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# From Bank Lending Standards to Bank Credit Conditions: An SVAR Approach*

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**Abstract**

This paper uses a structural vector autoregressive (SVAR) model—identified with an external monetary policy instrument and sign restrictions—to derive a measure of bank credit conditions from changes in bank lending standards. The model incorporates data on interest rates, bank credit, and survey-based measures of bank lending standards to identify monetary policy, credit demand, and credit supply shocks. Using these identified shocks, we construct a novel measure of bank credit conditions that corresponds to the component of credit growth that would occur if credit demand remained unchanged, reflecting solely the impacts of monetary policy and credit supply shocks. Using this measure, we find that credit supply–driven changes in bank credit conditions have a stronger impact on real outcomes in the euro area, whereas monetary policy–driven changes play a larger role in the U.S. economy.

*JEL classification codes*: C32, C36, G21.

*Keywords*: Bank Credit; Bank Lending Surveys; Monetary Policy; External Instruments; Sign Restrictions; SVAR

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# 1. Introduction

Central banks must assess whether credit conditions are expansionary or restrictive to effectively carry out their mandates. Excessively loose credit can fuel inflation and financial vulnerabilities through excessive lending, while overly tight conditions may dampen investment and consumption, constraining growth. One way in which central banks gauge credit conditions is by surveying banks on changes in lending standards. However, these surveys are mostly focused on capturing shifts in standards, not their absolute levels or overall credit conditions. This paper proposes a method to quantify the level of bank credit conditions using publicly available data on changes in lending standards and a state-of-the-art structural vector autoregressive (SVAR) identification methodology. Building on this measure, we examine how shifts in bank credit conditions impact key macroeconomic variables in the United States and the euro area.

The Federal Reserve Board (Fed) has conducted the Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS) since 1967, and, for most of the time this survey has been conducted, it has asked banks whether—during the past three months— their standards for approving loan applications of a certain type (e.g., commercial and industrial loans) had tightened, remained unchanged, or eased.[1] Similarly, many other central banks, such as the Bank of Japan, the Bank of England, and the European Central Bank (ECB), also run surveys that include similar questions about banks' lending standards in their respective jurisdictions.[2] In this paper we only use results from the Fed's SLOOS and the ECB's Euro-

[1]As discussed in Lown et al. (2000), between 1984 and 1990 the questions regarding standards were removed because at that time it was thought that, with the banking deregulation efforts that took place in the early 1980s, lending standards were no longer important, as only prices would matter for access to credit. Once it became clear that both prices and standards mattered for access to credit, the questions about lending standards were added back to the survey. For a recent version of the questions on lending standards, see `https://www.federalreserve.gov/data/documents/sloos-202404.pdf`.

[2]Starting in July 2011, the Federal Reserve Board began asking banks about the level of standards at an

area Bank Lending Survey (BLS), but the approach we propose can be easily implemented in other countries.

Because of the unique and rich information provided by the Fed's SLOOS and the ECB's BLS, their results have been widely utilized in academic research. In the rest of the introduction, we review related papers relevant to our research question to contextualize our contribution within the existing literature. One of the first papers to use bank lending standards in the context of a vector autoregressive (VAR) model was Lown and Morgan (2006).[3] These authors used a six-variable VAR model and identified the shocks of interest recursively. Although this approach to identifying shocks was standard at the time, it has since been replaced by more-advanced and less-restrictive methods. In our paper, we follow the methodology of Cesa-Bianchi and Sokol (2022) and identify shocks using an external instrument combined with sign restrictions. Bassett et al. (2014) use individual banks' responses and bank-specific and economy-wide variables to remove demand-related information from lending standards.[4] This is an important contribution because, as we also find in our approach, lending standards contain information on both credit demand and supply. We chose to not follow a similar methodology because we wanted our methodology to rely only on publicly available information. While Bassett et al. (2014) found similar dynamic responses of certain macroeconomic variables to credit supply shocks as previous studies, they also found that the relative importance of credit supply shocks for variation in the same macroeconomic variables is smaller than previously estimated.

annual frequency. This information is useful but not very timely. Also, there are no similar questions in the European Central Bank's Bank Lending Survey.

