors are obtained from a large information set of macroeconomic and financial variables in the FRED-MD dataset, as in McCracken and Ng (2016). Since the extracted factors depend on sample range of information set, I consider two ranges of information set, where one spans over the fullest available periods from 1959M1 to 2025M5, and the other one just matches my baseline sample period[14]. Factors are taken quarterly averages to match baseline frequency. I choose the default 7 factors and adjust the VAR model in Section 2 as

$$\begin{bmatrix} \boldsymbol{Y}_t \\ \boldsymbol{f}_t \end{bmatrix} = \tilde{\boldsymbol{C}} + \sum_{l=1}^{p} \tilde{\boldsymbol{B}}_l \begin{bmatrix} \boldsymbol{Y}_{t-l} \\ \boldsymbol{f}_{t-l} \end{bmatrix} + \tilde{\boldsymbol{u}}_t$$

where coefficients are adjusted for larger dimensions. Figure C.15 and C.16 present comparison results and they imply that baseline results are robust to a richer information set in both time ranges, thus information inefficiency is less of a concern for baseline specifications.

Sample Period. While there are several advantages for including Covid periods in the sample, as discussed in Section 3.1, and to address the concern that Covid sample would confound baseline results and interpretations, Figure C.17 present the result from a subsample that ends in 2019:IV, before the start of pandemics. The result for a pre-Covid sample turns out to be quite similar to baseline sample. The major difference between two samples is that subsample results are smaller in scale and slightly delayed in responses, specifically at short-run horizons, but they still remain significant. For example, the at-impact response from real output drops from 0.5% to 0.2%, while keeping significance. This can be due to drastic changes during Covid periods. The similarity between pre-Covid and full sample is consistent to the robustness check in Broadbent et al. (2024).

Alternative Specifications. To examine whether baseline results are not sensitive to the choice of lag order and forecast horizon, I check alternative lag order $p \in \{4, 6, 8\}$ and $H \in \{8, 16, 40\}$ quarters, presented in Figure C.18 and C.19. Also, to examine the effect of order of identification, I identify the surprise shock first followed by the news shock, and results are presented in Figure C.20. These result turn out be very similar to baseline version.

5 Extension Results

In this section, I mainly discuss three extensions from baseline results. In Section 5.1, I separate core loans into major loan categories to check there are any heterogeneity in

[14]The second information set spans over 1991M11 to 2023M12. The reason to include two more months at the beginning is that extracted factors will drop first two months of the information set.

responses of loans to a credit supply news shock. In Section 5.2, I examine evidence from Euro area. In Section 5.3, I perform counterfactual policy analyses to check the role of monetary policies in credit-news-driven cycles.

5.1 Responses from Loan Categories

In this section, I revisit the question proposed in Section 4.2 about drivers of temporary boom. The baseline results presented earlier show that credit supply news shocks generate a delayed but notable increase in responses of core loans outstanding. I argued that it reflects a preemptive borrowing behavior that contributes the temporary boom in output, as bank loans are a critical credit channel for propagating the real economy. To better understand the composition of this loan expansion, I decompose core loans into major subcategories and analyze their individual responses to an aggregate credit news shock. Identifying such underlying sources of credit expansion helps clarify the mechanism behind the temporary boom and allows for a more nuanced interpretation of how credit anticipations propagate through the real economy.

As a starting point, I briefly describe the composition of core loans outstanding from the balance sheets of banks. From H.8 releases in Federal Reserve Board, core loans outstanding are composed of three main categories in its term 9: Commercial & Industrial Loans (term 10, C&I), Real Estate Loans (term 11, RE) and Consumer Loans (term 20). While Real Estate Loans can be further decomposed into Residential (term 12, RRE) and Commercial (term 15, CRE) Real Estate Loans, their data availability start from June 2004, so I do not consider these two subcategories in major analyses. On the other hand, aggregate real estate loans, together with other two main categories, span over the full baseline sample periods.

Figure 9 illustrates how core loans are composed overtime from the availability from 1973 to 2024. Black lines indicate the window of which baseline sample spans over, and shadow area represent NBER recession periods. It clearly indicates that RE loans consistently make up the majority share of core loans throughout the baseline sample, often exceeding 50%. The dominance of real estate lending is particularly evident from the early 2000s onward, coinciding with the housing boom and continued through the post-GFC recovery period. In contrast, C&I loans account for roughly one-quarter to one-third of core loans, while consumer loans represent the smallest share. This composition might suggest that aggregate credit dynamics observed in response to news shocks are likely to be heavily influenced by the behavior of real estate lending.

In order to examine responses of different loan categories, I replace core loans with three major loan categories. Also, I replace baseline inflation measured by GDP deflator with the Consumer Price inflation measured by Consumer Price Index (CPI) to account for

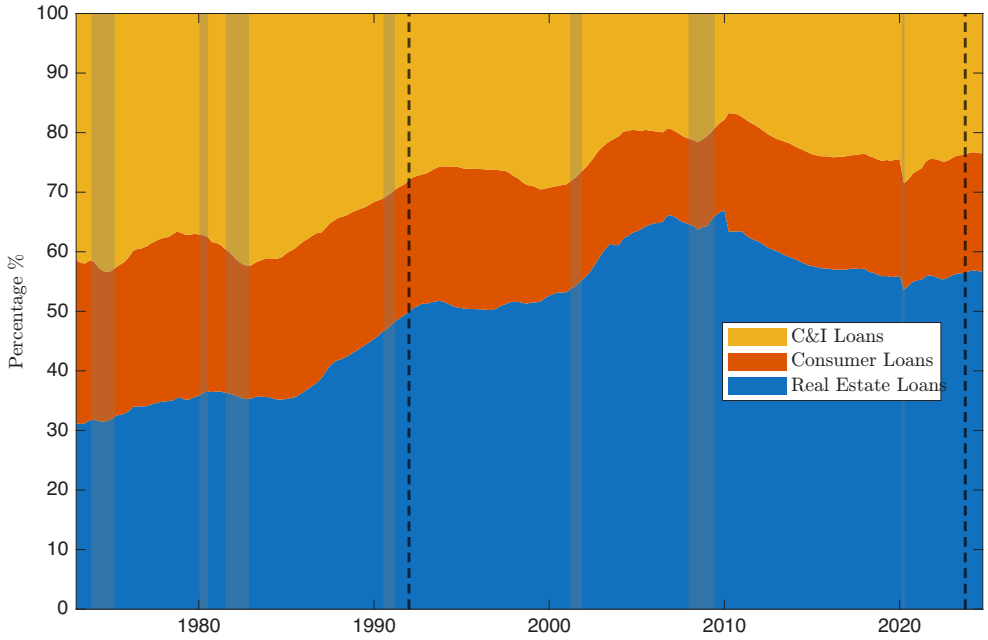


Figure 9: Composition of core loans outstanding for DCC banks

consumption good prices. Additionally, I include Production Price inflation, measured by the Production Price Index (PPI) and Home Price inflation, measured by the S&P CoreLogic Case-Shiller Home Price Index. Figure 10 presents only the results of each loan category for convenience, and variables from baseline model present robust results compared to before.

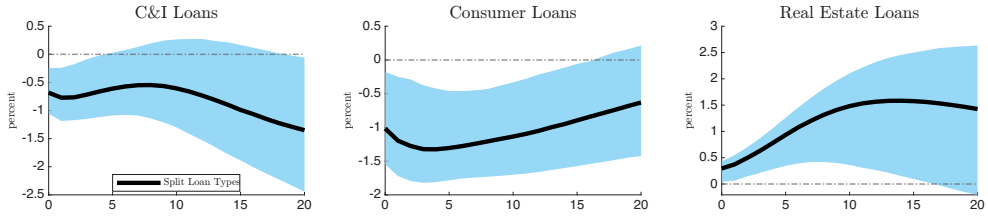


Figure 10: IRF of variables to a credit supply news shock, loan categories

Loan results present quite interesting features. Real estate loans, which are typically with long-term contracts in nature, increase steadily and persistently after the shock. This behavior is consistent with the interpretation that firms and households, anticipating tighter lending standards or higher future borrowing costs, preemptively lock in long-term credit conditions that are favorable at present. In other words, the credit supply news shock induces a form of strategic intertemporal borrowing, where agents move forward long-horizon debt issuance to benefit from relatively favorable terms before the expected tightening takes place. Such interpretation is further supported by the fact that real estate loans are typically with fixed term rate.

The response of shorter-term loan categories - namely C&I loans and consumer loans

- is even more interesting, that both exhibit a decline after the shock. Such heterogeneous responses compared to longer-term loans likely reflect the role of uncertainty and forward-looking caution: even though current lending standards remain favorable, firms and households may choose to delay or downsize short-term borrowing to avoid rollover risk or higher refinancing costs, especially when long-term credit is still accessible. Such argument is supported by the fact that terms for short run loans, unlike real estate loans, are usually float rates.

Overall, patterns from Figure 10 suggest that the temporary boom observed in earlier sections is not driven uniformly across all lending categories. Instead, it reflects a shift in borrowing behavior toward long-term credit instruments, supporting the narrative that expectations of future constraints induce agents to secure financing with longer maturities, while short-term lending dynamics remain more cautious. It might also suggest a preference of loans to borrow when the news shock hits, or a pattern of loan substitution. Responses of three loan categories, given that longer term loans dominate aggregate core loans, together contribute to the increases in core loans in baseline results. This asymmetric response across loan maturities deepens the understanding of how credit anticipations shape both financial flows and real activity in the short run.

Sensitivity Analyses. I run several simple robustness checks and extensions here. First, the S&P CoreLogic Case-Shiller Home Price Index, or its real version from Robert Shiller, is a commonly used index to measure residential real estate prices. While it's not a perfect measure for the analyses, as it does not account for CRE prices, such index is still informative to real estate prices in general. To address this concern, I replace HPI inflation with the inflation measured by the Commercial Property Price Index (CPPI) from Bank for International Settlements (BIS). Figure C.21 presents the result which turns out to be highly robust.

Second, while the data for CRE and RRE loans spans from 2004:III, I further split real estate loans into CRE and RRE loans. Similar to previous strategies for smaller samples, I revise the horizon to 12 quarters. Figure C.22 presents the results. Most results are robust to Figure 10, while the HPI price level is somewhat deflationary in short run. The decomposition of CRE and RRE loans further implies that RRE loans have a greater increase than CRE, showing a stronger responses from households than from firms. This behavior may reflect both greater rate sensitivity in mortgage markets and more acute exposure to credit access among households compared to commercial borrowers. The pre-Covid sample check is not stable, probably due to larger dimension of coefficients and smaller sample range.

Third, given that Cavallo et al. (2024b) provide credit supply indicators for each major loan categories, it allows me to further ask the question on whether loan responses are

different from credit tightening news within each loan sector. To answer this question, the most straightforward approach is just to replace aggregate CSI series with those to each loan category. Figure C.23 to C.26 present the results, which present further heterogeneous responses from credit tightening news from each loan category. First, responses of variables from baseline are again qualitatively consistent to baseline results. Second, real estate credit tightening news - both commercial and residential - generates consistent patterns of increased real estate loans and decreased/muted short term loans, which are similar to Figure 10. On the other hand, credit tightening news from C&I loans triggers significant increases in real estate borrowing, which further enhances the argument of a strategic shift toward secured, long-term financing when anticipating commercial credit restrictions. Credit tightening news from consumer loans shows more limited effects, suggesting greater segmentation in household lending markets than others. These patterns, while clearly showing heterogeneity, further reinforce the main findings in this section.

5.2 Euro-Area Evidence

In this section, I discuss the evidence from European area. Similar to SLOOS survey conducted by U.S. Fed, the European Central Bank (ECB) has been running the Bank Lending Survey (BLS) from 2003[15], which allows me to run similar methodologies to baseline U.S. case and examine if the credit supply news shock in Europe shares similar features.

Euro-area Data Source and Estimation. To begin with, the European BLS survey asks a similar question to U.S. SLOOS survey,

"*Over the past three months, how have your bank's credit standards as applied to the approval of loans or credit lines to X changed?*"

where the two major groups of loans are those to enterprises and households, and loans to households can be further split by consumer credit and loans to house purchases. Answers are categorized in a similar manner to SLOOS survey, that respondent banks can reply "tightened considerably", "tightened somewhat", "remained basically unchanged", "eased somewhat" and "eased considerably". Two indices are constructed based on answers. The first is net percentage index, which is similar to the net percentage index from SLOOS survey. The second is diffusion index, which weights answers with "somewhat" and "considerably"

[15]For more details of Euro-area BLS survey can be found in https://www.ecb.europa.eu/stats/ecb_surveys/bank_lending_survey/html/index.en.html#about. Specifically, it is conducted in a similar way to U.S. SLOOS survey. The respondents are senior loan officers from around 150 institutions representing all Euro-area countries.

by 0.5 and 1. In the baseline analyses, I use diffusion index to better capture aggregate changes.

The diffusion indices are constructed to each of three key loan categories in Europe: loans made to euro-area non-financial corporations (NFC), credit for consumption and lending for house purchases from households. These three categories are considered as counterparts of C&I loans, consumer loans and RRE loans in the U.S. There seems no proper data for CRE loans. According to user guide of BLS survey, bank-level responses are aggregated in two steps. First, bank replies are aggregated into national level with an equal weight, and second, national replies are aggregated using weights of national shares of loans to each category. Based on these calculations, I further aggregate diffusion indices to a Euro-area diffusion index, where I use the share of each loan outstanding in total loans in Euro area as weights. In previous literature, both concurrent weights (e.g., Kurtzman et al. (2020)) and weights lagging one quarter (e.g., Bassett et al. (2014)) are used, and I use the latter version for baseline. The former version is presented in Appendix C.2.

One thing to mention for the usage of raw diffusion index is that, similar to the construction of CSI series in the U.S. SLOOS survey, the information of respondent banks in Europe from BLS survey is confidential, so that I cannot replicate the approach to obtain orthogonal components from bank-level panel regressions. Previous literature has some contributions on this in Euro area and United Kingdom, e.g. Altavilla et al. (2019) and Will Banks et al. (2024), but their sample periods are too short to extract news shocks. In the sensitivity analyses of U.S. case, I have shown that using raw lending standard indices yield robust results, which justifies the usage of raw indices in the Euro case.

Similar to construction of U.S. variables, I take the cumulative version of Euro-area diffusion index as a proxy for lending standard level in Europe. As for other variables, due to a quite small range of sample, I consider a six-variable VAR model, which includes lending standard, real output, inflation, core loans outstanding, high-yield spread and interest rate, in line with the baseline setting in Broadbent et al. (2024) and Bassett et al. (2014). Specifically, inflation is the log-difference (times 100) of GDP deflator, core loans outstanding in the Euro area is defined as the summation of loans to NFCs, consumer credit and house purchases, high-yield spread is a spread from ICE BofA Euro High Yield Index where portfolios included have a below investment grade rating. Such selection is consistent with the Euro-area evidence from Jarociński and Karadi (2020) who use BBB bond spreads as counterparts of GZ spreads/EBP in the U.S. Interest rate is constructed by combining both EONIA and new short-term rates. Details of construction of these variables can be found in Appendix A.2.

The sample period is from 2005:I to 2023:IV, where the beginning time is from the data availability, and the ending time is to match U.S. sample period. Similar to U.S. case,

variables are entered with 100 times log-levels, except those stationary or percentage ones. The lag order is decided by BIC which yields $p = 2$. I choose a smaller horizon $H = 12$, i.e., up to 3 years to extract the news shock, simply due to a short sample periods with only about 76 observations. Replications are from 10,000 MCMC draws. Besides these, the estimation of VAR model as well as identifications is similar to U.S. case.

Baseline Results. Figure 11 and 12 present responses of variables to a credit supply surprise shock and news shock. One key observation is that results are quite similar to those from U.S. case. Specifically, responses from a surprise shock present a clear credit crunch with an easing in monetary stances, except that inflation remains insignificant, which is consistent with baseline inflation results. Such results are consistent with literature studying European credit supply shocks, e.g., Barauskaitė et al. (2022) and Altavilla et al. (2019), who find that a credit tightening surprise will cause decreases in output, price levels, loans and interest rates, as well as increases in high-yield spread.

On the other hand, following a Euro-area credit supply news shock, responses are generally similar to those using raw U.S. lending standard index presented in Figure C.1, except that the tightened lending standard and booming period are more persistent. These results reveal nuanced dynamics that support the preemptive borrowing hypothesis while highlighting important cross-country differences. Overall, even with raw bank lending indices, European results provide compelling evidence that credit supply news shocks operate through similar mechanisms across different national and institutional contexts.

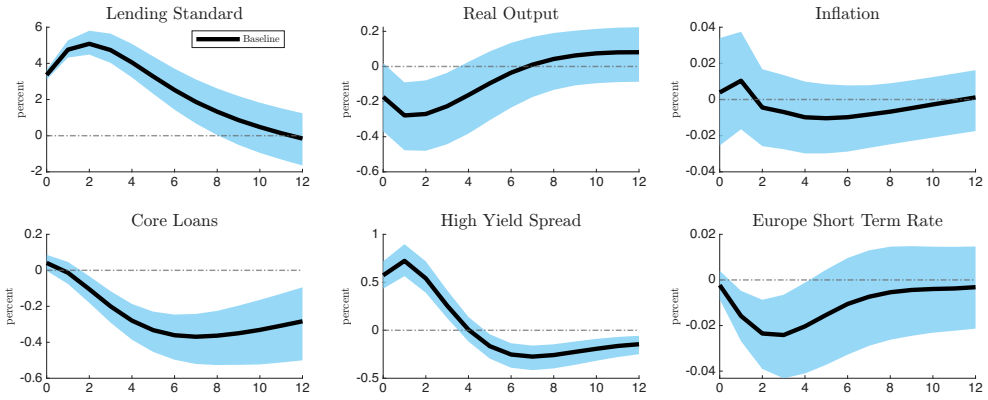


Figure 11: IRFs of variables to a Euro-area credit supply surprise shock

Sensitivity Analyses. To examine the robustness of Euro-area results, I perform several simple tests. First, I check the pre-Covid sample, presented in Figure C.27. A noteworthy observation is that the pre-Covid sample results are even more closed to U.S. case, that a

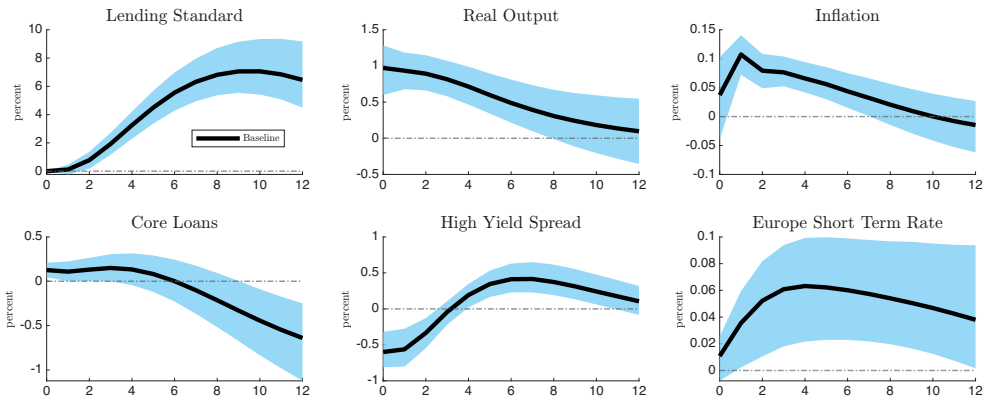


Figure 12: IRFs of variables to a Euro-area credit supply news shock

temporary booming feature follows by a bust-period. Responses from lending standard is also more closed to U.S. case, that it has a quite short persistence. Overall, pre-Covid sample results turn out to be generally robust.

Second, I examine whether baseline results are robust to alternative measurements. For lending standard, I use net percentage index to construct the lending standard level, and results are presented in Figure C.28. Also, I use the concurrent share of loans to aggregate loan-specific diffusion indices, and results are presented in Figure C.29. Moreover, I replace several key variables in the VAR model. Specifically, I replace the real output by Industrial Production, inflation by the one using Harmonized Index of Consumer Prices (HICP), and interest rate with Euro-area deposit facility rate. Results are presented in Figure C.30. These results imply that they are not sensitive to alternative measurements in general.

5.3 Counterfactual Monetary Policy Rule

In this section, I revisit the previous discussion on reactions of monetary policies to the credit supply news shock. The goal of this section is to impose one related question: Should central bank react to the news shock which triggers a short-run economic expansion? This section would provide some suggestive answers.

To answer this question, an intuitive approach is to derive proper structural models and examine reactions from real economies by setting up different monetary policy rules. However, the methodology introduced from McKay and Wolf (2023) provides a more convenient way to obtain counterfactual policy rules empirically. Specifically, given a target shock, their approach is to first obtain several well-established monetary policy shocks, and use them to derive IRFs to the target shock under a counterfactual monetary policy rule. Such approach aims to obtain a set of weights assigned to each monetary policy shock, which

has a closed-form solution in their online appendix,

$$\begin{aligned}\boldsymbol{s} = &- \left[(\tilde{\mathcal{A}}_x\Omega_{x,\mathcal{A}} + \tilde{\mathcal{A}}_z\Omega_{z,\mathcal{A}})'(\tilde{\mathcal{A}}_x\Omega_{x,\mathcal{A}} + \tilde{\mathcal{A}}_z\Omega_{z,\mathcal{A}})\right]^{-1} \\ &\times \left[(\tilde{\mathcal{A}}_x\Omega_{x,\mathcal{A}} + \tilde{\mathcal{A}}_z\Omega_{z,\mathcal{A}})'(\tilde{\mathcal{A}}_x\boldsymbol{x}_{\mathcal{A}}(\boldsymbol{\varepsilon}) + \tilde{\mathcal{A}}_z\boldsymbol{z}_{\mathcal{A}}(\boldsymbol{\varepsilon}))\right]\end{aligned}$$

where mappings $\tilde{\mathcal{A}}$s are target counterfactual monetary policy rules, Ωs are IRFs from multiple monetary policy shocks, and $\boldsymbol{x}, \boldsymbol{z}$s are IRFs from the target shock. A side notice for this approach is that it might not be as informative as counterfactual rules from full structural models, but it is able to provide insights of economic behavior under different policy rules.

Shock Series and Estimation. I consider four monetary policy shocks obtained in previous literature, which are used and obtained directly by replication packages of McKay and Wolf (2023). These four shocks are from Gertler and Karadi (2015), Romer and Romer (2004), Auroba and Drechsel (2024) and Miranda-Agrippino and Ricco (2021). For Romer and Romer shock, I use an updated version extended by Miguel Acosta[16]. The shock series span over different sample periods, presented in Table 3.

Table 3: Summary of various monetary policy shocks

Relevant Literature	Sample Range	Data Source
Gertler and Karadi (2015)	1988:IV - 2012:II	Replication file by McKay and Wolf (2023)
Romer and Romer (2004)	1969:I - 2018:IV	Replication file by Miguel Acosta website
Auroba and Drechsel (2024)	1982:IV - 2008:III	Replication file by McKay and Wolf (2023)
Miranda-Agrippino and Ricco (2021)	1980:I - 2014:IV	Replication file by McKay and Wolf (2023)

I choose the estimation sample from 1992:I to 2019:IV, i.e., the pre-Covid sample with two reasons. First, for missing values of these shocks, I follow Känzig (2021) to assign zero. The S. Boragan and Drechsel (AD, 2024) shocks have limited number of samples concerning my baseline range, so I choose not to expand the sample to 2023:IV as in my baseline here. In the later sensitivity analyses, I drop the AD shock to address concerns on too many censored zero values[17]. Second, some of these four shocks, similar to the shock from Bauer and Swanson (2023) in Sensitivity Analyses, do not perform reasonable results in the full baseline sample. Specifically, the rise of interest rate leads to rises in output and inflation when using full baseline sample, while pre-Covid samples show more reasonable outcomes.

[16]The updated RR shocks are available from the website of Miguel Acosta at https://github.com/miguel-acosta/RomerRomer2004.

[17]One might still be concerned on the limited sample periods of some shocks, e.g., the RR and AD shocks. However, in McKay and Wolf (2023) when their baseline result uses GK shocks, they assign zeros to almost half of their sample ranges for GK shocks. Therefore, the zeros assigned here in my case should be justified.

I reproduce impulse responses by closely following approaches in McKay and Wolf (2023). First for IRFs from credit supply news shock, I take the median shock series from baseline and put it in the first position in a recursive VAR setting. For IRFs from monetary policy shocks, I use the same settings mentioned in appendix of McKay and Wolf (2023) that federal fund rate is placed at the last position, persistent shocks are placed at first position and transitory shocks are placed second to last before federal fund rate. I do the exact two groups of shock identifications as in Mckay and Wolf, that the first group contains GK and RR shocks, and the second group contains AD and MAR shocks, as in their appendix.

The reason to jointly identify monetary policy shocks, as argued in their paper, is to jointly estimate uncertainties. I choose more shocks than two with the reason that, as argued by the theoretical part in their paper, more shocks are helpful to approximate target counterfactual rules, which is verified in my baseline result to be presented later. In the sensitivity analyses, I follow the standard approach as in McKay and Wolf paper by allowing only two shocks at each time. To address potential concerns for joint uncertainties, I fix all other settings when obtaining IRFs to these shocks. Specifically, I fix the sample period and lag order $p = 2$ across different shocks. In order to estimate responses under counterfactual policy rule, I fix the OLS estimate of responses to news shock. Lastly, when calculating weight $\boldsymbol{s}$, I use the same horizon $h = 100$ as in Mckay and Wolf for solutions.

Results from Interest Rate Peg. To answer the question at the beginning, the target counterfactual policy rule is interest rate peg, i.e., central bank has muted response to the news shock. Figure 13 presents corresponding results, where black lines are baseline IRFs from the news shock, green dashed lines are baseline IRFs from OLS estimates at the posterior mode[18] (the 'baseline' rule), and red dashed lines are IRFs to the news shock under rule of interest rate peg. Confidence bands are constructed using 10,000 MCMC replications as before, where the shadow and light grey area are 68% confidence bands.

The red dashed lines are what McKay and Wolf call the "best approximation" of counterfactual policy rules using available monetary policy shocks. The first observation from results is that the approximation is interest rate peg performs quite well. The red dash line for federal fund rate clearly mimics the muted response of policy rate. Such result supports the theoretical results from McKay and Wolf (2023) and provides better approximations in their baselines[19].

[18] McKay and Wolf (2023) fix the OLS estimate at posterior mode for baseline IRFs before constructing counterfactual rules. An obvious feature from the figure is that OLS lines are closely identical to median IRFs in baseline, which is from the fact that posterior distributions for VAR coefficients follow normality.

[19] In the online appendix of their paper, authors argue that with only two monetary policy shocks, the rule of interest rate peg is not spanned well. In my baseline result here, it turns out to be clear that more shocks indeed provide more accurate approximations. A side note for the joint estimation of MP shocks is that, if

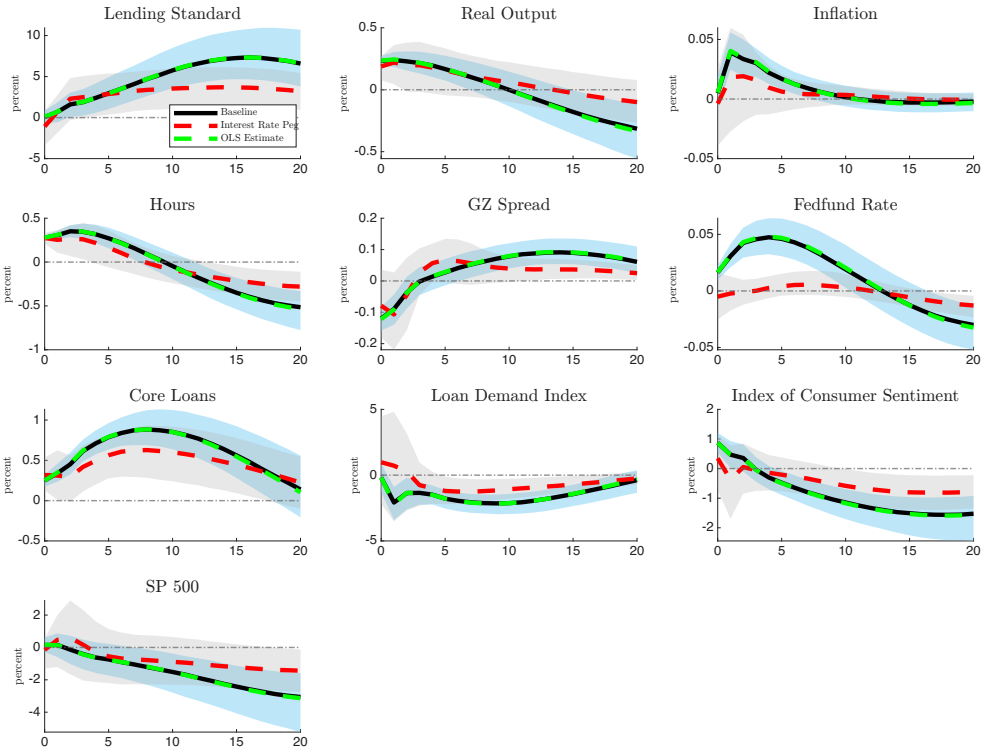


Figure 13: IRFs of variables to a credit supply news shock under interest rate peg

Turning to responses from real economies to the news shock under interest rate peg, a pronounced feature from results is that the hike of interest rate in the baseline rule tends to amplify the bust cycle in the medium run. To see this, first, the lending standard under baseline rule is tighter in the medium run than under interest rate peg, revealing the effect of monetary policies to bank decisions. This pro-cyclical response suggests that monetary policy may inadvertently validate and reinforce the negative credit expectations embedded in the original news shock.

Second, responses from real economies, e.g., real output and hours, indicate that monetary policies do not affect much on the temporary boom periods, but have substantial effects in the medium run when economy turns in the bust period. During the initial quarters following the credit news shock, both policy scenarios produce nearly identical real outcomes, suggesting that the rush-to-borrow behavior and immediate credit market adjustments dominate any interest rate effects. However, as the economy transitions into the bust phase, meaningful differences emerge. Specifically, without the hike of policy rate, bust reactions in the medium run are somewhat dampened, with real output declining less severely and employment showing more resilience. Inflation, however, does not show much difference under interest rate peg.

one can fix all other settings, separately obtaining IRFs from each MP shock should not be a concern for joint uncertainties.

This delayed but amplifying effect of monetary policy appears to operate through the interaction between systematic rate increases and banks' credit allocation decisions. While borrowers during the boom phase are relatively insensitive to modest rate changes due to their urgency to secure financing, the cumulative effect of higher rates compounds the natural credit tightening process, creating deeper contractions than would occur under no interventions of monetary policies. The interest rate peg, by avoiding this pro-cyclical amplification, allows the natural self-stabilizing forces in credit markets to operate more smoothly. Results from GZ spread and the last four variables at the end are generally consistent with those from real economic variables, showing that financial market indicators, consumer sentiment, and credit aggregates all exhibit similar patterns of limited immediate sensitivity but medium-term amplification to bust cycles under activist monetary policy. The only potentially puzzling response might come from core loans, that without interest rate hikes, the loan volumes decrease a small amount.

While two policy rules present differences in the median run, the magnitude differences of these effects are modest and limited. This limited transmission suggests that credit supply news shocks operate primarily through direct channels that are relatively insensitive to short-term interest rate adjustments. Several explanations may account for this limited effectiveness. First for the boom period, the rush-to-borrow behavior induced by credit tightening news creates interest-rate inelastic demand, as firms and households prioritize securing financing before anticipated restrictions take effect rather than responding to current funding costs. Second for the bust period, bank lending decisions during these episodes appear driven more by risk assessment and expected regulatory constraints than by marginal funding cost changes of a few basis points.

Sensitivity Analyses. I perform several robustness tests to the baseline result. First, I exclude the AD shock to address concerns on censored zeros, and results are presented in Figure C.31. Second, I include two identified monetary policy shocks in Section 5.1, namely monetary policy shocks from Jarociński and Karadi (2020) and Bauer and Swanson (2023). For the former one, I assign zeros to missing values of instruments in order to match the identical setting here. Results are presented in C.32. Both figures show similar trends to baseline results.

In Figure C.33 and C.34, I apply the standard approach as in McKay and Wolf (2023), where GK and RR shocks as well as AD and MAR shocks are used separately. The effect of interest rate peg is clearly dampened in this case, which again matches the discussion that mere two shocks may not span well on the space of monetary stances when one considers interest rate peg.

Policy Implications. The findings reveal that systematic monetary policy responses during credit supply news episodes may modestly amplify rather than stabilize economic fluctuations. The comparison between baseline policy and interest rate peg counterfactuals shows that federal fund rate increases during the boom phase — though intended to cool overheating — actually reinforce emerging credit restrictions and amplify subsequent contractions. This pattern reflects a fundamental timing mismatch: systematic tightening arrives precisely when credit conditions are already beginning to deteriorate, validating rather than offsetting negative credit expectations. Banks observing both credit tightening news and Fed rate increases interpret the policy response as official confirmation of worsening conditions, leading to more restrictive lending standard adjustments than would occur from credit news alone.

These results support a policy approach emphasizing strategic restraint rather than activist stabilization during credit supply disruptions. Credit supply disruptions require fundamentally different policy instruments than those effective for demand or inflation management. The evidence argues for institutional separation between conventional monetary policies which focus on price stability and aggregate demand management, and macroprudential policy designed to address credit supply dynamics directly. This separation reflects not merely the limited effectiveness of monetary tools during credit episodes, but more importantly the risk that systematic policy activism may inadvertently amplify the very fluctuations it aims to stabilize.

6 Conclusion

In this paper, I identify and analyze credit supply news shocks, which are anticipated future changes in lending conditions as a novel driver of macroeconomic fluctuations. Using Bayesian VAR with max-share identification methods on U.S. data from 1992-2023, this study provides the first explicit empirical characterization of how forward-looking credit market expectations shape economic dynamics.

The empirical evidence reveals a striking asymmetry between credit supply news and surprise shocks. While conventional surprise shocks generate immediate contractions in output, employment, and credit volumes, news shocks in credit supplies produce a median-run boom-bust cycle. When agents receive credible signals about future credit tightening, the economy experiences a short-run expansion lasting 6-10 quarters before transitioning into a contraction as anticipated restrictions materialize. This pattern reflects preemptive borrowing behavior: borrowers strategically accelerate financing decisions to lock in favorable terms before realized tightening.

Heterogeneous loan responses strongly support this mechanism, where long-term real estate loans increase substantially while short-term commercial loans decline, demonstrat-

ing that agents prioritize securing long-duration financing when expecting future credit constraints. Besides, credit supply news shocks account for approximately 20% of output volatility, and the shocks maintain distinctiveness from those established macroeconomic shocks. These findings establish credit supply news as an important but previously unrecognized source of economic fluctuations.

The findings evidence reveals interesting policy implications. The counterfactual analyses argue for institutional separation between conventional monetary policy and macroprudential tools designed to address credit supply dynamics directly. Policymakers should monitor forward-looking indicators of credit supply such as bank guidance and supervisory tone, rather than relying solely on contemporaneous measures that may lead to misinterpreting short-run expansions as demand-driven overheating.

Several avenues for future research emerge from these analyses. First, formal theoretical framworks of structrual models would clarify conditions under which preemptive borrowing dominates alternative mechanisms. Second, micro-level empricial anlyses using loan-level data from Dealscan around specific regulatory announcements like Basel III would complement the aggregate evidence. Finally, high-frequency identification approaches could provide additional validation of the news shock identification.

References

Altavilla, Carlo, Matthieu Darracq Pariès, and Giulio Nicoletti, "Loan supply, credit markets and the euro area financial crisis," *Journal of Banking & Finance*, December 2019, *109*, 105658. Publisher: Elsevier BV.

Angeletos, George-Marios, Fabrice Collard, and Harris Dellas, "Business-Cycle Anatomy," *American Economic Review*, October 2020, *110* (10), 3030–3070.

Auroba, S. Boragan and Thomas Drechsel, "Identifying Monetary Policy Shocks: A Natural Language Approach," November 2024.

Barauskaitė, Kristina, Anh D.M. Nguyen, Linda Rousová, and Lorenzo Cappiello, "The Impact of Credit Supply Shocks in the Euro Area: Market-Based Financing Versus Loans," *SSRN Electronic Journal*, 2022.

Barsky, Robert B. and Eric R. Sims, "News shocks and business cycles," *Journal of Monetary Economics*, April 2011, *58* (3), 273–289. Publisher: Elsevier BV.

_ and _, "Information, Animal Spirits, and the Meaning of Innovations in Consumer Confidence," *American Economic Review*, June 2012, *102* (4), 1343–1377. Publisher: American Economic Association.

_ , Susanto Basu, and Keyoung Lee, "Whither News Shocks?," *NBER Macroeconomics Annual*, 2015, pp. 225–264.

Bassett, William F., Mary Beth Chosak, John C. Driscoll, and Egon Zakrajšek, "Changes in bank lending standards and the macroeconomy," *Journal of Monetary Economics*, March 2014, *62*, 23–40. Publisher: Elsevier BV.

Bauer, Michael D. and Eric T. Swanson, "A Reassessment of Monetary Policy Surprises and High-Frequency Identification," *NBER Macroeconomic Annual*, 2023.

Beaudry, Paul and Franck Portier, "Stock Prices, News, and Economic Fluctuations," *American Economic Review*, September 2006, *96* (4), 1293–1307.

Boeck, Maximilian and Thomas O. Zörner, "The Impact of Credit Market Sentiment Shocks," *Journal of Money, Credit and Banking*, October 2024, *56* (7), 1645–1673. Publisher: Wiley.

Broadbent, Elijah, Huberto Ennis, Tyler Pike, and Horacio Sapriza, "Bank Lending Standards and the U.S. Economy," *Federal Reserve Bank of Richmond Working Papers*, August 2024, *24* (07), 1–74. Publisher: Federal Reserve Bank of Richmond.

Cascaldi-Garcia, Danilo and Ana Beatriz Galvao, "News and Uncertainty Shocks," *Journal of Money, Credit and Banking*, June 2021, *53* (4), 779–811. Publisher: Wiley.

Cavallo, Michele, Juan Morelli, and Rebecca Zarutskie, "Unpacking the Effects of Bank Credit Supply Shocks on Economic Activity," *FEDS Notes*, May 2024, (2024-05-24-2), None–None. Publisher: Board of Governors of the Federal Reserve System.

_ , _ , _ , and Solveig Baylor, "Measuring Bank Credit Supply Shocks Using the Senior Loan Officer Survey," *FEDS Notes*, May 2024, (2024-05-24-1), None–None. Publisher: Board of Governors of the Federal Reserve System.

Doan, Thomas, Robert Litterman, and Christopher Sims, "Forecasting and conditional projection using realistic prior distributions," *Econometric Reviews*, January 1984, *3* (1), 1–100. Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/07474938408800053.

Francis, Neville, Michael T. Owyang, Jennifer E. Roush, and Riccardo DiCecio, "A Flexible Finite-Horizon Alternative to Long-Run Restrictions with an Application to Technology Shocks," *Review of Economics and Statistics*, October 2014, *96* (4), 638–647. Publisher: MIT Press - Journals.

Gertler, Mark and Peter Karadi, "Monetary Policy Surprises, Credit Costs, and Economic Activity," *American Economic Journal: Macroeconomics*, January 2015, *7* (1), 44–76.

Giannone, Domenico, Michele Lenza, and Giorgio E. Primiceri, "Prior Selection for Vector Autoregressions," *Review of Economics and Statistics*, May 2015, *97* (2), 436–451. Publisher: MIT Press - Journals.

Gilchrist, Simon and Egon Zakrajšek, "Credit Spreads and Business Cycle Fluctuations," *American Economic Review*, June 2012, *102* (4), 1692–1720.

Görtz, Christoph, John D. Tsoukalas, and Francesco Zanetti, "News Shocks under Financial Frictions," *American Economic Journal: Macroeconomics*, October 2022, *14* (4), 210–243. Publisher: American Economic Association.

Hviid, Simon Juul and Christofer Schroeder, "Real Effects of Credit Supply Shocks: Evidence from Danish Banks, Firms, and Workers," *SSRN Electronic Journal*, 2024. Publisher: Elsevier BV.

Jarociński, Marek and Peter Karadi, "Deconstructing Monetary Policy Surprises— The Role of Information Shocks," *American Economic Journal: Macroeconomics*, April 2020, *12* (2), 1–43. Publisher: American Economic Association.

Kilian, Lutz, "Small-sample Confidence Intervals for Impulse Response Functions," *Review of Economics and Statistics*, May 1998, *80* (2), 218–230.

Kurmann, André and Eric Sims, "Revisions in Utilization-Adjusted TFP and Robust Identification of News Shocks," *The Review of Economics and Statistics*, May 2021, *103* (2), 216–235. Publisher: MIT Press - Journals.

Kurtzman, Robert, Rebecca Zarutskie, and David Glancy, "An Aggregate View of Bank Lending Standards and Demand," *FEDS Notes*, May 2020, *2020.0* (2546). Publisher: Board of Governors of the Federal Reserve System.

Känzig, Diego R., "The Macroeconomic Effects of Oil Supply News: Evidence from OPEC Announcements," *American Economic Review*, April 2021, *111* (4), 1092–1125.

_ **and Charles Williamson**, "Unraveling the Drivers of Energy-Saving Technical Change," *SSRN Electronic Journal*, 2024. Publisher: Elsevier BV.

López-Salido, David, Jeremy C. Stein, and Egon Zakrajšek, "Credit-Market Sentiment and the Business Cycle," *The Quarterly Journal of Economics*, August 2017, *132* (3), 1373–1426. Publisher: Oxford University Press (OUP).

McCracken, Michael W. and Serena Ng, "FRED-MD: A Monthly Database for Macroeconomic Research," *Journal of Business & Economic Statistics*, October 2016, *34* (4), 574–589. Publisher: ASA Website _eprint: https://doi.org/10.1080/07350015.2015.1086655.

McKay, Alisdair and Christian K. Wolf, "What Can Time-Series Regressions Tell Us About Policy Counterfactuals?," *Econometrica*, 2023, *91* (5), 1695–1725. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.3982/ECTA21045.

Miranda-Agrippino, Silvia and Giovanni Ricco, "The Transmission of Monetary Policy Shocks," *American Economic Journal: Macroeconomics*, July 2021, *13* (3), 74–107.

Ottonello, Pablo and Wenting Song, "Financial Intermediaries and the Macroeconomy: Evidence from a High-Frequency Identification," *Economic Journal*, October 2024, *Forthcoming.*

Romer, Christina D and David H Romer, "A New Measure of Monetary Shocks: Derivation and Implications," *American Economic Review*, September 2004, *94* (4), 1055–1084.

Uhlig, Harald, "What moves GNP?," Econometric Society 2004 North American Winter Meetings 636, Econometric Society August 2004.

Will Banks, Kunal Khairnar, and Inderjit Sian, "Identifying (un)warranted tightening in credit supply," October 2024.

Wu, Jing Cynthia and Fan Dora Xia, "Measuring the Macroeconomic Impact of Monetary Policy at the Zero Lower Bound," *Journal of Money, Credit and Banking*, 2016, *48* (2-3), 253–291. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jmcb.12300.

Zeev, Nadav Ben and Hashmat Khan, "Investment-Specific News Shocks and U.S. Business Cycles," *Journal of Money, Credit and Banking*, October 2015, *47* (7), 1443–1464. Publisher: Wiley.

Appendices

A Data Sources and Construction

A.1 U.S. Dataset

In this section, I mainly describe the data sources used in the paper to complement the discussions in Section 3.1. I divide the description into those in the major (baseline and extension) models, as well as those variables used for sensitivity analyses. Table A.1 presents original data series used in baseline models.