[3] Berrospide and Edge (2010) adopt the same VAR framework as Lown and Morgan (2006), but Berrospide and Edge (2010)'s key innovation is to augment the bank-credit block with a measure of bank capital, allowing them to identify and estimate the effects of exogenous capital shocks on bank lending.

[4] In recent work, Cavallo et al. (2024) use the Bassett et al. (2014) methodology as a starting point and expand it to better address recent changes in the U.S. banking system and also to better account for credit demand and credit supply effects on bank lending standards.

Despite the ECB having only started conducting the BLS in 2003, there is already a vast amount of research using the results from this survey. Two of the first research papers using the ECB's BLS results are Maddaloni et al. (2009) and De Bondt et al. (2010). De Bondt et al. (2010) find that the euro-area BLS data have predictive power for both future bank credit growth and GDP growth in the euro area and that this effect is particularly pronounced for the information on loans to enterprises. Maddaloni et al. (2009) find that lending standards are affected by monetary policy-specifically, that tighter monetary policy tends to lead to tighter lending standards, while looser monetary policy contributes to the easing of standards. Using a different approach to identify monetary policy shocks, we find a similar result and, in addition, quantify how much of the variation in lending standards can be attributed to current and past monetary policy surprises. A similar result pertaining to the effect of monetary policy on lending standards is also found in the literature for the case of the United States. For example, Afanasyeva and Güntner (2014) use a factor-augmented VAR (FAVAR) model and an external instrument to identify monetary policy shocks and find that lending standards co-move with monetary policy. Using our methodology, we also find the same result for both the United States and the euro area.

To the best of our knowledge, our paper is one of the few that uses the information on changes in lending standards to produce a measure of the level of credit conditions. One paper that also uses information on changes in lending standards to produce a measure of credit conditions is Van der Veer and Hoeberichts (2016). These authors use the directional information contained in the lending standards questions in the surveys to construct an index of the level of lending standards. One issue with the approach followed by these authors is that the "level" of lending standards is not comparable over time because the exact level of tightening or loosening is not observed. Moreover, the results cannot be compared across banks because individual banks tightening or loosening standards—even if in the same direction—can have different implications for the level of credit conditions. Related to this point, Bassett and Rezende (2015) compared the reported changes in credit standards with the also reported level of standards at the bank level for U.S. banks and found that the correlation between the two was tenuous at best.[5] Our proposed approach to measure bank credit conditions from bank lending standards will not suffer any of these issues, as the measure can be compared over time and across jurisdictions (it could also be made comparable across banks if the estimation was done at the bank level). Moreover, we are not using changes in credit standards directly—we are just using unobserved information about credit supply shocks that is embedded in results from bank lending surveys.

Using the proposed measure of bank credit conditions, we find that changes in these conditions matter more in the euro-area economy than in the United States, likely because of the euro area's greater reliance on bank funding. In the United States, changes in credit conditions driven by monetary policy have a larger impact on economic outcomes, whereas in the euro area, changes in credit conditions driven by credit supply shocks play a more significant role. Overall, these results suggest that monetary policy transmission through banks plays a stronger role in the United States, while changes in banks' credit supply policies have a greater impact on economic outcomes in the euro area.

The rest of the paper is organized as follows: in section 2 we briefly describe the econometric methodology as well as the identifying assumptions we use; in section 3 we describe

[5] In recent work, Berman et al. (2025) propose a mixed-frequency (MIDAS) approach to estimate quarterly levels of credit standards by combining the annual levels reported in the July SLOOS with the more frequent quarterly changes. This method represents a notable improvement over the naïve approach of simply cumulating quarterly changes, particularly in periods of financial stress. However, while the MIDAS-based estimates perform well in the U.S. context, their reliance on annual level data makes them difficult to implement in other jurisdictions—such as the euro area—where similar questions on the level of standards are not asked. Moreover, because the scale of the resulting series is still ultimately anchored to ordinal survey responses, the interpretation of magnitudes remains somewhat difficult and context-dependent.

the data sources; in section 4 we present and discuss the econometric results; in section 5 we introduce the proposed measure of bank credit conditions and assess the macroeconomic effects of bank credit conditions in the U.S. and euro-area economies; and in section 6 we provide some concluding remarks.