Table A.1: Data Series used for major models

Series Name	Units	Fred Code	Frequency	Source
Credit Supply Indicator	Percent		Quarter	Cavallo et al. (2024b)
Gross Domestic Product	Billion $, SA, CP	GDP	Quarter	Fred
Gross Domestic Product: Implicit Price Deflator	Index 2017 = 100, SA	GDPDEF	Quarter	Fred
Producer Price Index by Commodity: All Commodities	Index 1982 = 100, NSA	PPIACO	Month	Fred
S&P CoreLogic Case-Shiller Home Price Index	Index Jan 2000 = 100, SA	CSUSHPISA	Month	Fred
Nonfarm Business Sector: Hours Worked for All Workers	Index 2017 = 100, SA	HOANBS	Quarter	Fred
Population Level	Thousands Person, NSA	CNP16OV	Month	Fred
GZ Spread	Percent		Month	Gilchrist and Zakrajšek (2012)
Federal Funds Effective Rate	Percent, NSA	FEDFUNDS	Month	Fred
Loans and Leases in Bank Credit, DCC Banks	Billion $, SA, CP	LLBDCBW027SBOG	Week	Fred
Other Loans and Leases, DCC Banks	Billion $, SA, CP	AOLDCBW027SBOG	Week	Fred
Commercial and Industrial Loans, DCC Banks	Billion $, SA, CP	CILDCBW027SBOG	Week	Fred
Consumer Loans, DCC Banks	Billion $, SA, CP	CLSDCBW027SBOG	Week	Fred
Real Estate Loans, DCC Banks	Billion $, SA, CP	RELDCBW027SBOG	Week	Fred
Loan Demand Index	Percent		Quarter	Cavallo et al. (2024b)
S&P 500 Index	Index Point		Month	Robert J. Shiller Website
Index of Consumer Sentiment	Index point		Month	Surveys of Consumers, UMichigan
TFP utilization adjusted	Index Point		Quarter	San Francisco Fed

Note: Sample period is from 1992:I to 2023:IV. '(N)SA' means (not) seasonally adjusted, 'CP' means current price, 'DCC Banks' means Domestically Chartered Commercial Banks.

Most variables are retrieved from Federal Reserve of St. Louis (Fred hereafter) which are linked to multiple original sources like BEA and BLS, while some others come from previous literature, individual calculations, or survey data[1]. The frequency used in this paper is quarterly throughout, and those series with higher frequency are taken quarterly averages. Current-price variables and S&P 500 Index (following the setting of Görtz et al. (2022)) are deflated by GDP Implicit Price Deflator, and aggregate variables are taken per-capita form by dividing Population Level (in the Million person unit). Variables are entered in 100 times log level except those that are in percentage or stationary. Price indices are entered in the 100 times log-difference form. Therefore, the impulse responses are in the unit of percentage change from zero.

[1]Up-to-date series of GZ Spread and Excess Bond Premium are available at Favara et al. (2016), or directly from https://www.federalreserve.gov/econres/notes/feds-notes/ebp_csv.csv. The S&P 500 Index data is available at https://shillerdata.com/. The Index of Consumer Sentiment and other related series from UMichigan Survey are available at https://data.sca.isr.umich.edu/. TFP data is available from https://www.frbsf.org/research-and-insights/data-and-indicators/total-factor-productivity-tfp/.

Below I describe the constructed variables. The key target variable, Lending Standard, is defined as the cumulative version of the Credit Supply Indicator throughout sample period. The CSI series is obtained from the accessible version of Figure 3 in Cavallo et al. (2024b)[2]. Inflation is defined as 100 times log-difference of GDP deflator. Inflation from other price indices is constructed in similar ways. Nominal Core Loans for Domestically Chartered Commercial Banks is defined as Loans and Leases in Bank Credit minus All Other Loans and Leases from H.8 releases of Federal Reserve Board, which then consists of three major core loan types: Commercial and Industrial Loans, Consumer Loans and Real Estate Loans[3]. TFP is the cumulative version of `dtfp_util` variable in the original dataset divided by 4, which presents a 100 times log TFP series, matching with other variable transformations. The effective federal fund rate, after its transformation of quarterly average, is divided by 4 to match quarterly frequency. Other policy rate measures for sensitivity analyses like one-year bond rate and shadow federal fund rate are transformed in a similar way.

A minor issue for the timing of SLOOS survey is that, normally the releases of SLOOS results correspond to the changes of lending standard and loan demand in the previous quarter, where the label of quarters might sometimes present discrepancy in the previous literature. For example, the Demand Index in Figure 1 of Cavallo et al. (2024b) is exactly one quarter earlier to the Demand Index in Figure 6 of Kurtzman et al. (2020), implying that the former one measures changes within the quarter that align with when the economic changes actually occurred, while the latter one uses survey-date timing that reflects when the survey outcome was released. While the latter one is published in Fred (SUBLPDMOSXWBNQ for lending standard and SUBLPDMODXWBNQ for demand), I choose the series in Cavallo et al. (2024b) to ensure quarter labels match the timing index of other variables that represents within-quarter measures. To further address the concern that the baseline CSI and Loan Demand Index might reflect the changes one quarter earlier, and to match the timing in Kurtzman et al. (2020), I lead and lag two series for one quarter and result is highly robust.

To better illustrate time path of major variables, Figure A.1 presents the time series of variables in the baseline model, after transformations described above. The red dashed line is period 2020:I. Shadow areas are NBER recession periods. One can see that dramatic changes of variables, if any, come mainly since 2020:II.

Table A.2 presents variables used for sensitivity analyses. Transformations are similar to

[2]One may notice a small typo in this Fed Note that the column names should be reversed in the table corresponding to Figure 3.

[3]In H.8 releases, bank credit (term 1) consists of two broad categories, namely Securities in bank credit (term 2) and Loans and leases in bank credit (term 9). The latter one is further decomposed into 4 categories: Commercial and industrial loans (term 10), Real estate loans (term 11), Consumer loans (term 20) and All other loans and leases (term 25). Core loans is then defined as term 9 minus term 25, which excludes securities and other loan and leases.

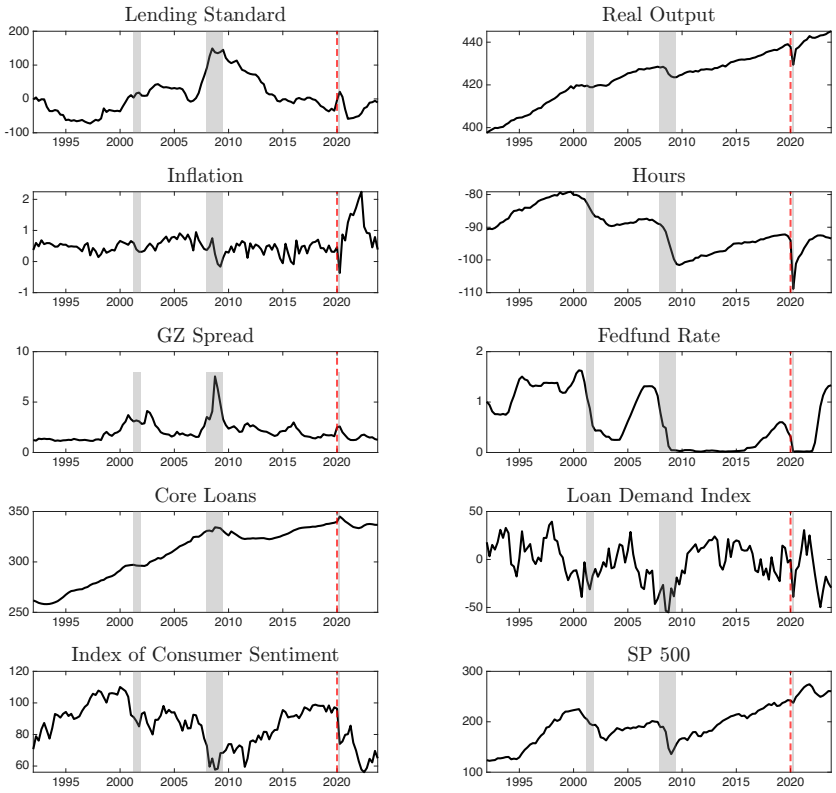


Figure A.1: Data Series for baseline model

the description before. There are for sure other alternative candidates to perform sensitivity analyses. For example, Industrial Production (IP) is another measure for real output, and Consumer Price Index (CPI) is another measure for inflation. Results are robust when replacing these alternative measures, but for convenience I do not report here.

While most variables span over the full sample from 1992:I to 2023:IV, several variables span over subsample periods: There is no subsample variables in Table A.1, but in Table A.2, the Aggregate CSI is available from 1996:II to 2023:IV[4], and Shadow Federal Fund Rate is available from 1992:I to 2023:II. For CSI for specific loans, the one for CRE loans starts from 1996:II, and the one for consumer loans starts from 1996:I. For Commercial and Residential Real Estate Loans, they start from June 2004 thus 2004:III.

As for the extraction of factors from FRED-MD database, the current version of all relevant series, as of writing this paper, spans from 1959M1 to 2025M5. The raw data and codes of factor extraction are available from the note in Fed St. Louis[5]. There is no explicit

[4]The main difference between Aggregate CSI and CSI can be found in Cavallo et al. (2024b). Basically it is the order difference when aggregating series, and authors have verified that two series are mostly identical.

[5]Details of FRED-MD database can be found in https://www.stlouisfed.org/research/economists/mccracken/fred-databases. One may also find the quarterly version FRED-QD, which is a quarterly companion of FRED-MD database. Since I do not find explicit codes to run quarterly data, I skip testing FRED-QD for now.

arguments in the provided code to decide number of factors, except that I set `kmax = 8`, then 7 factors are extracted.

Table A.2: Data Series used for sensitivity analyses

Series Name	Units	Fred Code	Frequency	Source[6]
Aggregate Credit Supply Indicator and Bank Lending Standard Index	Percent		Quarter	Cavallo et al. (2024b)
Credit Supply Indicator: C&I, Consumer, CRE, RRE Loans	Percent		Quarter	Cavallo et al. (2024b)
Nonfarm Business Sector: Real Value-Added Output for All Workers	Index 2017 = 100, SA	OUTNFB	Quarter	Fred
Personal Consumption Expenditures: Chain-type Price Index	Index 2017 = 100, SA	PCEPI	Month	Fred
Commercial property price index, all properties	Index 2010 = 100		Quarter	Bank for International Settlements
Unemployment Rate	Percent, SA	UNRATE	Month	Fred
Excess Bond premium	Percent		Month	Gilchrist and Zakrajšek (2012)
Business Conditions Expected in 5 Years	Percent		Month	Surveys of Consumers, UMichigan
Shadow Federal Fund Rate	Percent		Month	Wu and Xia (2016)
Loans and Leases in Bank Credit, All Commercial Banks	Billion $, SA, CP	TOTLL	Week	Fred
Other Loans and Leases, All Commercial Banks	Billion $, SA, CP	AOLACBW027SBOG	Week	Fred
Commercial Real Estate Loans, DCC Banks	Billion $, SA, CP	CREDCBW027SBOG	Week	Fred
Residential Real Estate Loans, DCC Banks	Billion $, SA, CP	RREDCBW027SBOG	Week	Fred

Note: Sample period is from 1992:I to 2023:IV. '(N)SA' means (not) seasonally adjusted, 'CP' means current price, 'DCC Banks' means Domestically Chartered Commercial Banks.

A.2 Euro Area Dataset

This section will describe the data sources used for Euro-area evidence, which is quite analogous to U.S. data sources. Table A.3 presents the sources.

Table A.3: Data Series used for Euro-area evidence

Series Name	Units	ECB/Fred Code	Frequency	Source[7]
Credit standards Overall Enterprise Diffusion Index, ECC	Percent	BLS.Q.U2.ALL.O.E.Z.B3.ST.S.WDINX	Quarter	ECB
Credit standards Consumer Credit Diffusion Index, ECC	Percent	BLS.Q.U2.ALL.Z.H.C.B3.ST.S.WDINX	Quarter	ECB
Credit standards Loan for House Purchase Diffusion Index, ECC	Percent	BLS.Q.U2.ALL.Z.H.H.B3.ST.S.WDINX	Quarter	ECB
Gross domestic product at market prices Euro 20 countries	Million €, NSA, CP	MNA.Q.N.U2.W2.S1.S1.B.B1GQ._Z._Z._Z.EUR.V.N	Quarter	ECB
Gross domestic product deflator EFC	Index, SA	MNA.Q.Y.I9.W2.S1.S1.B.B1GQ._Z._Z._Z.IX.D.N	Quarter	ECB
Working-age population Age 15 or older EFC	Thousands Person, SA		Quarter	OECD
ICE BofA Euro High Yield Index Option-Adjusted Spread	Percent, NSA	BAMLHE00EHYIOAS	Daily	Fred
Euro EONIA rate	Percent	EON.D.EONIA_TO.RATE	Daily	ECB
Euro short-term rate	Percent	EST.B.EU000A2X2A25.WT	Daily	ECB
Loans vis-a-vis euro area NFCs ECC	Million €, NSA, CP	BSI.M.U2.N.A.A20.A.1.U2.2240.Z01.E	Month	ECB
Credit for consumption ECC	Million €, NSA, CP	BSI.M.U2.N.A.A21.A.1.U2.2250.Z01.E	Month	ECB
Lending for house purchase ECC	Million €, NSA, CP	BSI.M.U2.N.A.A22.A.1.U2.2250.Z01.E	Month	ECB

Note: Sample period is from 2005:I to 2023:IV. '(N)SA' means (not) seasonally adjusted, 'CP' means current price. 'ECC' means Euro changing composition, and 'EFC' means Euro 20 fixed composition.

Most data come from European Central Bank (ECB), and most constructions are similar to those of U.S. dataset with several exceptions. Specifically, the aggregate lending standard index is constructed as follows. Denote the credit standard diffusion indices for three loan categories as DI_{kt}, where k is each loan category, and denote L_{kt} as the loan outstanding for each category. The share of each loan category is then $\omega_{kt} = L_{kt}/\sum_{m=1}^{K} L_{mt}$. The aggregate lending standard diffusion index is then $DI_t = \sum_{k=1}^{K} \omega_{k,t-1} DI_{kt}$, i.e., the weighted summation by the share of loan outstanding in the last quarter and loans outstanding in the current quarter. The aggregate core loan measurement is just $L_t = \sum_{k=1}^{K} L_{kt}$.

[6]Details of Commercial Property Price Index from BIS can be found in https://data.bis.org/topics/CPP and the series for United States. Up-to-date series for shadow federal fund rate can be found in https://sites.google.com/view/jingcynthiawu/shadow-rates.

[7]Data from ECB are via the ECB data portal https://data.ecb.europa.eu/. The data for working age population is from the Organisation for Economic Co-operation and Development (OECD) Data Explorer https://data-explorer.oecd.org/.

Other than the aggregate lending standard diffusion index, current price variables are deflated by GDP deflator, and aggregate variables are taken per capita terms by working age population in million persons. Also, I express GDP and core loans in billion euros to match U.S. units. Series with higher frequencies are taken quarterly averages. For not-seasonal-adjusted series, I use X-13ARIMA-SEATS from U.S. Census Bureau.

The European short-term rate combines EONIA and the new short-term rate (STR). Specifically, the new STR began to be released from October 2, 2019, and the EONIA rate keeps released until January 2, 2022. After October 2019, the EONIA rate is calculated as STR rate plus 8.5 basis point. To combine two series, I take EONIA rate until 2019:III and minus it with 8.5 basis point, and take STR rate for post-2019:III periods. After transformations, I divide it by 4 for quarterly frequency.

The baseline reference area for data series is changing composition of Euro-area countries that reflects the varying number of countries using euros over time. Alternative reference area is fixed Euro 20 composition, indicating the current 20 European countries which use euros. Most series from ECB have both versions of reference area. In terms of variables used for Euro-area analyses, most of them have the version with changing composition, but few has fixed Euro 20 composition. For example, the GDP deflator does not have changing composition version. To keep consistency with U.S. data construction, I still use GDP deflator in the baseline analyses. An alternative measure for inflation is from harmonized index of consumer prices (HICP), and I include it in the sensitivity analyses. The population data is from OECD, as the population data from ECB only has annual version.

To better illustrate series, Figure A.2 presents them after transformations. A clear difference from U.S. dataset is that the aggregate lending standard index presents more I(1) features, which is consistent to the fact that such series is not adjusted demand or macroeconomic conditions.

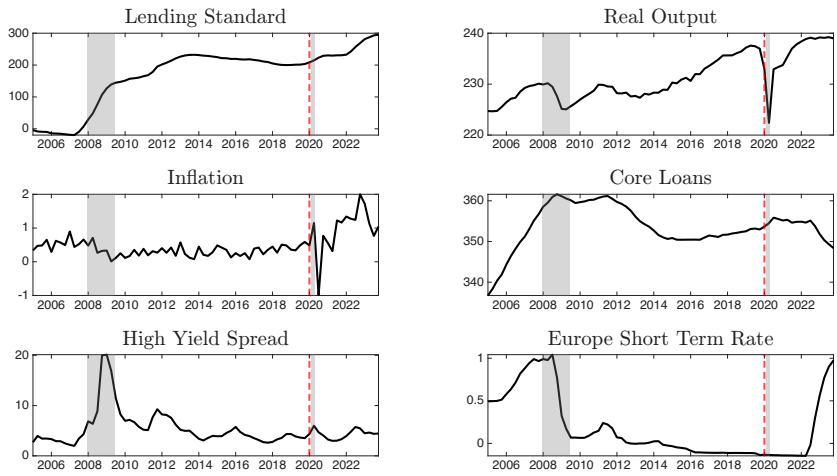


Figure A.2: Data Series for Euro area evidence

Table A.4 presents variables used for sensitivity analyses of Euro area results. The major difference between a "net percentage index" and "diffusion index" is that, the latter one weight the answers containing "somewhat" and "considerably". For example, the latter one treats "somewhat tightened" or "considerably tightened" with weights 0.5 and 1, while the former treats both as one. In the baseline analyses, I use diffusion index to better capture aggregate changes of lending standards. Other than this, the construction of aggregate index with net percentage indices is similar to baseline.

Other variables for sensitivity analyses include the Industrial Production for real output, GDP deflator for inflation and Euro Deposit Facility Rate for interest rate stances. Industrial Production excludes construction to match the convention for Industrial Production in the U.S., and GDP deflator is another commonly used series for price levels other than HICP index. For alternatives of European short-term rates, there are three major interest rates in Europe, namely rates of deposit facility, main refinancing operations and marginal lending facility. I choose the first one as it is the one from which European Governing Council steers monetary policy stances.

Table A.4: Data Series used for Euro-area sensitivity analyses

Series Name	Units	ECB/Fred Code	Frequency	Source
Credit standards Overall Enterprise Net Percentage Index, ECC	Percent	BLS.Q.U2.ALL.O.E.Z.B3.ST.S.WFNET	Quarter	ECB
Credit standards Consumer Credit Net Percentage Index, ECC	Percent	BLS.Q.U2.ALL.Z.H.C.B3.ST.S.WFNET	Quarter	ECB
Credit standards Loan for House Purchase Net Percentage Index, ECC	Percent	BLS.Q.U2.ALL.Z.H.H.B3.ST.S.WFNET	Quarter	ECB
Industrial production excluding construction EFC	Index 2021 = 100, SA	STS.M.I9.Y.PROD.NS0020.4.000	Month	ECB
HICP Overall index ECC	Index 2015 = 100, SA	ICP.M.U2.Y.000000.3.INX	Month	ECB
Euro Deposit Facility Rate	Percent	FM.D.U2.EUR.4F.KR.DFR.LEV	Daily	ECB

Note: Sample period is from 2005:I to 2023:IV. '(N)SA' means (not) seasonally adjusted, 'CP' means current price. 'ECC' means Euro changing composition, and 'EFC' means Euro 20 fixed composition.

B Technical Supplement

B.1 Identification Details

In this section, I provide details of how to implement identification strategies of shocks. I discuss two cases. The first is how to incorporate zero at-impact restrictions, illustrated by the implementation of news shock. The second is how to identify shocks conditional on other shocks, illustrated by the implementation of surprise shock. Other shock identifications are all based on these two cases. (Two cases in fact are similar) Additionally, I describe how to jointly identify shocks that come from max-FEV methods and methods using external instruments.

Consider the setup of VAR model in Section 2. The maximization problem for news shock can be rewritten as

$$\max_{\boldsymbol{q}_j} \ \boldsymbol{q}_j' \underbrace{\left(\sum_{l=0}^{H} \boldsymbol{\Phi}_l'(\tilde{\boldsymbol{S}}) \boldsymbol{e}_i \boldsymbol{e}_i' \boldsymbol{\Phi}_l(\tilde{\boldsymbol{S}}) \right)}_{\boldsymbol{M}_H} \boldsymbol{q}_j, \ \text{s.t.} \ \boldsymbol{q}_j' \boldsymbol{q}_j = 1, \boldsymbol{e}_i' \tilde{\boldsymbol{S}} \boldsymbol{q}_j = 0$$

where the denominator of $\Omega_{i,j}(H)$ is ignored since it is independent of $\boldsymbol{q}_j$, and the numerator follows that $\boldsymbol{e}_i' \boldsymbol{\Phi}_l(\tilde{\boldsymbol{S}}) \boldsymbol{q}_j$ is one-dimensional. For the zero at-impact restriction, let $\mathcal{N} = null(\boldsymbol{e}_i' \tilde{\boldsymbol{S}})$ be the null space of $\boldsymbol{e}_i' \tilde{\boldsymbol{S}}$ where $\boldsymbol{q}_j \in \mathcal{N}$. Let $\boldsymbol{N}$ be the orthonormal basis of $\mathcal{N}$[8] where columns of $\boldsymbol{N}$ represent basis vectors, then one can write $\boldsymbol{q}_j = \boldsymbol{N}\boldsymbol{z}$ where $\boldsymbol{z}$ is a column vector. The original orthonormal restriction to $\boldsymbol{q}_j$ is equivalent to $\boldsymbol{z}'\boldsymbol{z} = 1$, and the problem is transformed as

$$\max_{\boldsymbol{z}} \ \boldsymbol{z}' \left(\boldsymbol{N}' \boldsymbol{M}_H \boldsymbol{N} \right) \boldsymbol{z}, \ \text{s.t.} \ \boldsymbol{z}'\boldsymbol{z} = 1$$

Following Uhlig (2004), the problem is equivalent to find the eigenvector associated with the largest eigenvalue to $\boldsymbol{N}'\boldsymbol{M}_H\boldsymbol{N}$. The vector $\boldsymbol{q}_j$ is recovered by $\boldsymbol{q}_j = \boldsymbol{N}\boldsymbol{z}$. The surprise shock is then conditional on the identified $\boldsymbol{q}_{news}$. The maximization problem is rewritten as

$$\max_{\boldsymbol{q}_{surp}} \ \boldsymbol{q}_{surp}' \underbrace{\left(\tilde{\boldsymbol{S}}' \boldsymbol{e}_i \boldsymbol{e}_i' \tilde{\boldsymbol{S}} \right)}_{M_0} \boldsymbol{q}_{surp}, \ \text{s.t.} \ \boldsymbol{q}_{surp}' \boldsymbol{q}_{surp} = 1, \boldsymbol{q}_{news}' \boldsymbol{q}_{surp} = 0$$

Now the null space is $\mathcal{N} = null(\boldsymbol{q}_{news}')$ and one can follow similar steps as before. In the special case when $i = 1$ and two shocks are ordered first to identify, given the Cholesky

[8] In Matlab it is convenient to use `null` function to derive orthonormal basis of certain matrix/null space. Alternative to a standard QR decomposition, the `null` function uses a more efficient and stable approach of SVD decomposition.

matrix $\tilde{\boldsymbol{S}}$, the second restriction in news shock is just $\boldsymbol{q}_j(1) = 0$, then it is equivalent to drop $\boldsymbol{N}$ and replace $\boldsymbol{M}_H$ with its lower-right $(n-1) \times (n-1)$ sub-matrix. The problem for surprise shock is simplified to $\max_{\boldsymbol{q}_{surp}, \|\boldsymbol{q}_{surp}\|=1} \boldsymbol{q}_{surp}(1)^2 \boldsymbol{\Sigma}_{u,11}$, which yields $\boldsymbol{q}_{surp} = \boldsymbol{e}_1$ and the second original restriction is slack.

When more shocks are identified, steps are similar, except that shocks to be identified later are limited to more restricted vector space. For example, consider a shock $\boldsymbol{q}_{k+1}$ to be identified after k shocks whose vectors in the rotation $\boldsymbol{Q}$ matrix are $[\boldsymbol{q}_1, ...\boldsymbol{q}_k]$, and it has its own restrictions $\boldsymbol{A}'\boldsymbol{q}_{k+1} = 0$. The null space is then $\mathcal{N} = null([\boldsymbol{q}_1, ...\boldsymbol{q}_k, \boldsymbol{A}]')$ and follow similar steps to before. When all shocks are identified in terms of their vectors in the $\boldsymbol{Q}$ matrix, one may make up the rest part of $\boldsymbol{Q}$ (which has no structural meanings) by finding again the null space of shock vectors, and recover the at-impact structural matrix $\boldsymbol{S} = \tilde{\boldsymbol{S}}\boldsymbol{Q}$. As the responses to shocks are up to signs, I normalize the news shock (both credit supply and TFP) that it has positive at-impact effect to real output, and normalize other shocks to have positive at-impact effect to their own underlying variables, if necessary. If there is an impact vector identified from other methods (e.g., external instruments), say $\boldsymbol{S}_j$ the jth column of at-impact matrix $\boldsymbol{S}$, then its corresponding vector in $\boldsymbol{Q}$ matrix is just $\boldsymbol{q}_j = \tilde{\boldsymbol{S}}^{-1}\boldsymbol{S}_j$.

B.2 Estimation Details

In this section, I briefly provide details of estimation methods of VAR model and statistical inference, which basically follows Giannone et al. (2015) but a simpler version. Specifically, the original paper has 4 hyper-parameters, which, other than λ, also include μ, δ and ψ. The first two hyper-parameters are used to limit the explanatory power of deterministic components (initial observations mainly) and to improve the forecasting performance of Bayesian VARs. The last hyper-parameter relaxes the prior for matrix $\boldsymbol{\Psi}$ from sample estimations. I do not consider the first two hyper-parameters because major analyses do not include forecasting tasks, and not the last one to inherit more on sample information.

Consider the VAR framework in Section 2. The VAR model can be written in a condense way that

$$\boldsymbol{Y} = \boldsymbol{X}\beta + \boldsymbol{\epsilon}$$

where $y = [y_{p+1}, ..., y_T]', \boldsymbol{Y} = vec(y), x_t = [1, y'_{t-1}, ..., y'_{t-p}]', x = [x_{p+1}, ..., x_T]', \boldsymbol{X} = I_n \otimes x, \varepsilon = [\varepsilon_{p+1}, ..., \varepsilon_T]', \boldsymbol{\epsilon} = vec(\varepsilon)$ and $\boldsymbol{B} = [\boldsymbol{C}, \boldsymbol{B}_1, ..., \boldsymbol{B}_p]', \beta = vec(\boldsymbol{B})$. Let $k = np + 1$.

As mentioned in Section 3.2, the VAR model is estimated in a Bayesian approach with

Normal-Inverse Wishart prior,

$$\boldsymbol{\Sigma}_u \sim IW(\boldsymbol{\Psi}, d),\ \beta|\boldsymbol{\Sigma}_u \sim N(b, \boldsymbol{\Sigma}_u \otimes \boldsymbol{\Omega})$$

where $d = n + 2$ is the degree of freedom for Inverse Wishart distribution, $\boldsymbol{\Psi}$ is a diagonal matrix with diagonal elements the variance of the residuals of an AR(1) process with a constant for each variable, i.e., $\boldsymbol{\Psi} = diag([\hat{\sigma}_1^2, ..., \hat{\sigma}_n^2])$.

The moment parameters for β, namely $b, \boldsymbol{\Omega}$ are determined by Minnesota prior. For the prior mean (persistence) of coefficients b, I let it be one if the variable is I(1) and zero if the variable is I(0), following the setting in Görtz et al. (2022). I(1) variables in the baseline models include Lending Standard, Real Output, Hours, Core Loans and S&P 500 Index. In other words, denote v be a function indicating the prior persistence of variables, then

$$\mathbb{E}[(\boldsymbol{B}_s)_{ij}|\boldsymbol{\Sigma}_u] = \begin{cases} v_i & \text{, if } i = j \text{ and } s = 1 \\ 0 & \text{, Otherwise} \end{cases}, v_i \in \{0, 1\}, i, j = 1, ..., n, s = 1, ..., p$$

The prior mean for the constant vector $\boldsymbol{C}$ is set to zero. The other parameter $\boldsymbol{\Omega}$ is set as

$$\boldsymbol{\Omega} = diag\left(\left[10^6, \frac{\lambda^2}{\hat{\sigma}_1^2}, ..., \frac{\lambda^2}{\hat{\sigma}_n^2}, \frac{1}{2^2}\frac{\lambda^2}{\hat{\sigma}_1^2}, ..., \frac{1}{2^2}\frac{\lambda^2}{\hat{\sigma}_n^2}, ..., \frac{1}{p^2}\frac{\lambda^2}{\hat{\sigma}_1^2}, ..., \frac{1}{p^2}\frac{\lambda^2}{\hat{\sigma}_n^2}\right]\right)$$

where the first term ensures that the constant vector has flat prior, and subsequent terms allow for gradual shrinkage of distributions. Now denote the inverse vector version of b as $\boldsymbol{b}$, i.e., $b = vec(\boldsymbol{b})$. The posterior distributions of coefficients are then

$$\boldsymbol{\Sigma}_u|\boldsymbol{Y} \sim IW(\hat{\boldsymbol{S}}, T - p + d),\ \beta|\boldsymbol{\Sigma}_u, \boldsymbol{Y} \sim N\left(\hat{\beta}, \boldsymbol{\Sigma}_u \otimes \left(x'x + \boldsymbol{\Omega}^{-1}\right)^{-1}\right), \hat{\beta} = vec(\hat{\boldsymbol{B}})$$
$$\text{where } \hat{\boldsymbol{S}} = \boldsymbol{\Psi} + \hat{\varepsilon}'\hat{\varepsilon} + (\hat{\boldsymbol{B}} - \boldsymbol{b})'\boldsymbol{\Omega}^{-1}(\hat{\boldsymbol{B}} - \boldsymbol{b}), \hat{\boldsymbol{B}} = \left(x'x + \boldsymbol{\Omega}^{-1}\right)^{-1}(x'y + \boldsymbol{\Omega}^{-1}\boldsymbol{b}), \hat{\varepsilon} = y - x\hat{\boldsymbol{B}}$$

The likelihood function of the hyper-parameter λ is given as

$$\begin{aligned} p(\lambda|\boldsymbol{Y}) &\propto p(\boldsymbol{Y}|\lambda) \cdot p(\lambda), \\ p(\boldsymbol{Y}|\lambda) &= \left(\frac{1}{\pi}\right)^{\frac{n(T-p)}{2}} \frac{\Gamma_n\left(\frac{T-p+d}{2}\right)}{\Gamma_n\left(\frac{d}{2}\right)} |\boldsymbol{\Psi}|^{-\frac{T-p}{2}} |\boldsymbol{D}_\Omega' x' x \boldsymbol{D}_\Omega + I_k|^{-\frac{n}{2}} \\ &\quad \cdot \left| I_n + \boldsymbol{D}_\Psi' \left[\hat{\varepsilon}'\hat{\varepsilon} + (\hat{\boldsymbol{B}} - \boldsymbol{b})'\boldsymbol{\Omega}^{-1}(\hat{\boldsymbol{B}} - \boldsymbol{b})\right] \boldsymbol{D}_\Psi \right|^{-\frac{T-p+d}{2}} \end{aligned}$$

where $\boldsymbol{D}_\Omega \boldsymbol{D}_\Omega' = \boldsymbol{\Omega}$ and $\boldsymbol{D}_\Psi \boldsymbol{D}_\Psi' = \boldsymbol{\Psi}^{-1}$. The hyper-prior of λ is set as a Gamma density of mode 0.2 and standard deviation 0.4, following the setup of Giannone et al. (2015). The sampling of λ is obtained by the MCMC using a standard Metropolis algorithm. Specifically,

the initialization is to pick λ around its posterior mode, and in round j, the candidate value of a new λ^* is drawn from a Gaussian distribution, with mean equal to λ^{j-1}, the last-round value, and variance equal to $k^2 \cdot IH$, where IH is the inverse Hessian of the negative of the log-posterior of λ the at the mode. k is a scaling parameter and it is chosen to keep the acceptance rate at around 25%.

The candidate is accepted with probability $\alpha = \min\left\{1, \frac{p(\lambda^*|\boldsymbol{Y})}{p(\lambda^{j-1})|\boldsymbol{Y})}\right\}$. If not accepted, the round j value will be $\lambda^j = \lambda^{j-1}$. After sampling, given each draw of λ, I proceed with Bayesian VAR estimation described above.

In order to check if the sampling proceeds correctly, I show the sampling distribution and path in the 6- and 10-variable baseline models. Figure B.1 presents the posterior likelihood density, where lines are theoretical densities, bars are sampling histograms and dashed lines are posterior mode; Figure B.2 presents the sampling path of λ over 10,000 draws used for inference. Both figures verify that the sampling fits theoretical density and paths are stationary. (Thus no burn-in period is needed) They are also consistent with one key conclusion in Giannone et al. (2015) that a larger-scale VAR model tends to pick a smaller λ.

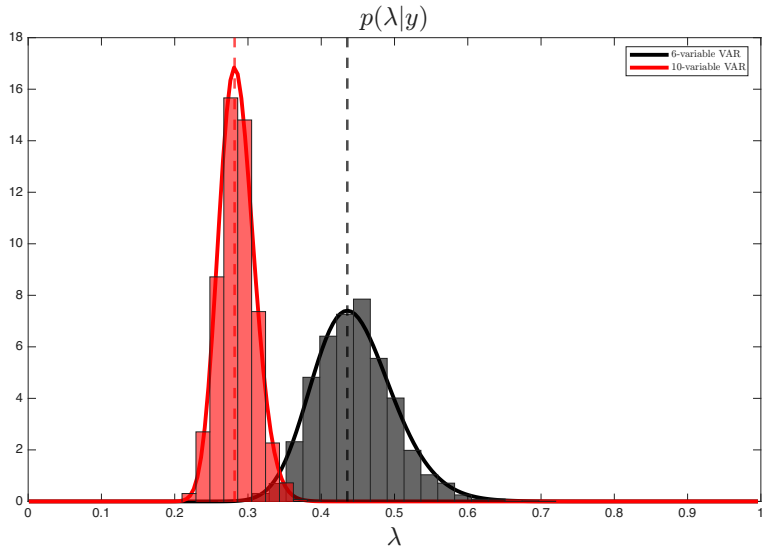


Figure B.1: Density of posterior likelihood of λ in baseline models

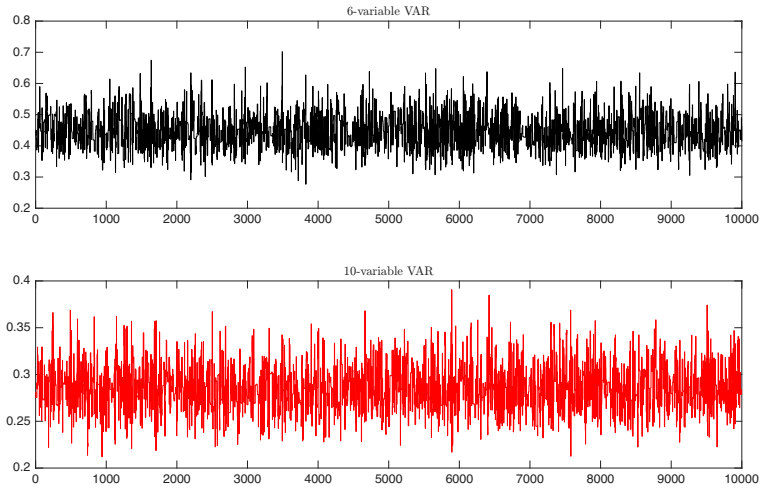


Figure B.2: Sampling path of λ in baseline models

C Sensitivity Analyses

This Appendix mainly includes figures in Section 4.5 Sensitivity Analyses and robustness checks in Section 5.

C.1 Robust Figures for Baseline Results

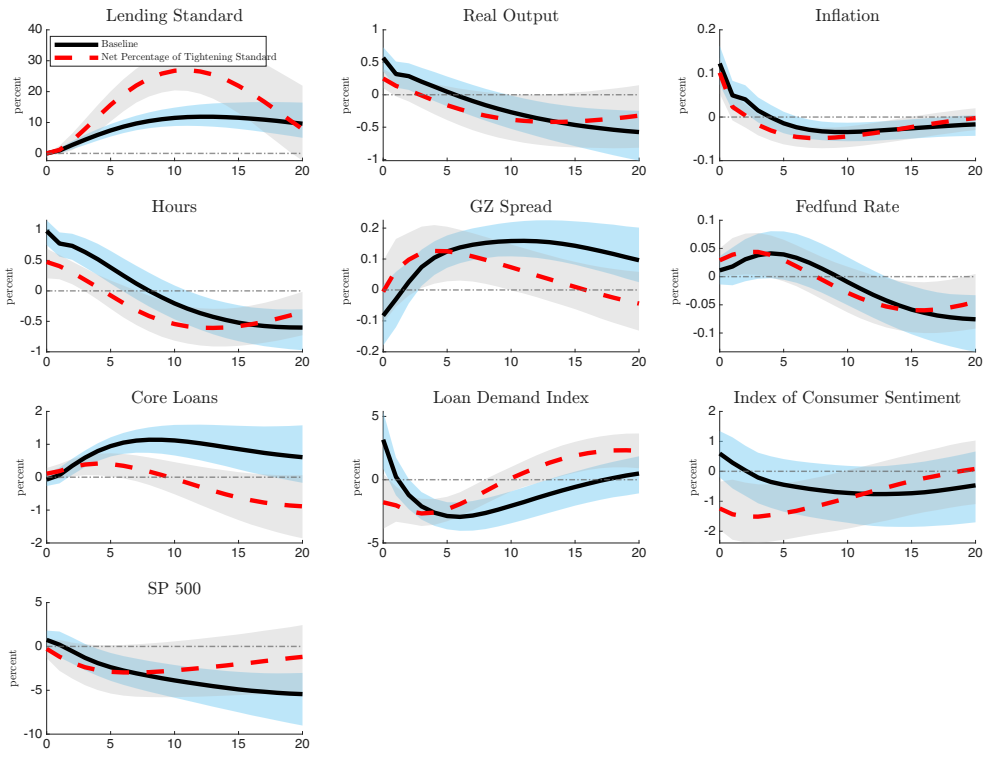


Figure C.1: IRFs to a credit supply news shock, bank lending standard index as measure

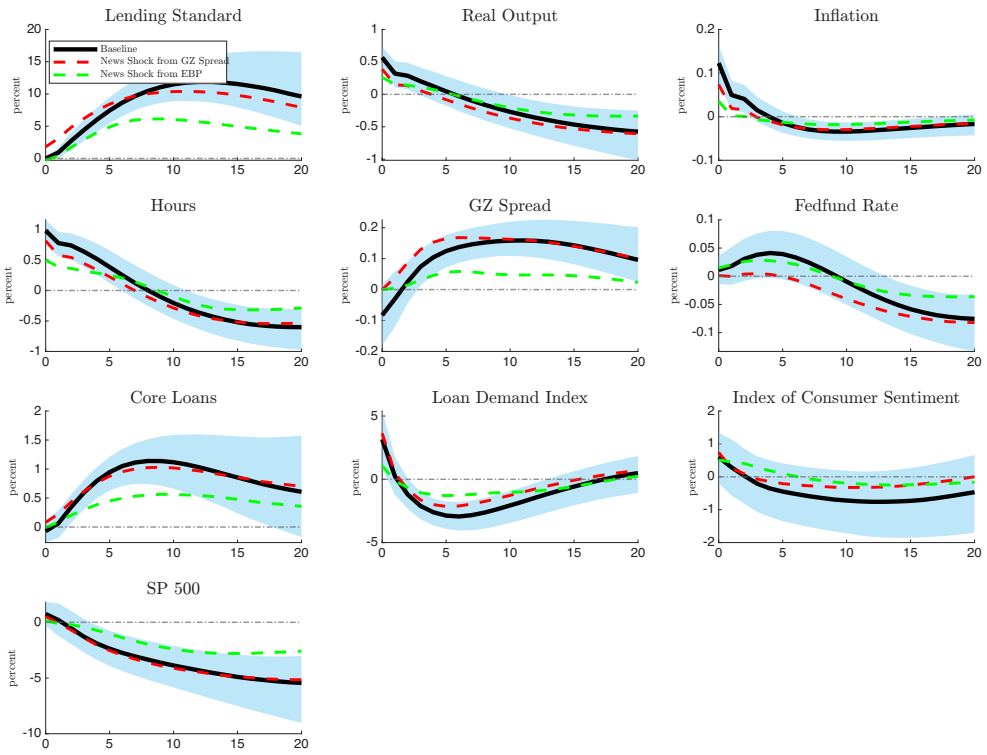


Figure C.2: IRFs to a credit supply news shock, GZ spread and EBP as measure

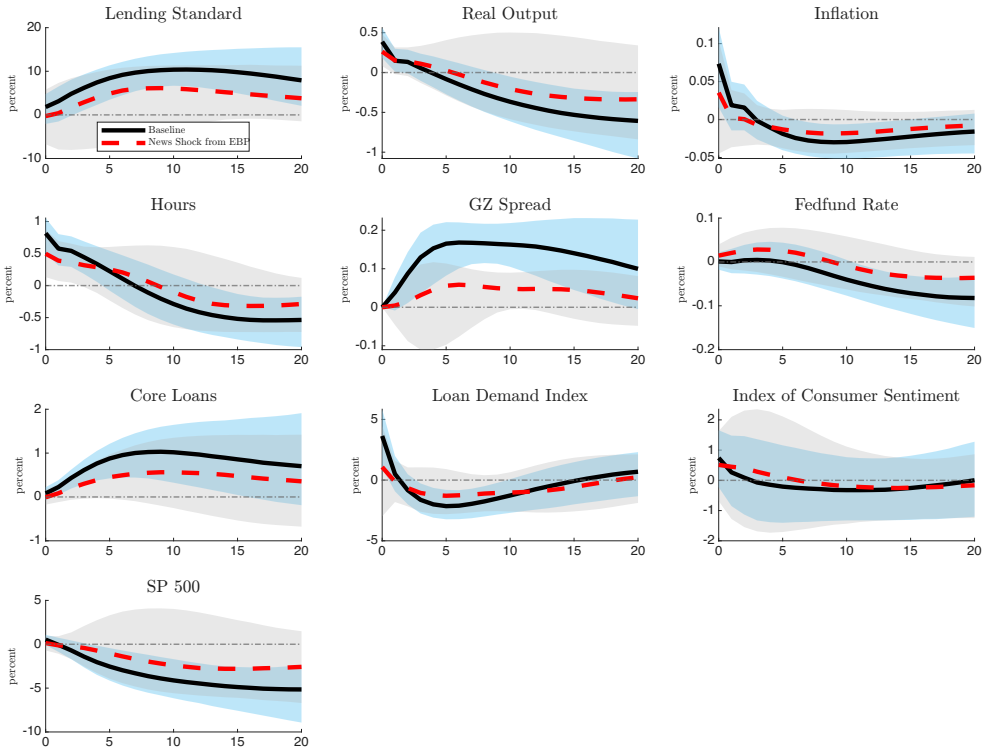


Figure C.3: IRFs to a credit supply news shock, GZ spread and EBP details (Baseline here means news shock from GZ spread)

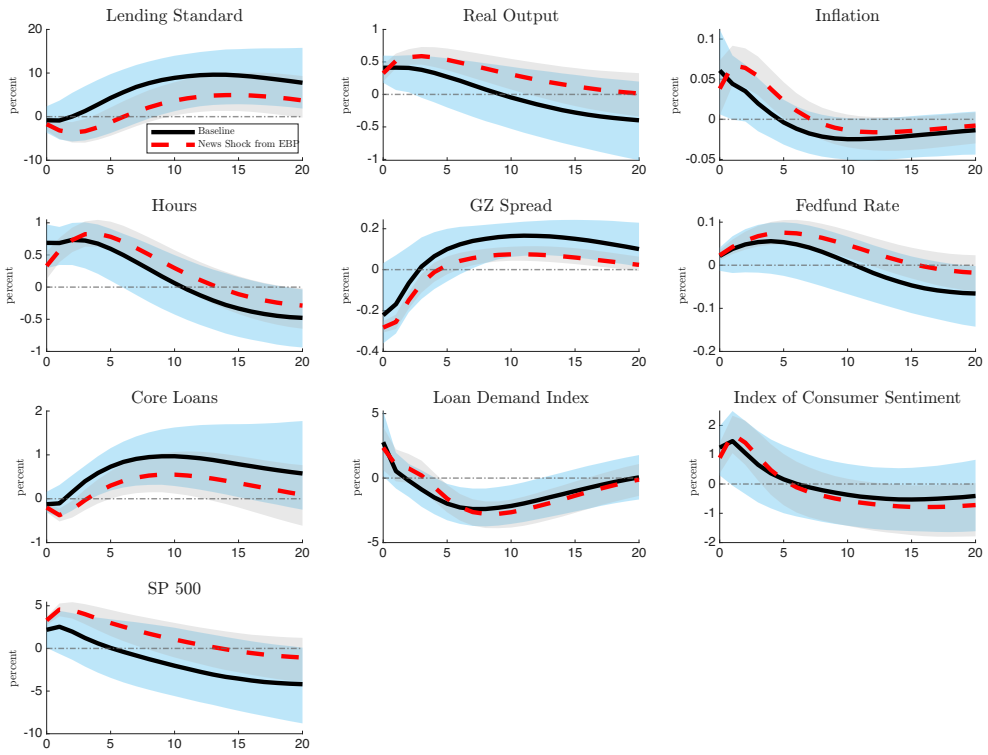


Figure C.4: IRFs to a credit supply news shock, GZ spread and EBP without zero at-impact restrictions (Baseline here means news shock from GZ spread)