# 2. Econometric Methodology

To separately identify monetary policy, bank credit supply, and bank credit demand shocks in an SVAR model, we follow the methodology proposed by Cesa-Bianchi and Sokol (2022), which combines external instruments (Stock and Watson, 2012; Mertens and Ravn, 2013; Gertler and Karadi, 2015) and sign restrictions (Faust, 1998; Uhlig, 2005; Rubio-Ramirez et al., 2010) to identify the structural shocks driving the variables of interest. In this section we first briefly describe the methodology underlying the identification strategy and then provide all the details pertaining to the implementation of the methodology and the data we use.

## 2.1. Identification Strategy

As already noted, we follow the method proposed by Cesa-Bianchi and Sokol (2022) to identify the structural shocks of interest. The discussion that follows is a summary of section 2.1 in Cesa-Bianchi and Sokol (2022). In this discussion we cover only the main aspects of the method and refer the interested reader to the original source.

Let $y_t$ be an $n \times 1$ vector of variables, whose dynamics are assumed to follow the following structural VAR model:

$$A(L)Y_t = H\varepsilon_t. \tag{1}$$

In equation (1) $A(L) = I_n - \sum_{l=1}^{p} A_l(L^l)$. Each matrix $A_l(L^l)$, for $l \geq 1$, is an $n \times n$ matrix of coefficients associated with lag $l$, $I_n$ is an $n \times n$ identity matrix, $H$ is an $n \times n$ matrix of impact coefficients, and $\varepsilon_t$ is a vector of $n$ structural shocks.[6] This equation characterizes all the non-deterministic dynamics of the variables in the model. As usual, the structural shocks are assumed to have a linear effect on the variables included in the model, to have a mean of 0 ($\mathbb{E}[\varepsilon_t] = 0$), to have an identity covariance matrix ($\mathbb{E}[\varepsilon_t, \varepsilon_t'] = I_n$), and to be uncorrelated in all leads and lags ($\mathbb{E}[\varepsilon_t, \varepsilon_s'] = 0$ for $s \neq t$).

The identification issue in SVAR models arises from the fact that the reduced-form residuals, $u_t = H\varepsilon_t$, are consistent with an infinite number of different structural impact matrices $H$ (Sims, 1986). There have been many proposals in the literature about how to best select a matrix (or matrices) $H$ that is either consistent with economic theory or implied by the data. In order to identify $H$, we apply Cesa-Bianchi and Sokol (2022)'s approach, which combines two widely used methodologies—external instruments and sign restrictions—to identify the short-run impact matrix $H$ and, with that, the structural shocks. In general, the identification of shocks and/or impulse responses via external instruments is seen as the preferred method. However, external instruments aren't always available for all possible shocks and other methods of identification must be used if the identification of all shocks is the goal. This methodology of Cesa-Bianchi and Sokol (2022) allows us to use external instruments when available and sign restrictions based on economic theory for the shocks for which no external instrument exists.

[6]For notational simplicity and without loss of generality, the specification in (1) omits deterministic terms, such as a constant or a trend. All the discussions about the identification strategy are unchanged when deterministic terms are added to the model.

As noted in Cesa-Bianchi and Sokol (2022), it is generally possible to identify $k < n$ structural shocks—these are denoted by $\epsilon_{i,t}^{IV}$, $i = 1, ..., k$—with the external instruments method. It is also generally possible to identify the remaining $n-k$ structural shocks—these are denoted by $\epsilon_{i,t}^{SR}$, $i = k+1, ..., n$—using sign restrictions.[7] In our application we want to identify three shocks in a three-variable SVAR. Since we use one external instrument and the model has three variables, the number of instruments is $k = 1$, the number of variables is $n = 3$, and the number of shocks identified with sign restrictions is $n - k = 2$.