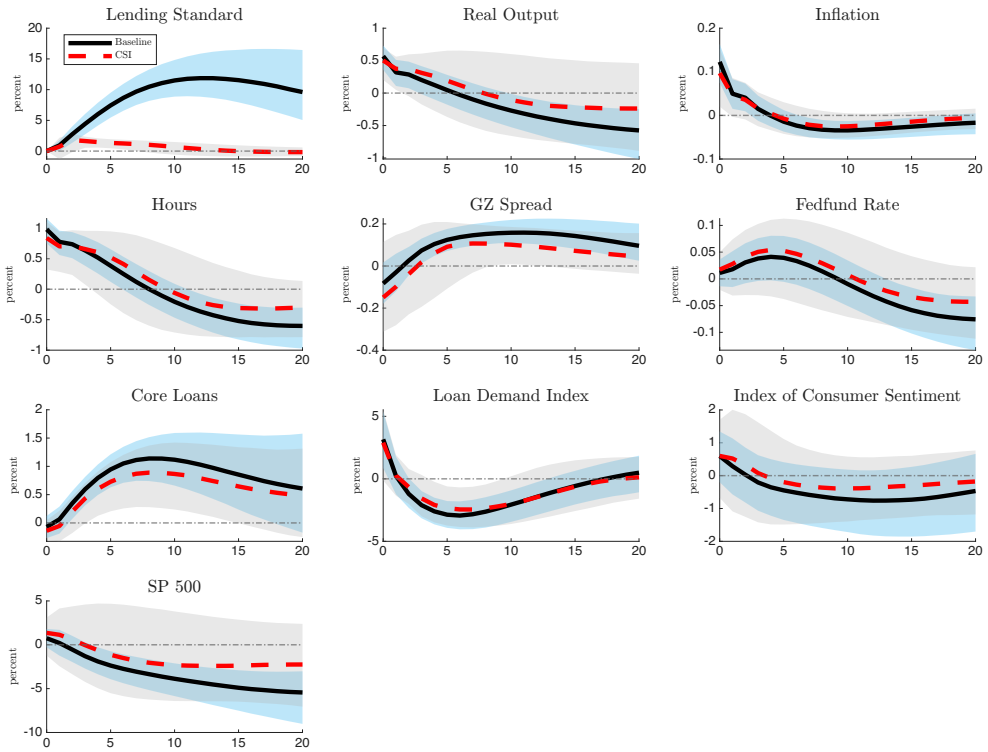


Figure C.5: IRFs to a credit supply news shock, CSI as measure

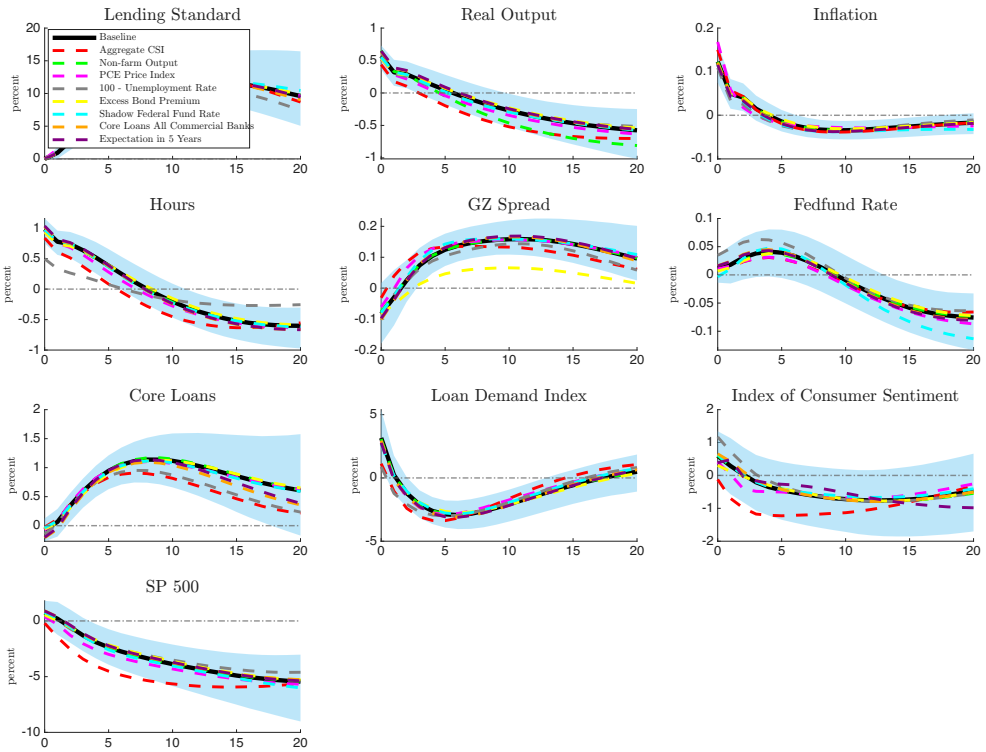


Figure C.6: IRFs to a credit supply news shock, alternative other measures

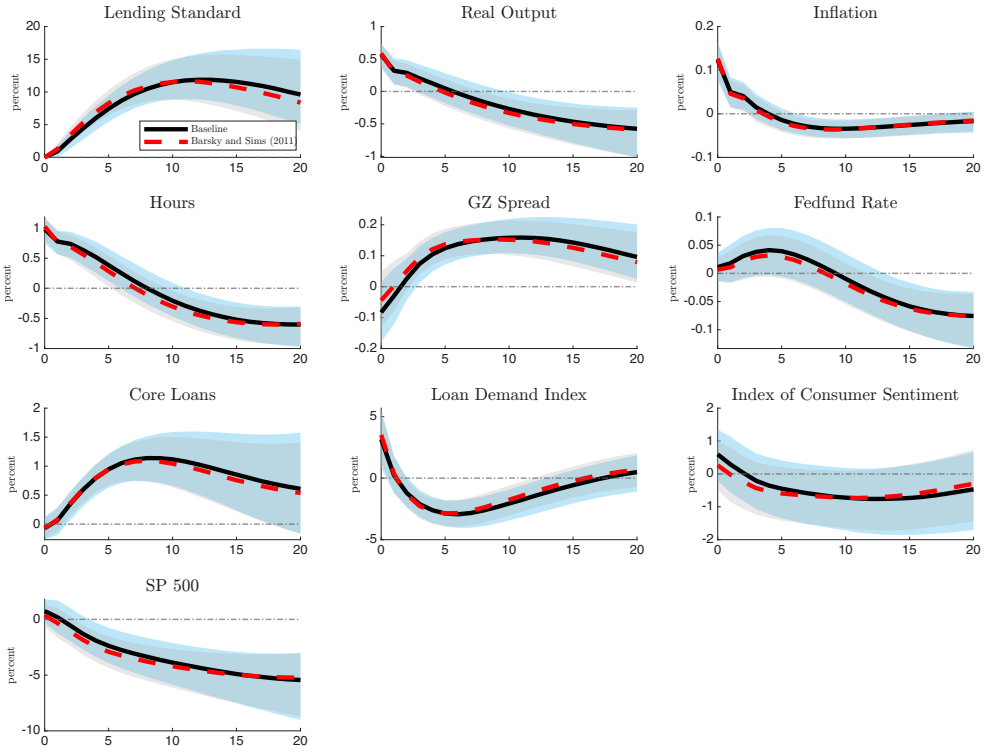


Figure C.7: IRFs to a credit supply news shock, Barsky strategy

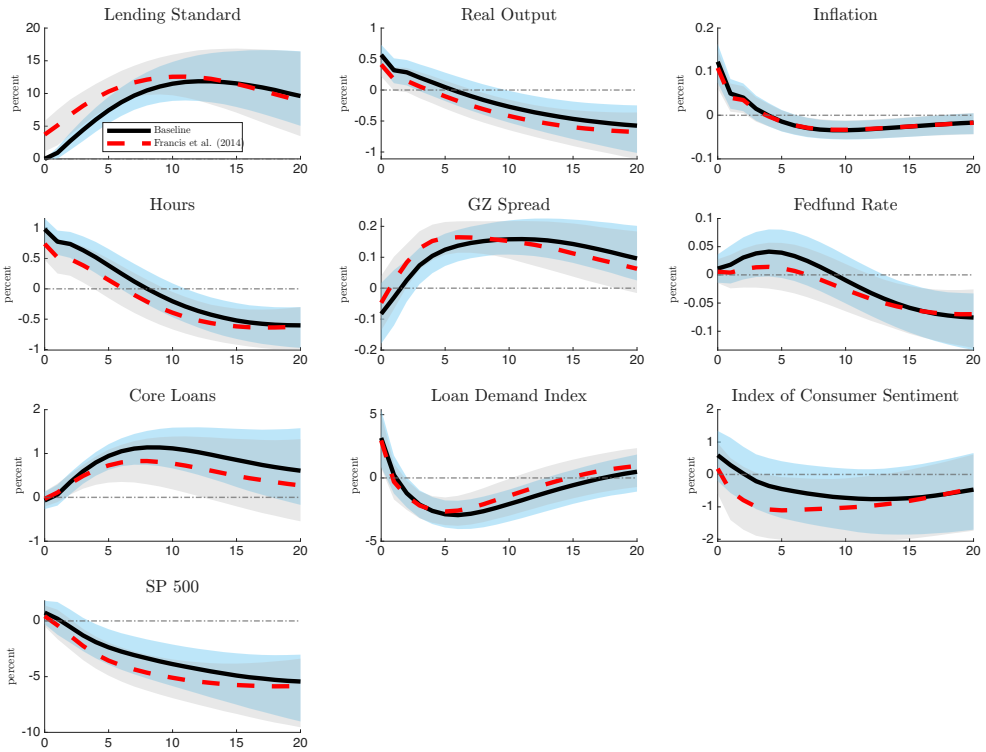


Figure C.8: IRFs to a credit supply news shock, Francis strategy

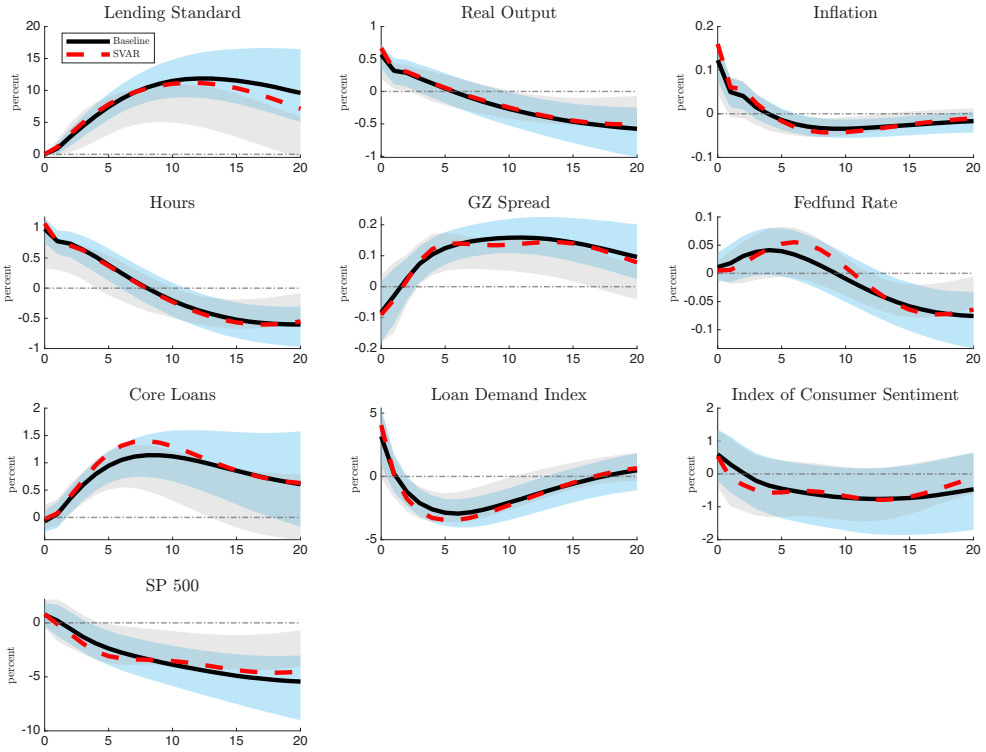


Figure C.9: IRFs to a credit supply news shock, frequentist SVAR

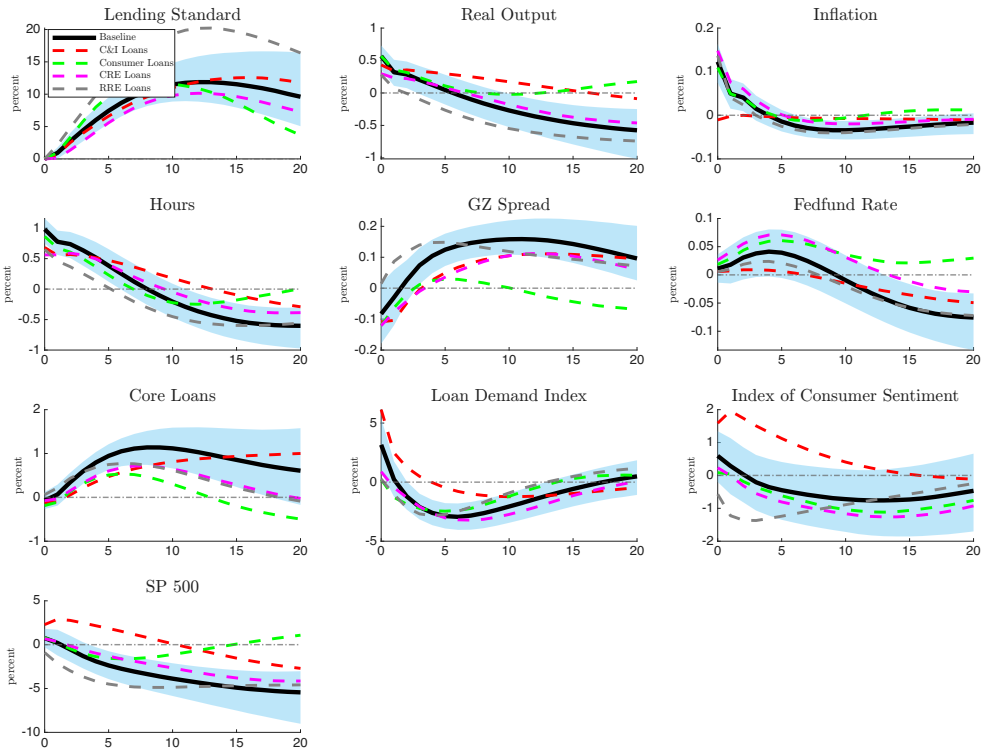


Figure C.10: IRFs to a credit supply news shock, loan-specific shocks

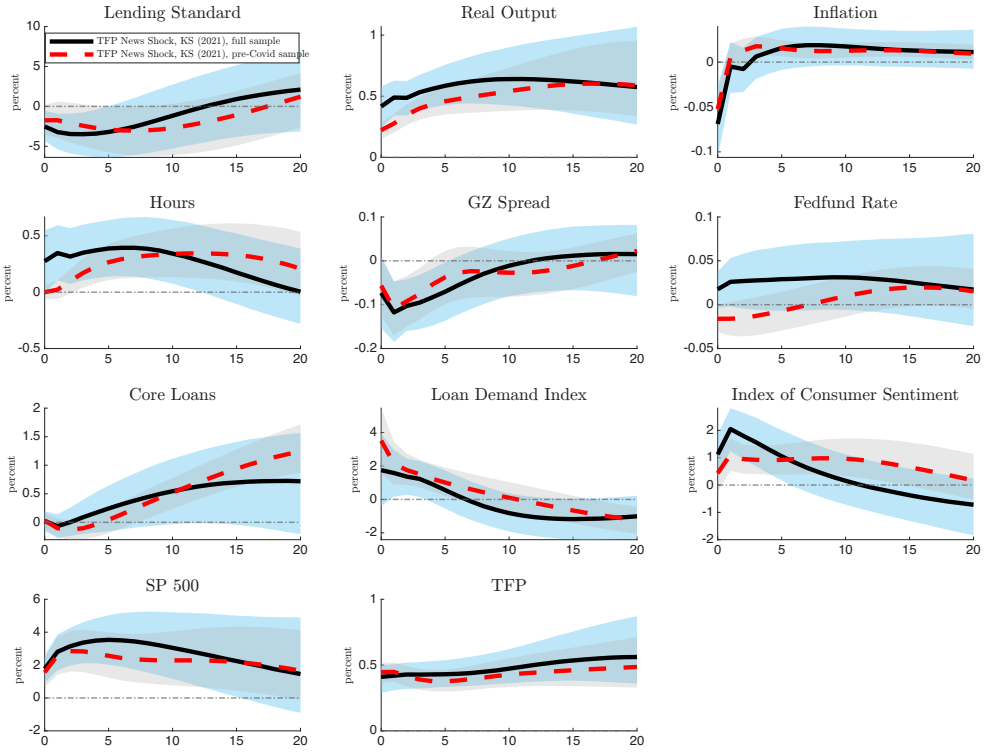


Figure C.11: IRFs to a TFP news shock, two samples

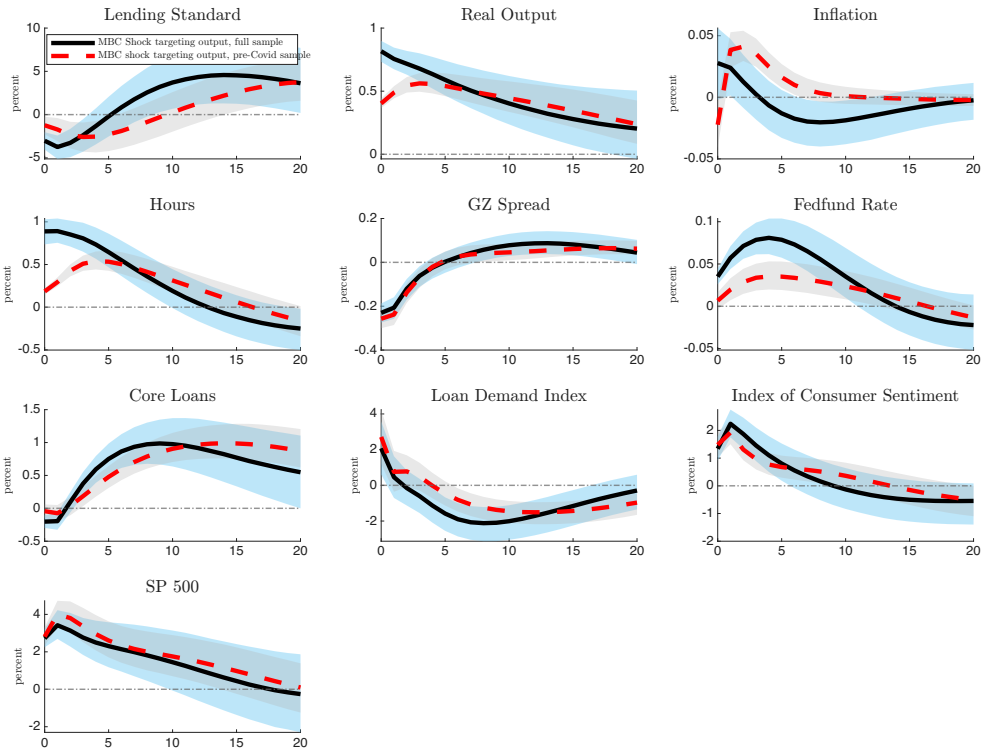


Figure C.12: IRFs to a MBC shock targeting output, two samples

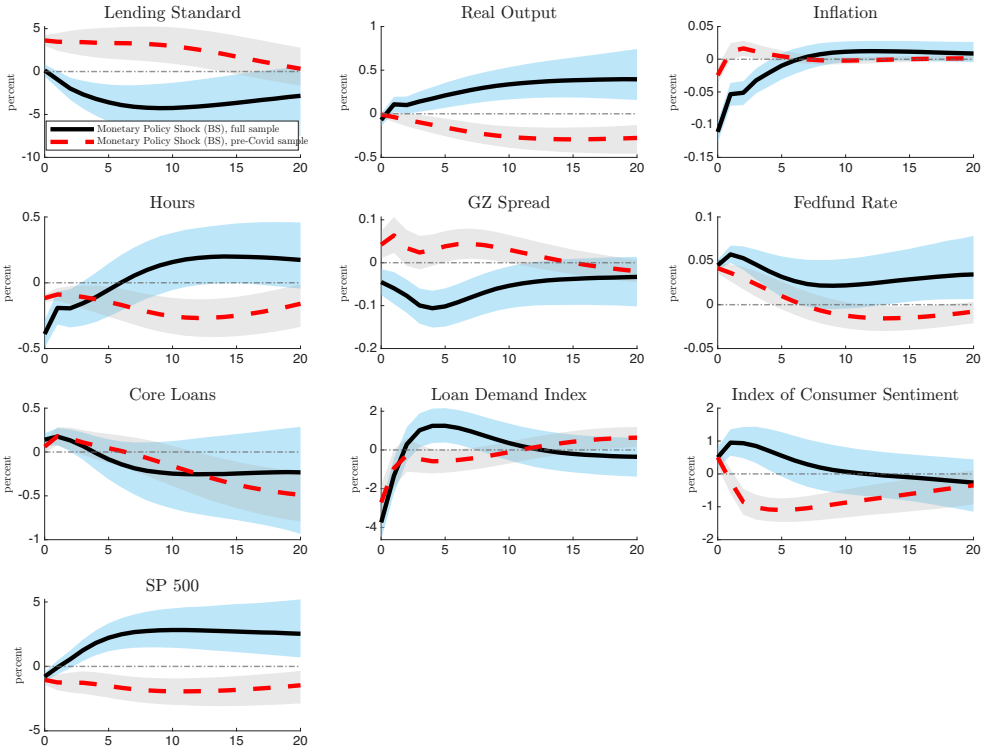


Figure C.13: IRFs to a Monetary Policy Shock, two samples

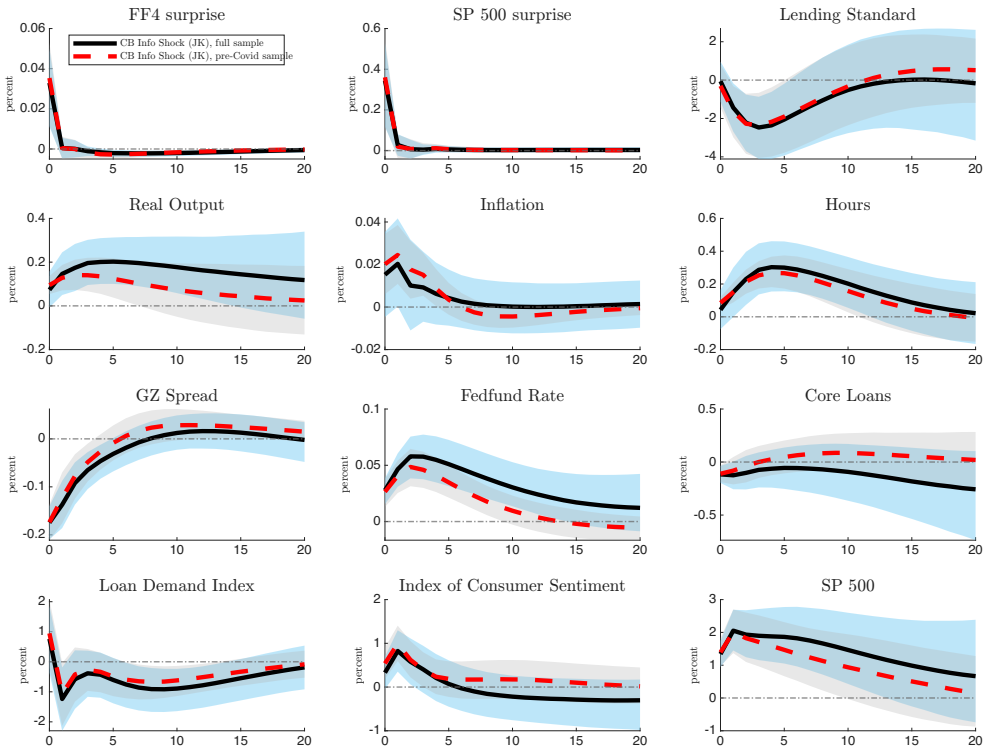


Figure C.14: IRFs to a Central Bank Information shock, two samples

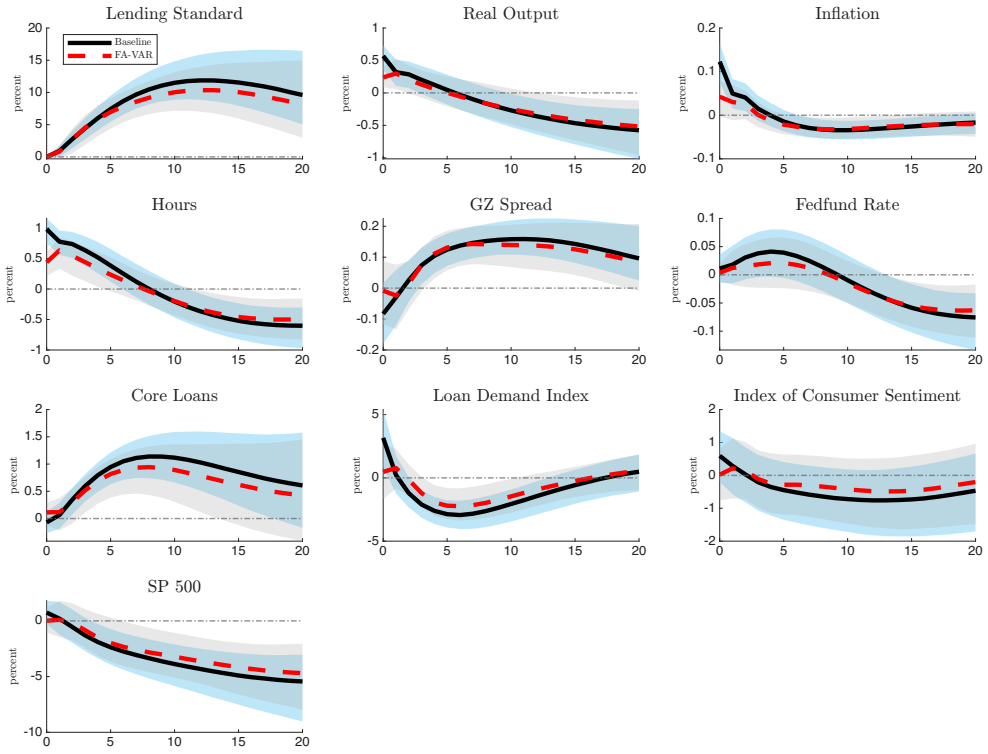


Figure C.15: IRFs to a credit supply news shock, FA-VAR

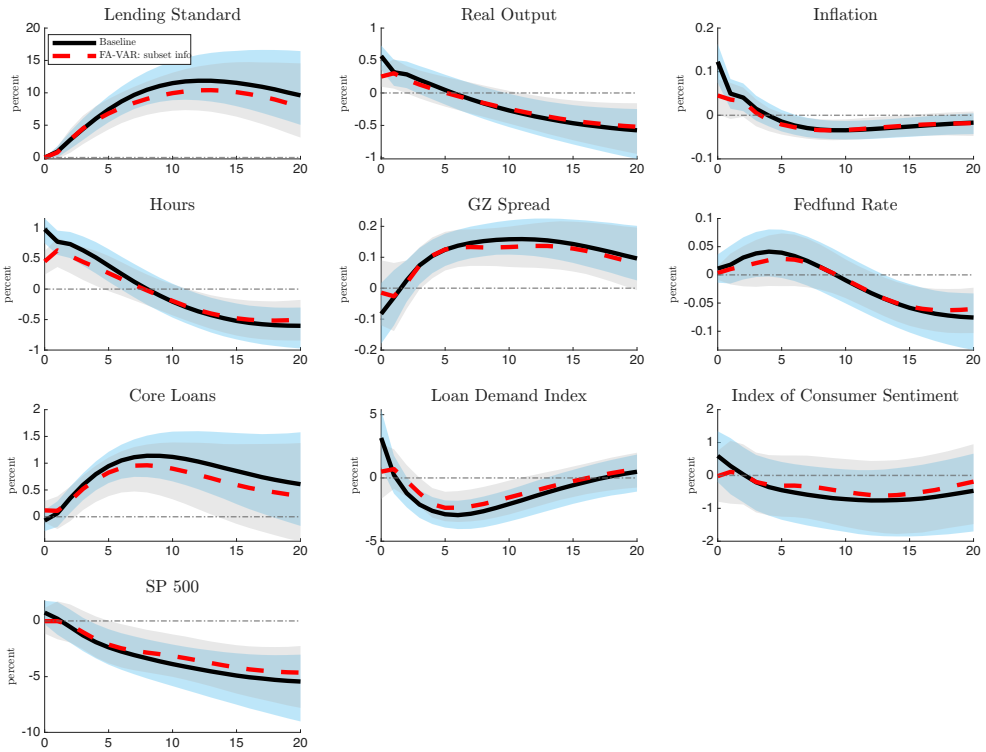


Figure C.16: IRFs to a credit supply news shock, FA-VAR using sub-info set

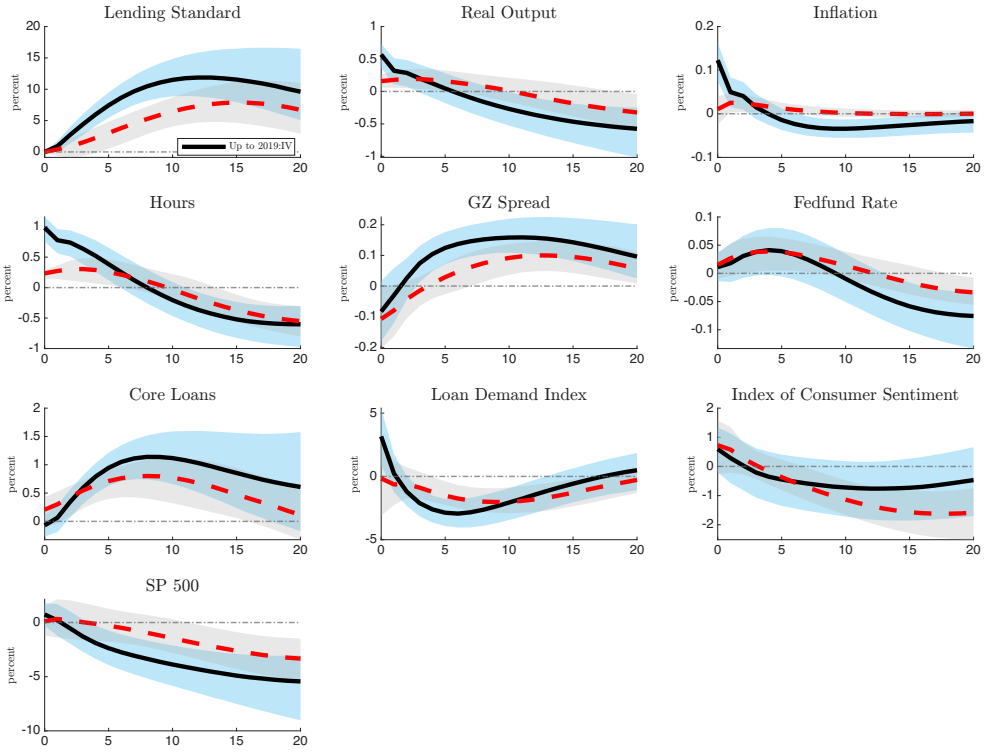


Figure C.17: IRFs to a credit supply news shock, pre-Covid sample

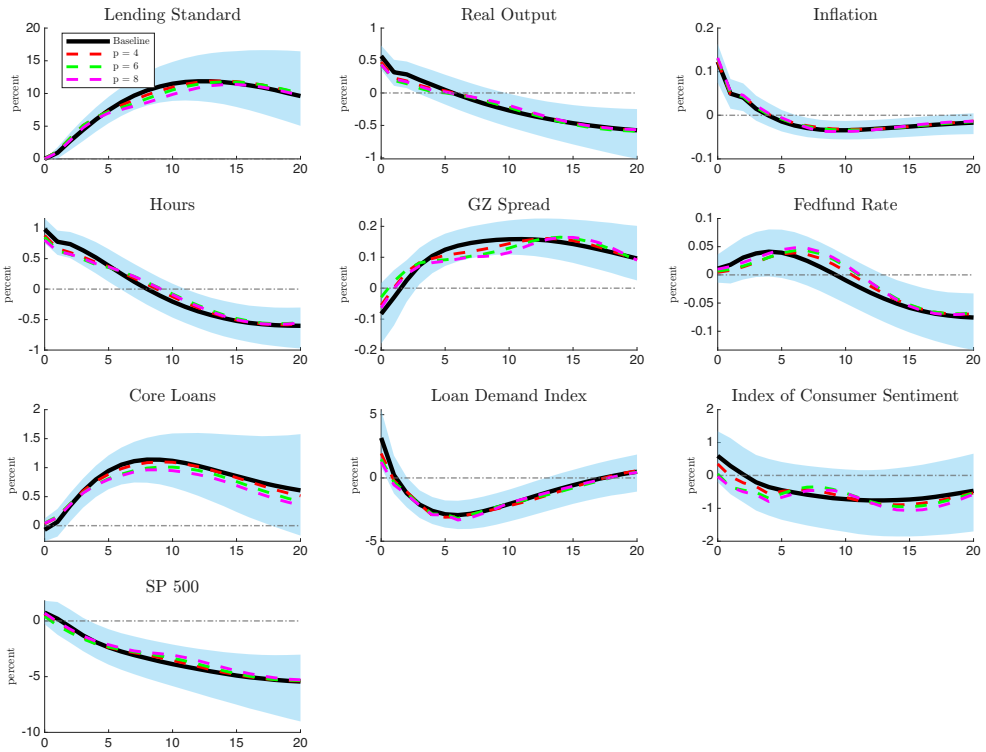


Figure C.18: IRFs to a credit supply news shock, lag order changes

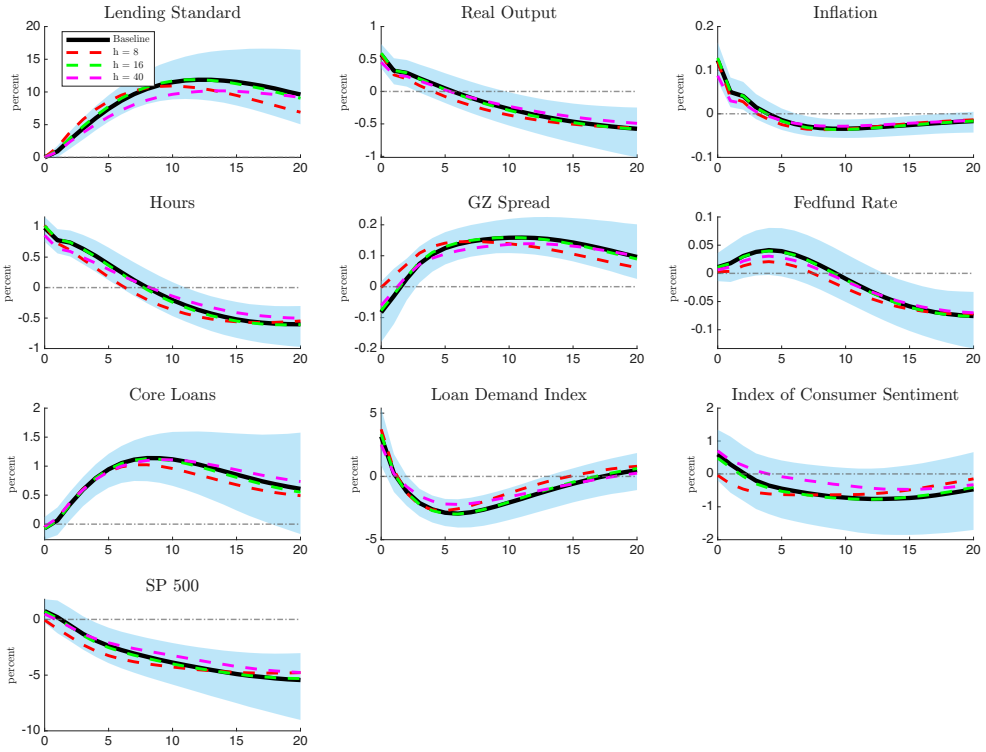


Figure C.19: IRFs to a credit supply news shock, horizon changes

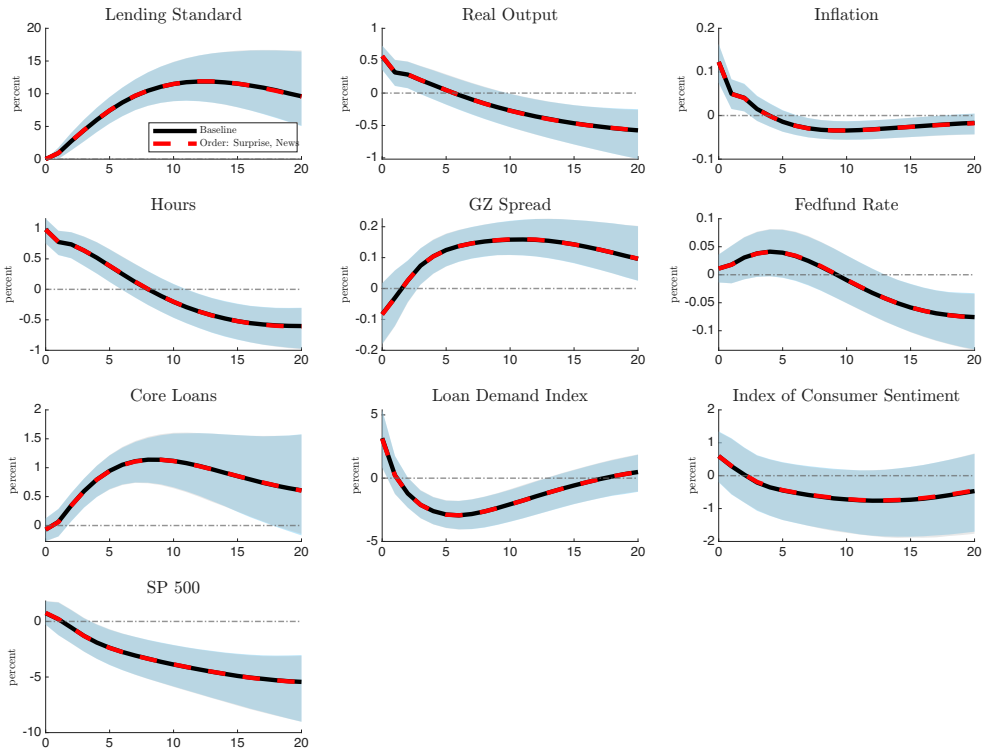


Figure C.20: IRFs to a credit supply news shock, order change

C.2 Robust Figures for Extension Results

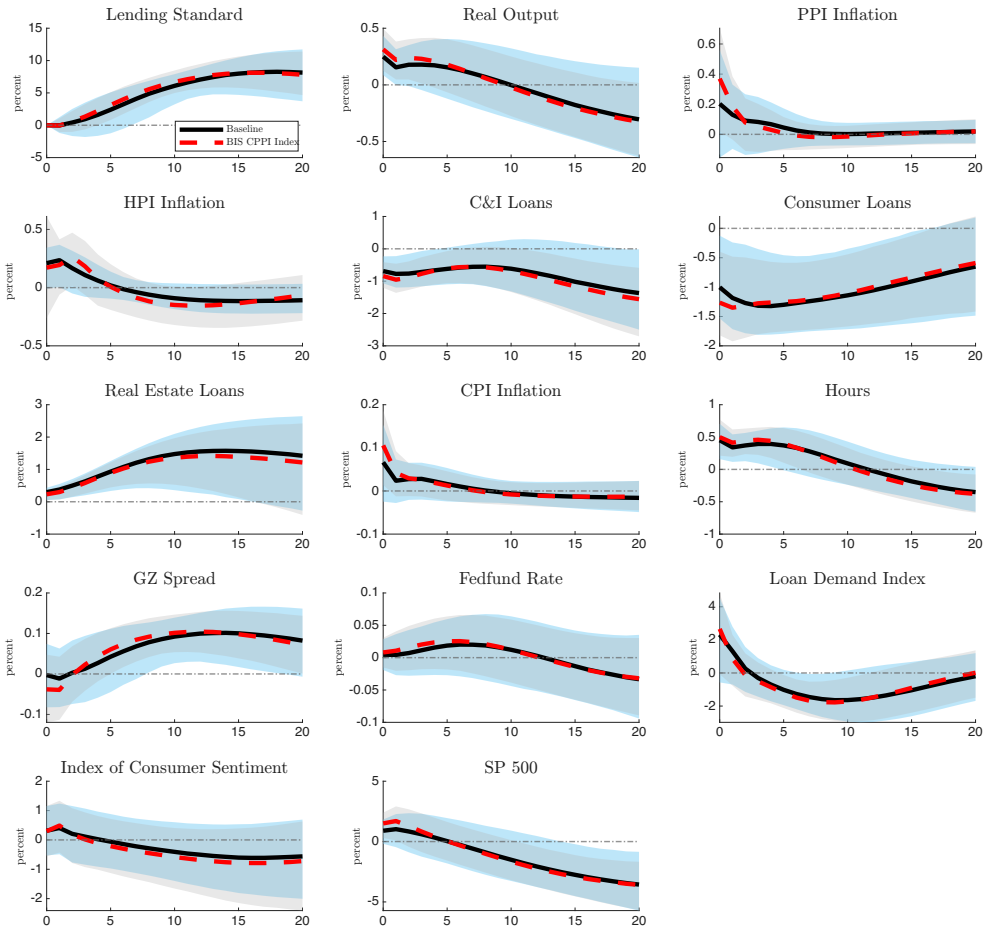


Figure C.21: IRFs to a credit supply news shock, alternative BIS CPPI index

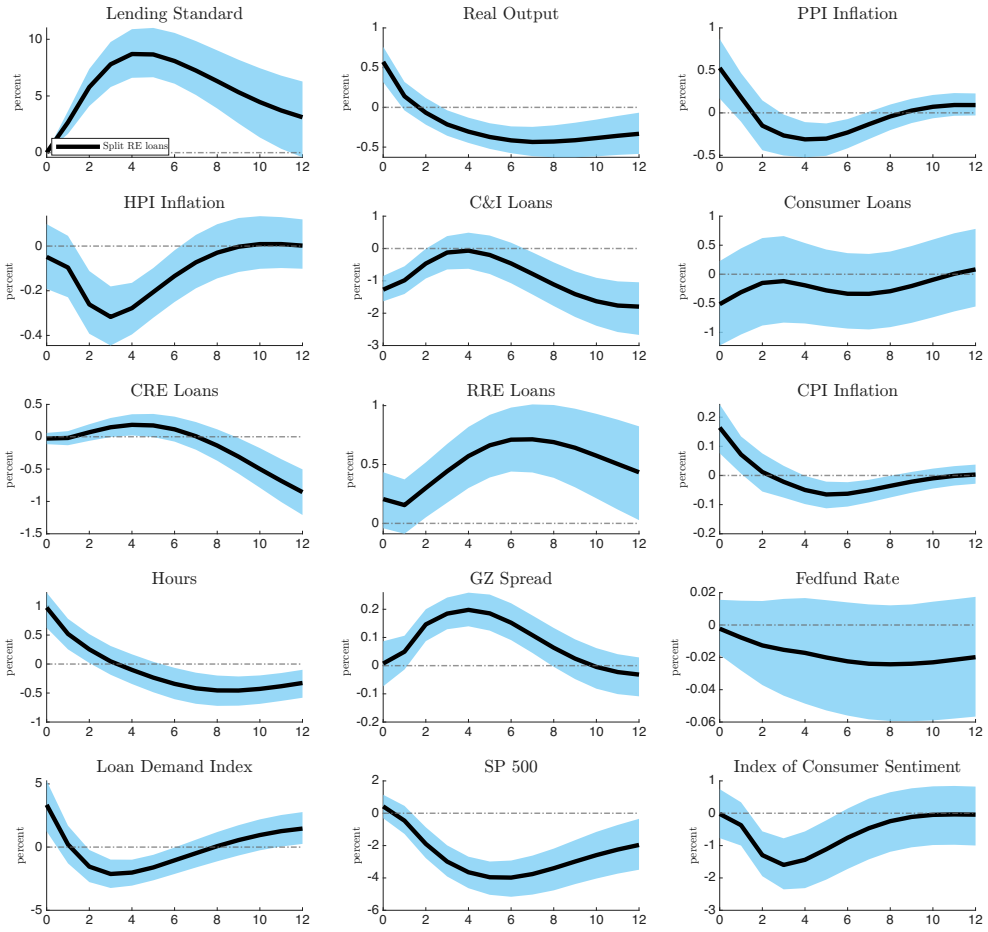


Figure C.22: IRFs to a credit supply news shock, splitting real estate loans

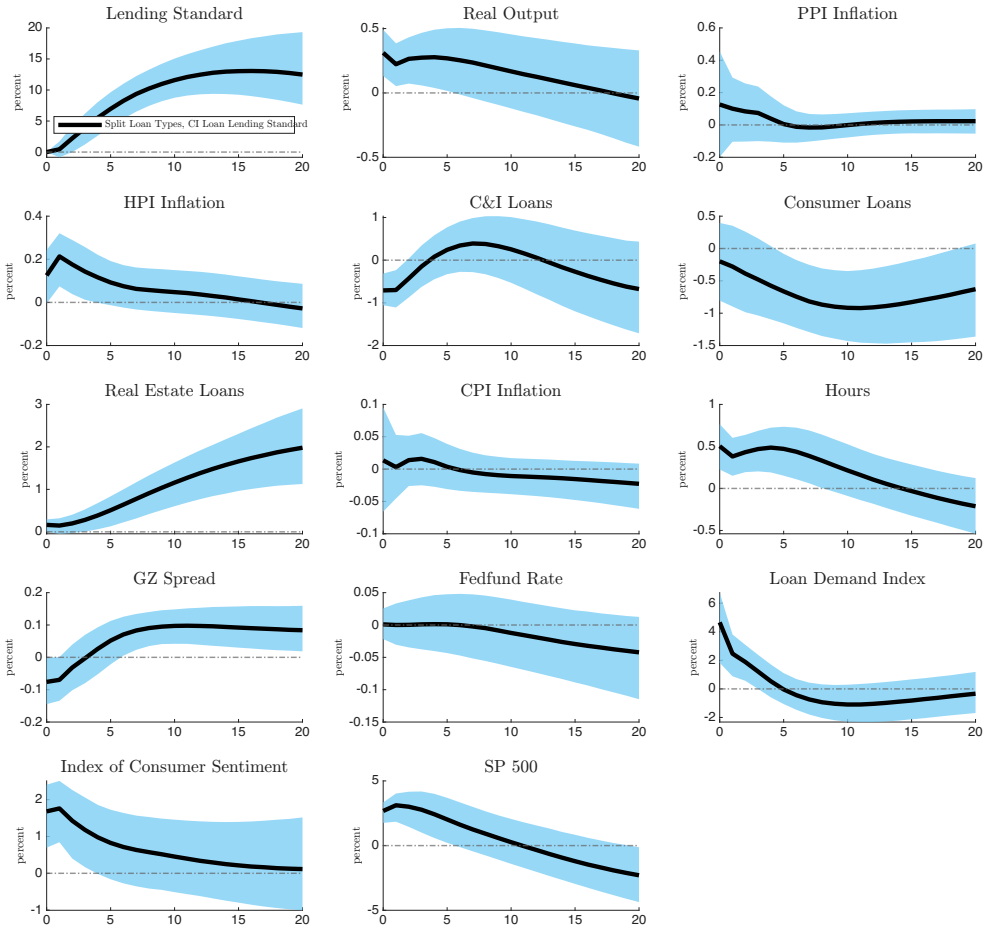


Figure C.23: IRFs to a credit supply news shock in C&I loans