Following the methodological discussion in Cesa-Bianchi and Sokol (2022), the impact matrix $H$ can be split into two subcomponents: (1) $H^{IV}$, which is a $k \times n$ matrix of coefficients associated with the shocks identified with external instruments and (2) $H^{SR}$, which is a $(n-k) \times n$ matrix of coefficients associated with the shocks identified with sign restrictions. Following this notation, $H$ can be written as the following:

$$H = \begin{bmatrix} H^{IV} & H^{SR} \end{bmatrix}. \tag{2}$$

As usual, for the identification using external instruments, we need $k$ instruments $z_t = (z_{1,t}, ..., z_{k,t})$, which must satisfy the relevance and exogeneity conditions:

1. **Relevance**: $E[\epsilon_{i,t} Z_t] \neq 0$

2. **Exogeneity**: $E[\epsilon_{j,t} Z_t] = 0 \ \ \forall \ \ i \neq j$

To identify the elements in $H^{IV}$, Cesa-Bianchi and Sokol (2022) followed Mertens and Ravn (2013)'s approach, which allows for the identification of the elements in $H^{IV}$.[8] The

[7]Note that the order of shocks is not relevant—we chose to order the shocks identified with external instruments first and the shocks identified with sign restrictions last for expositional purposes only.

[8]While Mertens and Ravn (2013) propose a method to obtain the level of the elements in $H^{IV}$—see part A of the Appendix—in most applications that use external instruments to identify structural shocks,

novel part of the methodological contribution is identifying the remaining shocks, $\epsilon_{i,t}^{SR}$, using sign restrictions. We refer the reader to Cesa-Bianchi and Sokol (2022) for a more detailed discussion of the method; here we just discuss the main idea of the method.

First, using equation (2), it is possible to write the covariance matrix of reduced-form residuals as the following:

$$\Sigma_u = HH' = \begin{bmatrix} H^{IV} & H^{SR} \end{bmatrix} \begin{bmatrix} H^{IV} & H^{SR} \end{bmatrix}' \tag{3}$$

As noted earlier, there isn't a unique $H$ matrix that is consistent with $\Sigma_u$. In this particular case, since $B^{IV}$ is identified in a first step, there are still, in general, many $B^{SR}$ matrices that are consistent with $\Sigma_u$ and $B^{IV}$. Given that the reduced-form residual covariance matrix $\Sigma_u$ can be Choleski decomposed and that matrix $Q$ is an orthonormal matrix such that $QQ' = I$, $\Sigma_u$ can be re-written as the folllowing:

$$\Sigma_u = CC' = CQQ'C' = (CQ)(CQ)' \tag{4}$$

where, $C$ is the Choleski decomposition of $\Sigma_u$. The procedure then follows a similar approach to that of the standard sign restrictions approach and is based on generating a large number of orthonormal matrices $Q$ that satisfy the following:

$$CQ = \begin{bmatrix} H^{IV} & H^{SR} \end{bmatrix} \tag{5}$$

with $B^{SR}$ satisfying a set of sign restrictions (which are usually derived from a theoretical

the scale of $H^{IV}$ is not identified, which leads to the corresponding impulse response functions only being relative to a certain shock; see, for example, Gertler and Karadi (2015). However, to be able to combine external instruments with sign restrictions, it is necessary to identify the scale of all shocks, and for that it is necessary to follow the approach described in Mertens and Ravn (2013).

model).

## 2.2. A Bank Credit SVAR

Observed outcomes in bank credit markets are the result of the interaction between the supply of and the demand for bank credit. As such, one way of modeling bank credit would be to consider movements (beyond those determined by exogenous factors such as trends or seasonality) in bank credit market outcomes as resulting from either credit supply or credit demand shocks. These supply and demand shocks can themselves include effects from other shocks, such as monetary policy or productivity shocks. Because of their importance for bank credit and for being relatively easier to measure (given recent developments in the literature), we chose to consider monetary policy shocks separately from credit supply and credit demand shocks. Besides allowing for better understanding of the effect of monetary policy shocks on bank credit, considering monetary policy shocks also helps with the identification of the other shocks, as it will allow us to separate the effects of monetary policy from both the supply of and the demand for bank credit.