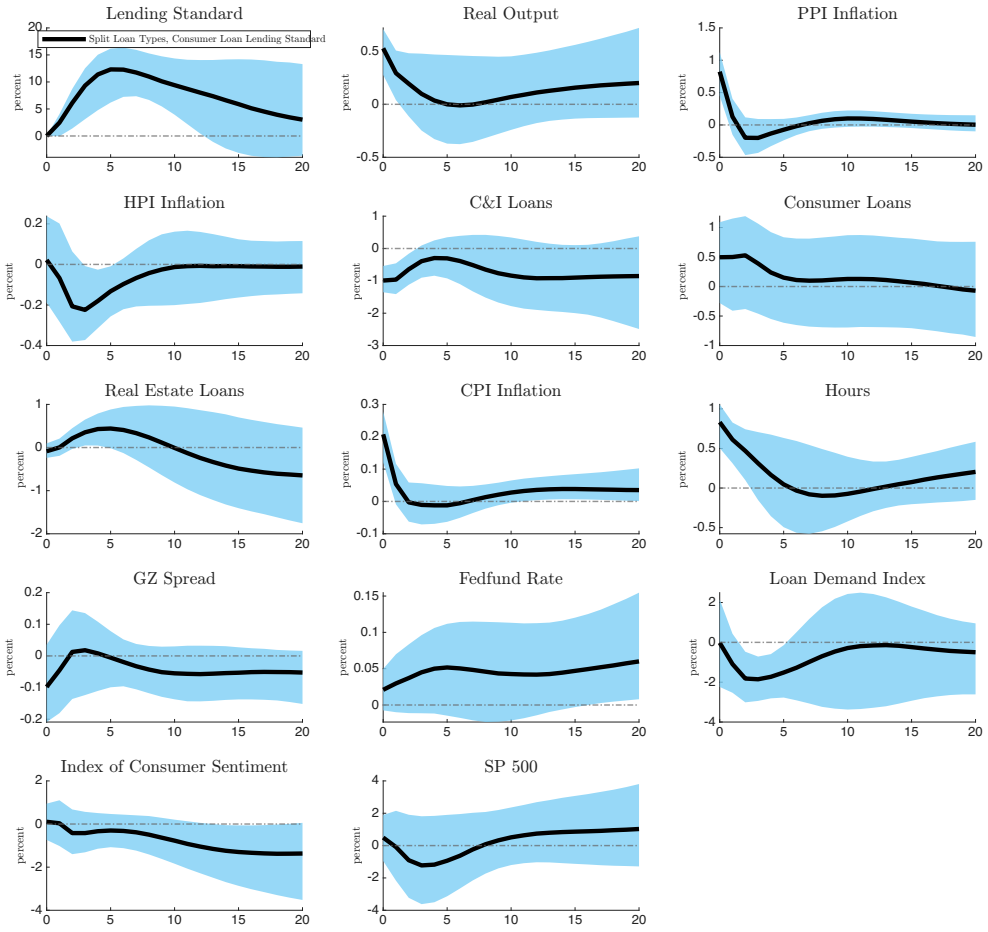


Figure C.24: IRFs to a credit supply news shock in consumer loans

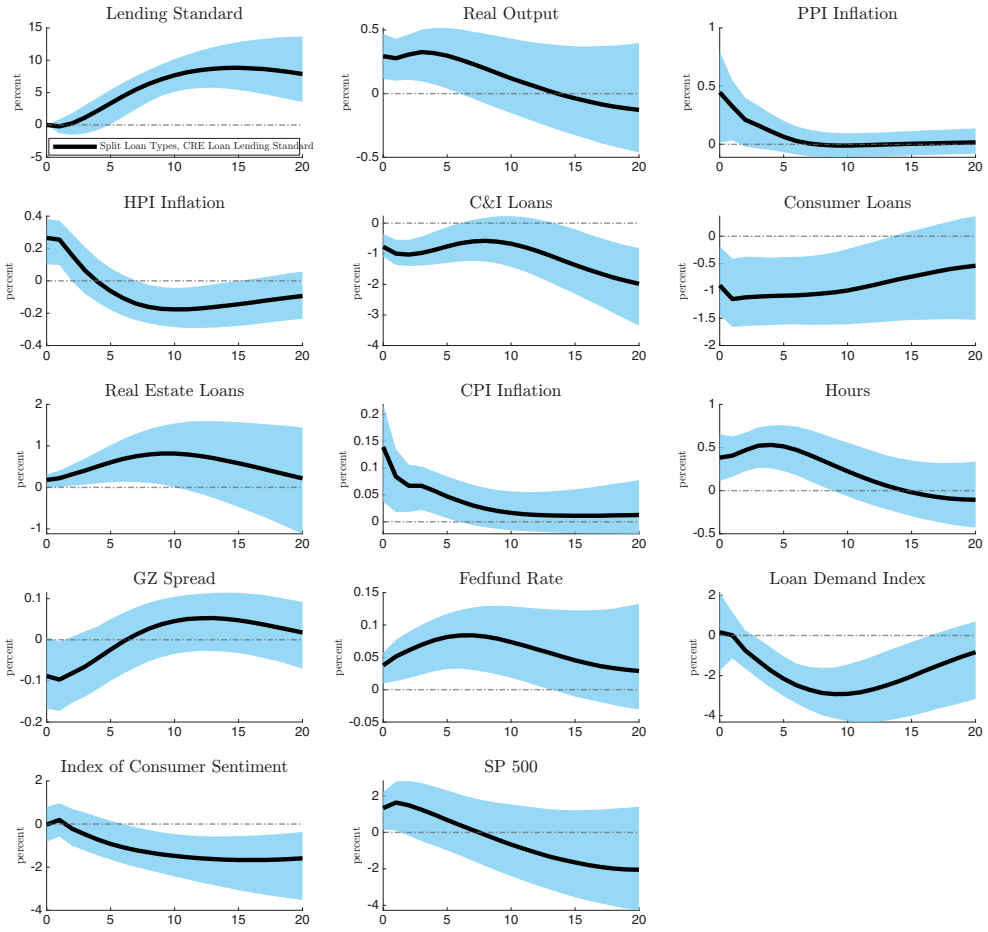


Figure C.25: IRFs to a credit supply news shock in CRE loans

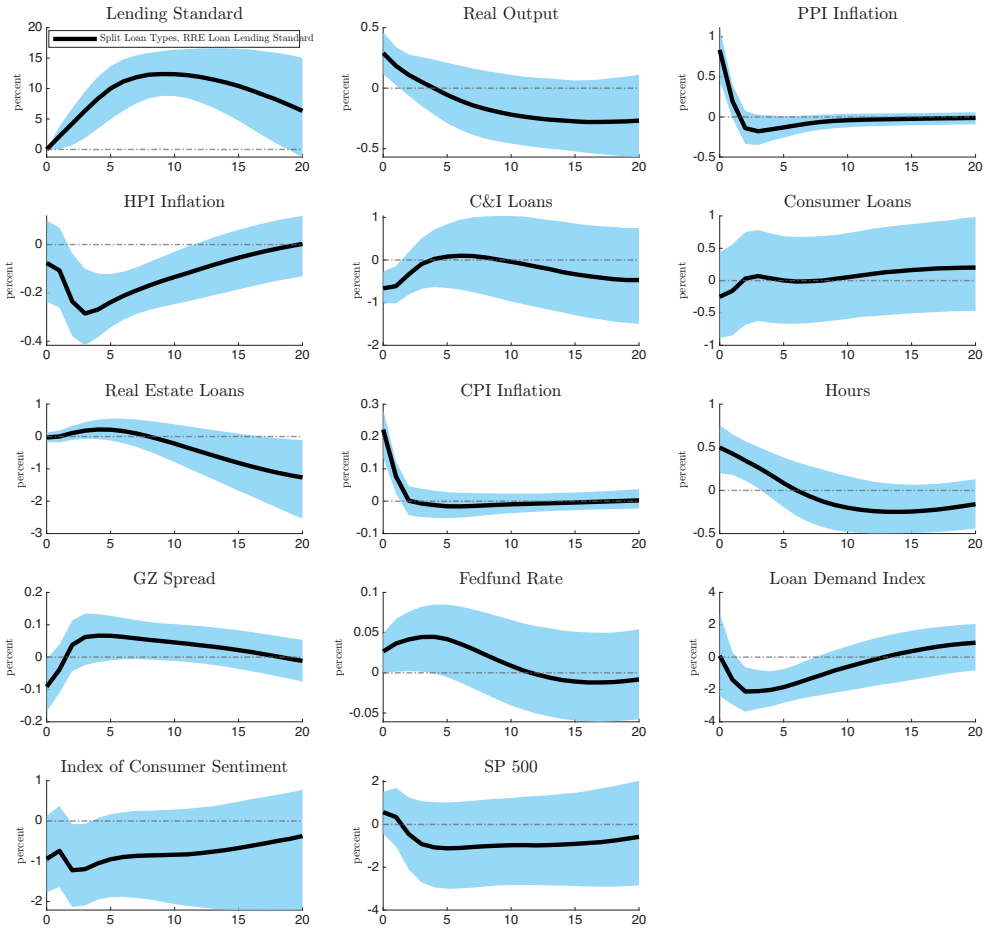


Figure C.26: IRFs to a credit supply news shock in RRE loans

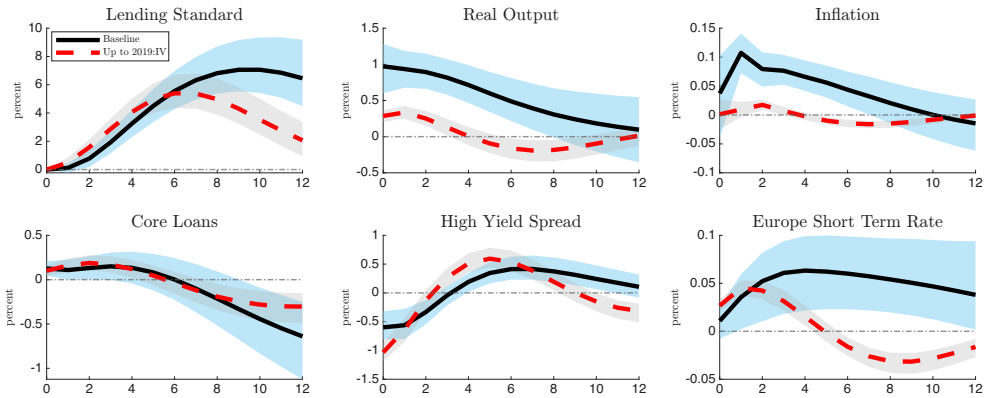


Figure C.27: IRFs to a Euro-area credit supply news shock, pre-Covid sample

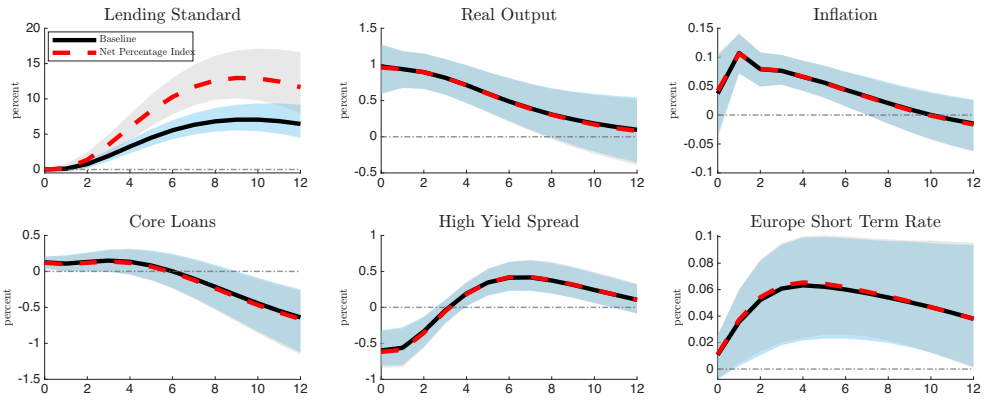


Figure C.28: IRFs to a Euro-area credit supply news shock, net percentage index

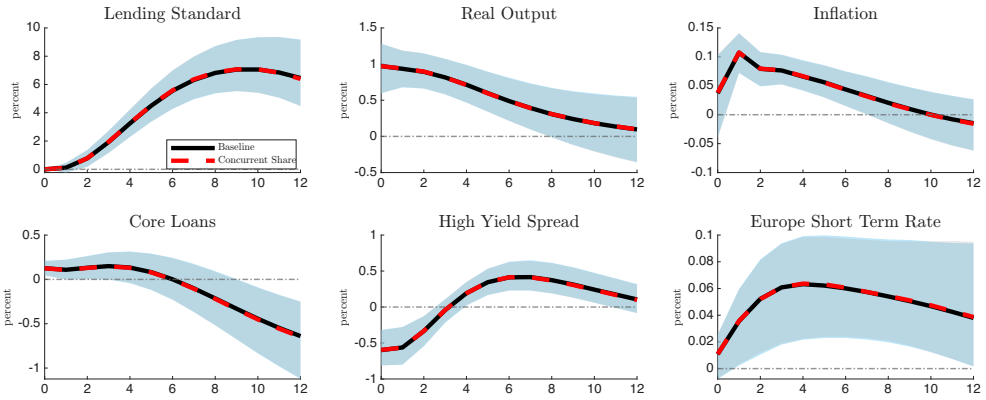


Figure C.29: IRFs to a Euro-area credit supply news shock, concurrent weights

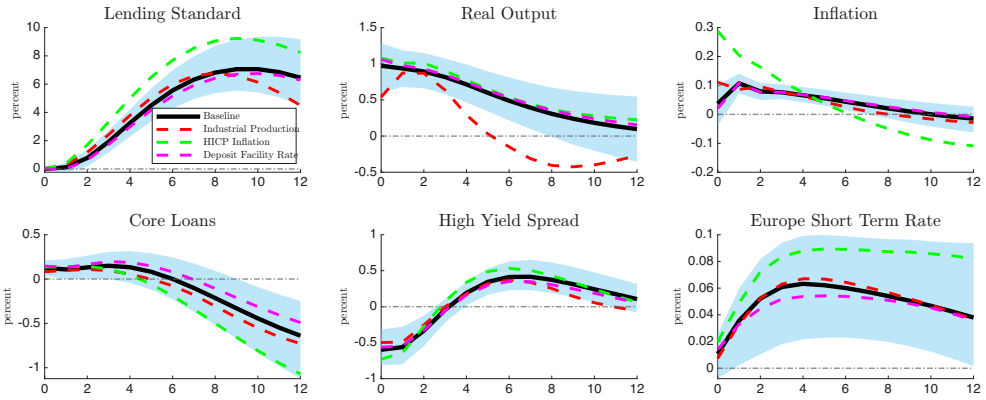


Figure C.30: IRFs to a Euro-area credit supply news shock, alternative other measures

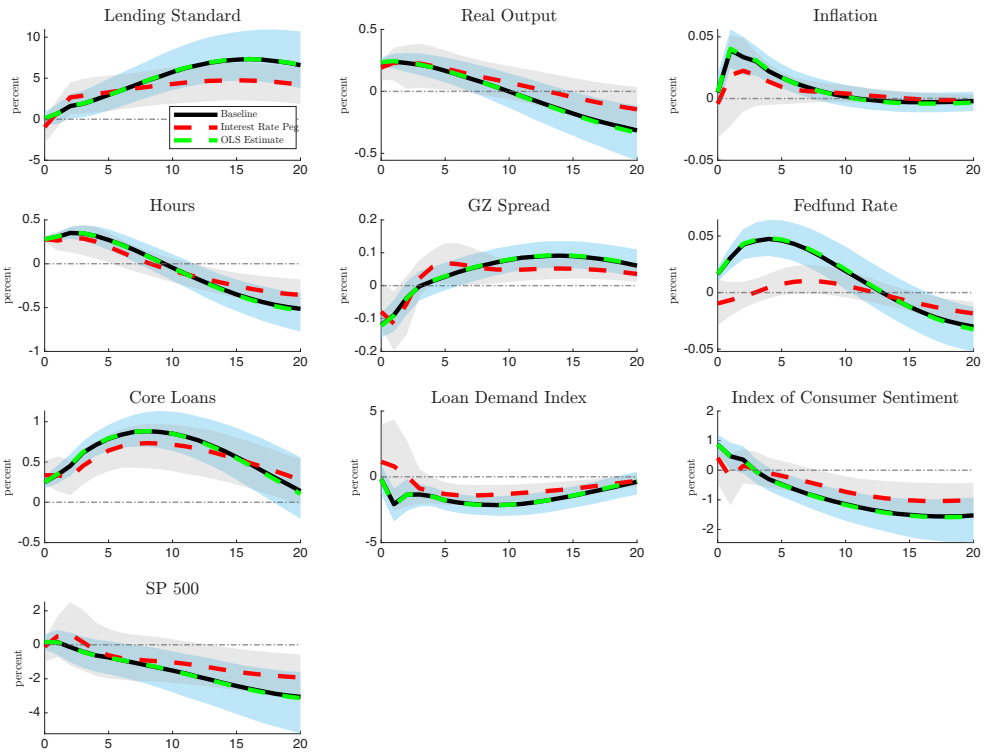


Figure C.31: IRFs to a credit supply news shock, interest rate peg excluding AD shocks

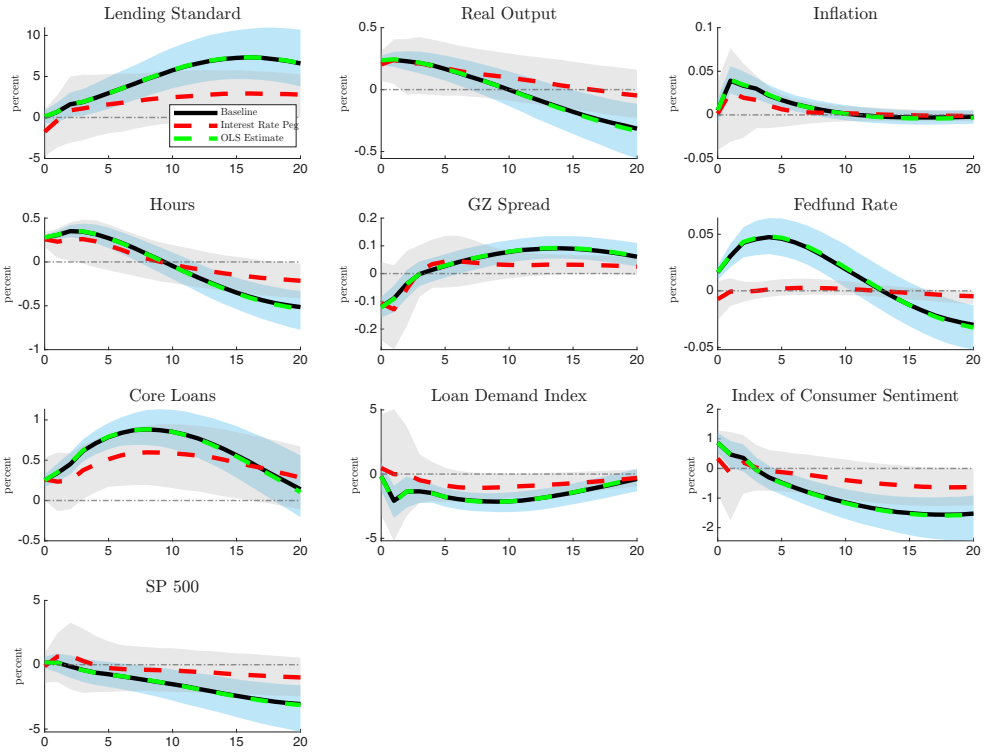


Figure C.32: IRFs to a credit supply news shock, interest rate peg including JK and BS shocks