In this application, we consider that bank credit developments are driven by monetary policy, credit supply, and credit demand shocks. Monetary policy shocks are unexpected movements in the stance of monetary policy; credit supply shocks are unexpected changes in banks' willingness to lend, which can result from changes in the banks' balance sheet, changes in banks' risk tolerance, or regulatory changes that affect banks' ability and/or willingness to lend; and credit demand shocks are unexpected changes in firms' (or consumers'—in case the application was specific to consumer credit) investment opportunities or financing needs.

In the SVAR model we include three variables: (1) interest rate ($IR_t$), (2) changes in credit standards, as measured by central bank surveys ($Stand_t$), and (3) credit growth ($CG_t$).

For now—abstaining from dynamics and deterministic factors—we write the model of bank credit as the following:

$$\begin{bmatrix} IR_t \\ Stand_t \\ CG_t \end{bmatrix} = \begin{bmatrix} \theta_{1,1} & \theta_{1,2} & \theta_{1,3} \\ \theta_{2,1} & \theta_{2,2} & \theta_{2,3} \\ \theta_{3,1} & \theta_{3,2} & \theta_{3,3} \end{bmatrix} \begin{bmatrix} \epsilon_t^{MP} \\ \epsilon_t^{CS} \\ \epsilon_t^{CD} \end{bmatrix}. \tag{6}$$

Equation (6) has all variables in the model depending on the three structural shocks. To identify the first column in the impact matrix—the $\theta_{i,1},\ i = 1, 2, 3$ parameters—we use an external instrument. To identify the remaining parameters—the $\theta_{i,j},\ i = 1, 2, 3$ and $j = 2, 3$ parameters—we use sign restrictions.

In terms of sign restrictions, we impose two restrictions:

1. We assume that the credit standards variable ($Stand_t$) is positively correlated with banks' willingness and ability to lend. As such, we assume that a positive (negative) credit supply shock ($\epsilon^{CS}$) will have a positive (negative) effect on credit standards, which is equivalent to imposing the condition that $\theta_{2,2} > 0$. This assumption is equivalent to assuming that credit standards based on surveys contain information about banks' credit practices and that a credit supply shock moves the credit supply curve vertically.[9]

2. The second restriction is that a positive (negative) credit demand shock ($\epsilon^{CD}$) has a positive (negative) effect on credit growth ($CG_t$). This assumption is equivalent to assuming that credit demand shocks move the credit demand curve vertically.

These restrictions can be summarized as follows:

[9] Note that, in general, credit standards data from bank lending surveys take a positive value when banks are tightening their standards—which could result in fewer loans extended—but in our application we reverted this variable so that a higher value means looser standards and therefore possibly more lending.

$$
\begin{bmatrix} IR_t \\ Stand_t \\ CG_t \end{bmatrix} = \begin{bmatrix} \theta_{1,1} & \theta_{1,2} & \theta_{1,3} \\ \theta_{2,1} & \theta_{2,2} > 0 & \theta_{2,3} \\ \theta_{3,1} & \theta_{3,2} & \theta_{3,3} > 0 \end{bmatrix} \begin{bmatrix} \epsilon_t^{MP} \\ \epsilon_t^{CS} \\ \epsilon_t^{CD} \end{bmatrix} \tag{7}
$$

We estimate the SVAR models of the U.S. economy and the euro area economy with four lags of the endogenous variables. Additionally, we include quarterly time dummies for the first year of the pandemic to capture the unusual variations in the data that occurred during this period.

In principle, we could have also used restrictions on loan rates to identify credit supply and credit demand shocks. However, we only observe average loan rates for all outstanding loans independently of their riskiness. As such, the effect of credit supply and credit demand shocks can have different effects on the average loan rate depending on the type of borrowers that are affected by these shocks. In contrast, the directional effects on loan volumes from credit demand and credit supply shocks are unambiguous regardless of the composition of lending in terms of riskiness of the loans.[10]

# 3. Data

In our application we consider bank loans to non-financial firms. As such, following the model structure discussed in the previous section, for both the United States and the euro area, we use data on interest rates (the central bank policy rate), the amount of firm loans outstanding, and changes in credit standards based on bank lending surveys.[11] The data

[10] It is worth noting that while credit supply and/or credit demand shocks could, alter the composition of banks' balance sheets, this is highly improbable, as the banking system as whole in general typically has room to expand even if some individual banks face balance sheet constraints.

[11] We use only publicly available data because we want the method to be widely applicable and accessible to other researchers and practitioners.

for the United States and the euro area are similar in nature, but there are some slight conceptual differences. In what follows, we briefly describe the data we use, and we provide more details about the data and how they can be obtained in Appendix A.

**United States:**

To estimate the SVAR for the United States, we use the commercial and industrial (C&I) loan data from the Federal Reserve statistical release H.8 that are published weekly, but we use end-of-quarter values to get quarterly values. As a measure of interest rates, we use the average of the effective federal funds rate at a quarterly frequency. Finally, as a measure of credit standards we use the changes in credit standards for C&I loans from SLOOS, which is published every quarter by the Federal Reserve.[12] The three series run from 1990:Q1 to 2024:Q4. In our application we change the sign of the credit standards variable relative from how it is published so that a higher number means looser standards; therefore, a positive credit supply shock implies an increase in lending.

In addition to the three variables used in the SVAR, we also use a high-frequency monetary policy shock instrument developed by Miranda-Agrippino and Ricco (2021), which separates pure monetary policy from economic outlook information shocks. To aggregate these shocks, and following the recommendations in Kilian (2024), we use a time-weighted average of the monthly shocks to aggregate those at a quarterly frequency.[13]

[12] The SLOOS is a periodic survey conducted by the Federal Reserve Board in which, among other things, banks are asked whether credit standards have changed relative to the previous quarter—and then a measure of the number of banks reporting net tightening standards is published.

[13] More specifically, letting $z_{i,t,j}$ denote the value of the external instrument at month $m = 1, 2, 3$ within quarter $t$, the aggregate external instrument in period $t$ is given by $z_{i,t} = \sum_{m=1}^{J} \frac{(3-m-1)z_{i,t,m}}{3}$. With this aggregation, a shock that occurs earlier in the quarter has a greater weight in the quarterly measure than a shock that occurs later in the quarter. The external instrument for U.S. monetary policy runs from 1991:Q1 through 2009:Q4.

**Euro Area:**

For the estimation of the euro-area SVAR, we use data on bank loans to non-financial corporations (NFCs), which are published by the ECB. As a measure of interest rates, we use values of the ECB's Euro Overnight Index Average (EONIA) through 2019:Q3 (the date of its discontinuation) and use the euro short-term rate (€STR) afterwards. As measure of credit standards, we use the ECB's bank lending survey results for credit standards for firm loans. We change the sign of the credit standards variable, as we do in the U.S. data, so that an increase in the variable implies looser standards on firm loans. The three series run from 2003:Q1 through 2024:Q4. The sample for the euro area is significantly shorter than that of the United States because aggregate euro-area data are only available starting in 2003:Q1.

For the euro area, for the high-frequency monetary policy shock instrument, we use data from Altavilla et al. (2019). We combine the data on moves in bond prices and equity prices to obtain the *poor man's* version of the monetary policy shock that isolates pure monetary policy innovations from information on the economic outlook that is contained in central bank communications. As in the case of the United States, we use a time-weighted average of the shock relative to the time within the quarter that the shock was observed to aggregate the daily shocks to a quarterly shock.[14]

[14] To be more specific, letting $z_{i,t,j}$ denote the value of the external instrument at time $j = 1, ..., J$ within quarter $t$, then, the aggregate external instrument in period $t$ is given by $z_{i,t} = \sum_{j=1}^{J} \frac{(J-j-1)z_{i,t,j}}{J}$. Because we have daily data for the euro area for the high-frequency shocks, we aggregate the information from a daily to a quarterly frequency using the respective weights for when the shock occurred in a given quarter. Again, with this aggregation, a shock that occurs earlier in the quarter has a greater weight in the quarterly measure than a shock that occurs later in the quarter. Also, note that this formula accounts for days during which no shock is measured—that is, $z_{i,t,j} = 0$. The external instrument for euro-area monetary policy runs from 2003:Q3 to 2023:Q2.