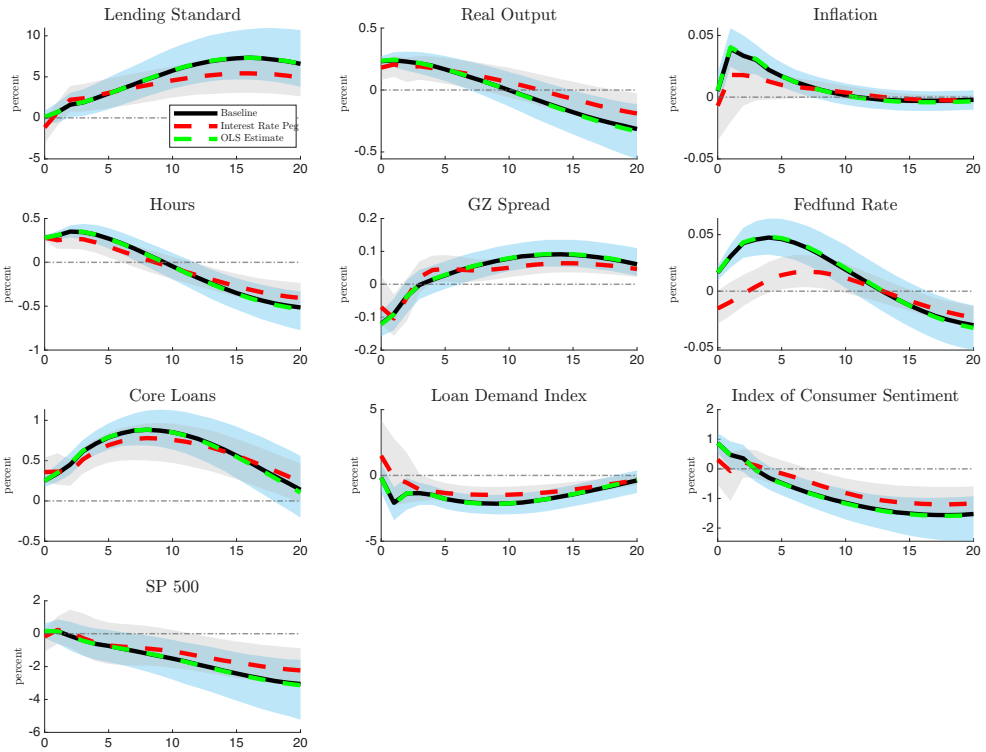


Figure C.33: IRFs to a credit supply news shock, interest rate peg GK and RR shocks

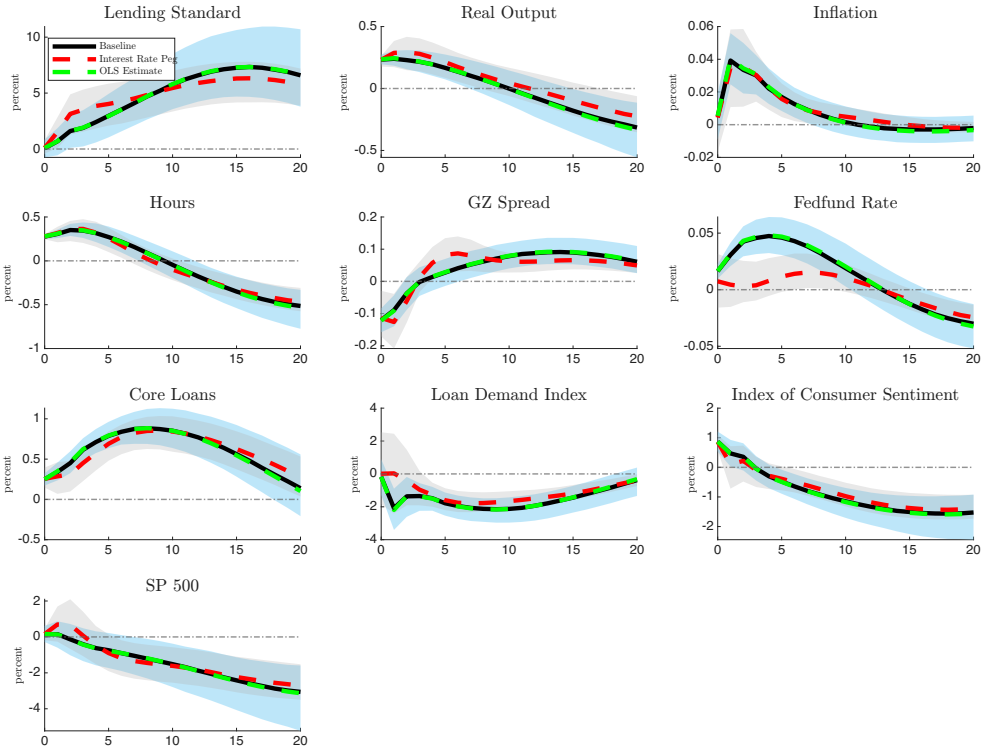


Figure C.34: IRFs to a credit supply news shock, interest rate peg AD and MAR shocks

D Supplementary Figures

This appendix mainly includes supplementary figures mentioned in the main body. In Appendix **??**, I also show discussions on identifications of a conventional monetary policy shock using high frequency surprises as external instruments.

D.1 Supplementary Figures for Baseline Results

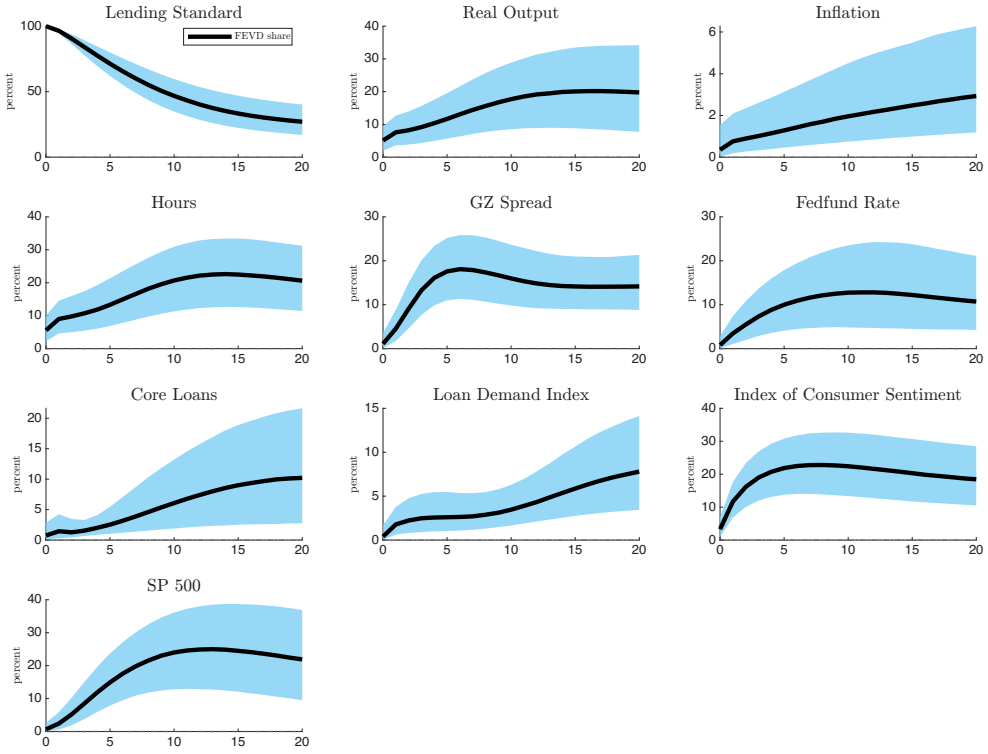


Figure D.1: FEVD to a credit supply surprise shock

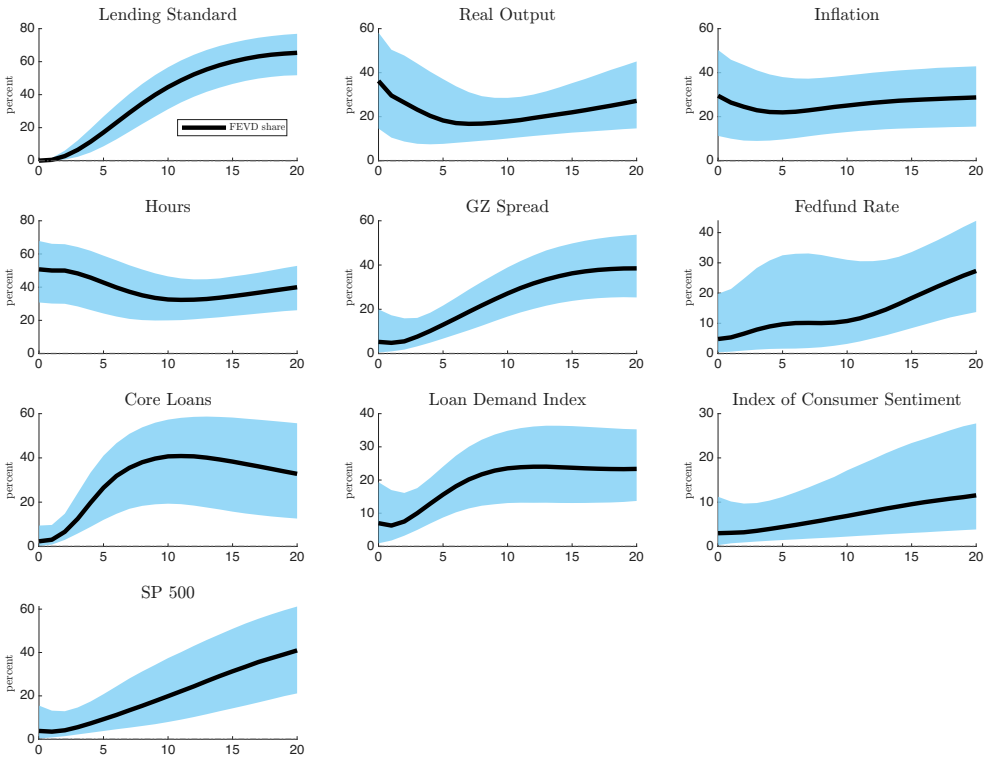


Figure D.2: FEVD to credit supply news shock

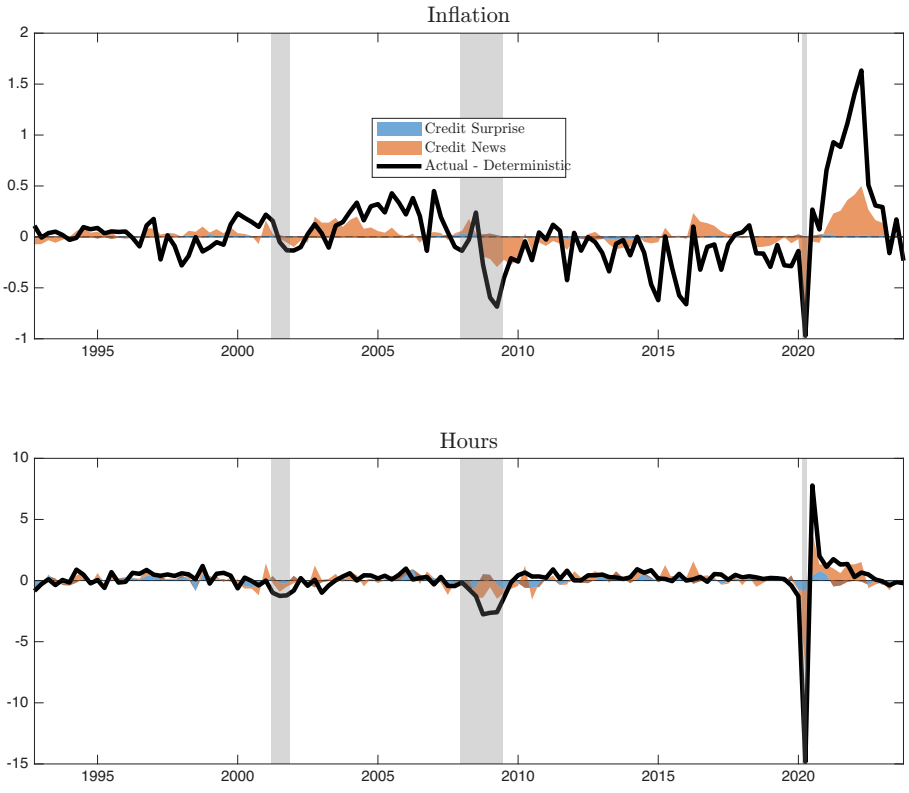


Figure D.3: HD to credit supply shocks

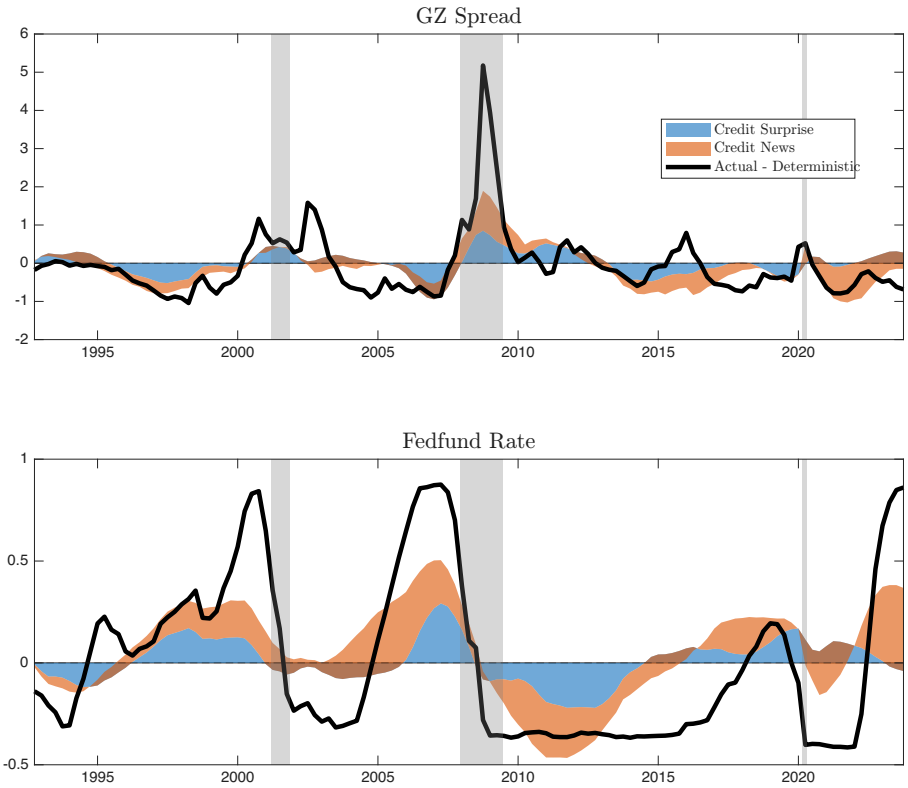


Figure D.4: HD to credit supply shocks

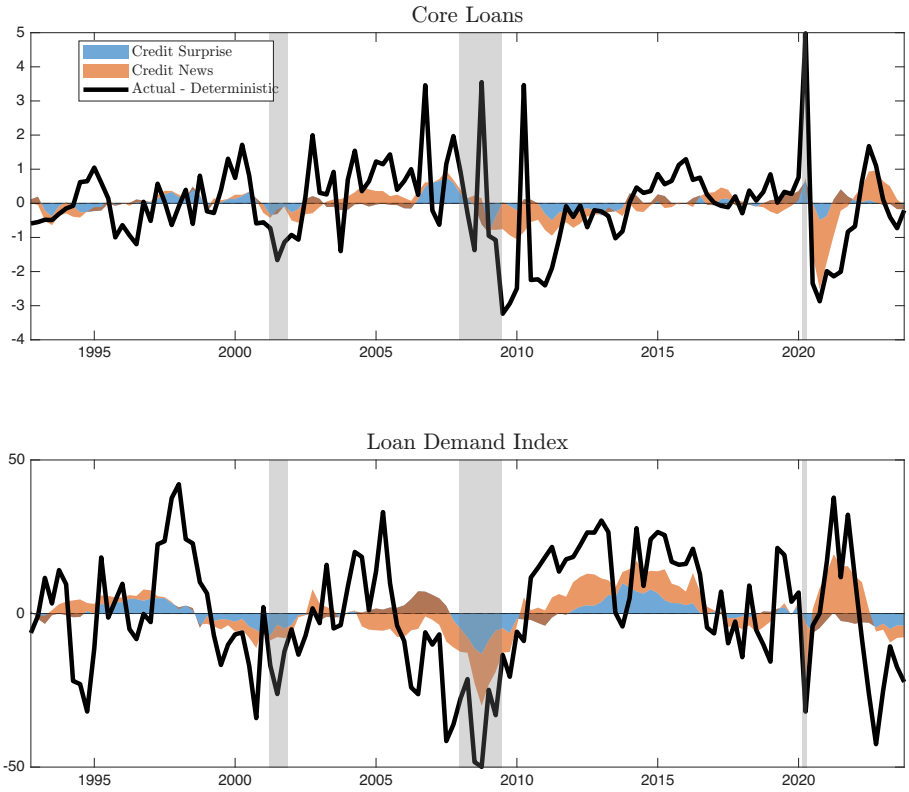


Figure D.5: HD to credit supply shocks

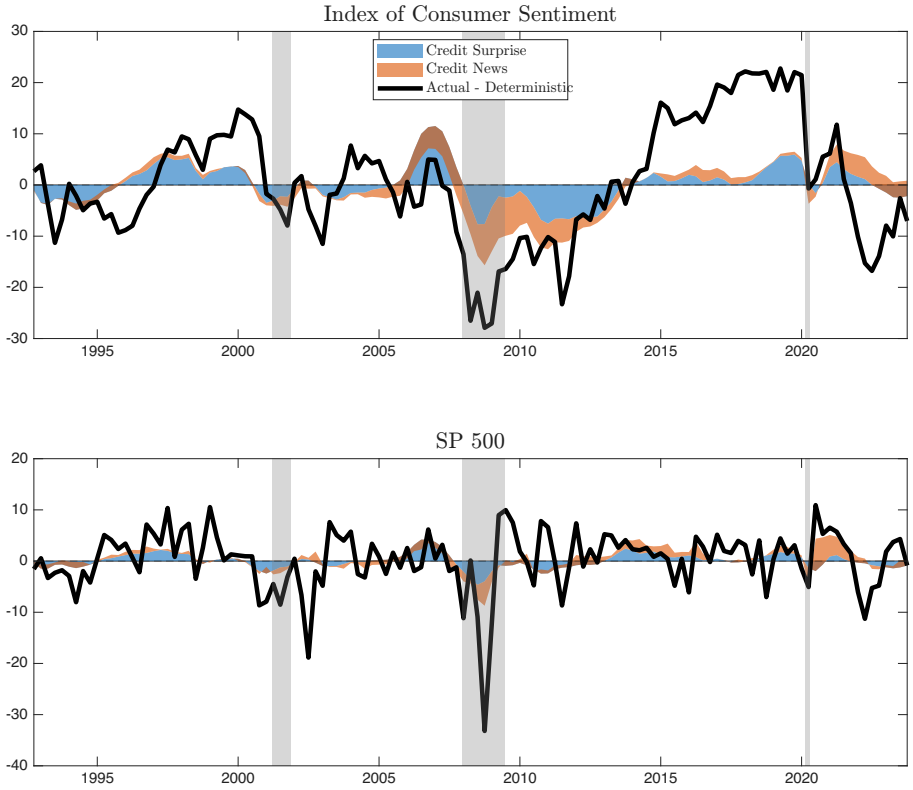


Figure D.6: HD to credit supply shocks

References for Appendices

Cavallo, Michele, Juan Morelli, Rebecca Zarutskie, and Solveig Baylor, "Measuring Bank Credit Supply Shocks Using the Senior Loan Officer Survey," *FEDS Notes*, May 2024, (2024-05-24-1), None–None. Publisher: Board of Governors of the Federal Reserve System.

Favara, Giovanni, Simon Gilchrist, Kurt F. Lewis, and Egon Zakrajsek, "Updating the Recession Risk and the Excess Bond Premium," *FEDS Notes*, October 2016, *2016.0* (1836). Publisher: Board of Governors of the Federal Reserve System.

Giannone, Domenico, Michele Lenza, and Giorgio E. Primiceri, "Prior Selection for Vector Autoregressions," *Review of Economics and Statistics*, May 2015, *97* (2), 436–451. Publisher: MIT Press - Journals.

Gilchrist, Simon and Egon Zakrajšek, "Credit Spreads and Business Cycle Fluctuations," *American Economic Review*, June 2012, *102* (4), 1692–1720.

Görtz, Christoph, John D. Tsoukalas, and Francesco Zanetti, "News Shocks under Financial Frictions," *American Economic Journal: Macroeconomics*, October 2022, *14* (4), 210–243. Publisher: American Economic Association.

Kurtzman, Robert, Rebecca Zarutskie, and David Glancy, "An Aggregate View of Bank Lending Standards and Demand," *FEDS Notes*, May 2020, *2020.0* (2546). Publisher: Board of Governors of the Federal Reserve System.

Uhlig, Harald, "What moves GNP?," Econometric Society 2004 North American Winter Meetings 636, Econometric Society August 2004.

Wu, Jing Cynthia and Fan Dora Xia, "Measuring the Macroeconomic Impact of Monetary Policy at the Zero Lower Bound," *Journal of Money, Credit and Banking*, 2016, *48* (2-3), 253–291. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jmcb.12300.