# 4. Estimation Results

In this section we present and discuss the main empirical results. First, we show the impulse response functions, followed by the the forecast error variance decomposition for each structural shock, and then the historical decomposition of credit standards and credit growth to assess the importance of each shock for the historical evolution of these two variables.

## 4.1. Impulse Response Functions

Figure 1 shows the impulse response functions (IRFs) of interest rates, credit standards, and credit growth to a one standard deviation increase in each of the structural shocks for the United States (panel (a)) and for the euro area (panel (b)).

We start with the results pertaining to the monetary policy shock, as shown in the first row of panels (a) and (b) of Figure 1. When monetary policy is tightened, interest rates increase (the first column of each panel), banks tighten credit standards (the second column), and credit growth declines (the third column) in both the United States and the euro area. In the United States, credit growth initially rises but then begins to decline two quarters after this initial increase, eventually falling by an estimated 1.75 percent five years after the shock. In the euro area, by contrast, credit growth declines immediately after the shock and returns to baseline about four to four and a half years later, with a cumulative decline of approximately 0.75 percent. The stronger response of credit growth in the United States appears to be linked to a more intense and prolonged tightening of credit standards compared to the euro area (the second columns in panels (a) and (b)).

For the United States, credit standards tighten substantially following a monetary policy shock and only go back to baseline after about four years. In the case of the euro area, however, credit standards are basically unchanged in the quarter the monetary policy shock occurs and only turn negative after one quarter—reaching the trough effect after two quarters and returning to baseline after about eight quarters.

The initially muted response of credit standards in the euro area after a monetary policy shock is somewhat surprising, given the similarities of the SLOOS and the ECB bank-lending survey in both frequency and question framing. Moreover, the Federal Reserve and the ECB hold monetary policy meetings at comparable intervals, making it unlikely that scheduling differences explain this divergence. One possible explanation—though admittedly conjectural—is that euro area banks may rely on a more rigid or committee-based process for adjusting their credit standards, whereas U.S. banks can modify underwriting guidelines more continuously or at a decentralized level. Another possible explanation is that differences in competition in the U.S. and euro area banking sectors as well as a more relationship-based banking in the euro area could make the transmission of monetary policy to bank credit standards slower in the euro area than in the United States.

Abstracting from the initially muted response of credit standards in the euro area, the overall responses of credit standards and credit growth are broadly in line with the existing literature on the transmission of monetary policy to bank lending and bank credit standards (see, for example, Bassett et al. (2014) or Gertler and Karadi (2015) for the United States, and Ciccarelli et al. (2015) or Altavilla et al. (2020) for the euro area).

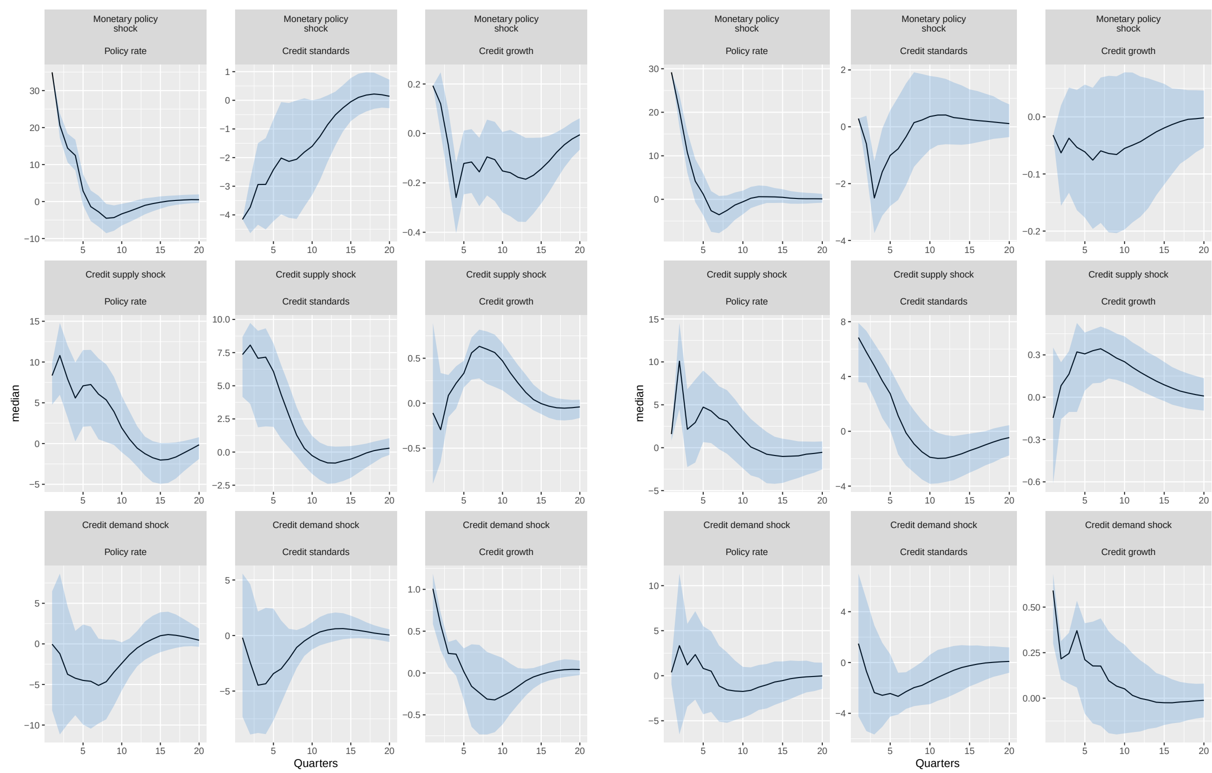
The IRFs associated with an expansionary credit supply shock are presented in the second rows of Figure 1. The typical expansionary credit supply shock leads to a 7.4 percentage point (pp.) increase in the net fraction of banks easing in the United States and about 6.8 pp. in the euro area. This easing of credit standards leads to greater credit availability and, consequently, stronger credit growth (the third columns). The response of credit growth to a credit supply shock is slightly stronger in the United States, where it increases by more than 3.75 percent after three years, compared to only 2.9 percent in the euro area. Interest rates also rise after an expansionary credit supply shock (the first columns) and continue to increase for almost three years—moving up by about 65 basis points (bps) in the United States and 33 bps in the euro area. The observed increase in interest rates following a credit supply shock suggests that central banks tend to undo some of the expansionary effects of credit supply shocks.

Finally, credit demand shocks, as shown in the third rows of Figure 1, increase credit growth by 1 percent and 0.6 percent on impact in the United States and the euro area, respectively. The positive effect of a credit demand shock on credit growth remains for about six quarters in the United States, with cumulative growth peaking at a little over 2 percent, while in the euro area this positive effect remains for three years, with cumulative growth peaking at 2.35 percent.

Figure 1. Effects of monetary policy, credit supply, and credit demand shocks on loan rates, credit standards, and credit growth.

(a) United States

(b) Euro area




Note: The figure shows the IRFs associated with a one standard deviation shock for each of the structural shocks based on the estimated SVAR—panel (a) for the United States and panel (b) for the euro area. The shaded areas represent the 68% confidence bands around the median impulse response.

## 4.2. Forecast Error Variance Decomposition

Next, we analyze the forecast error variance decomposition (FEVD) of the variables included in the model to quantify the importance of each structural shock for the dynamics of lending rates, credit standards, and credit growth at various horizons. The results of this analysis are shown in Figure 2, with the results for the U.S. economy in panel (a) and in panel (b) for the euro area.

At the one-quarter horizon, monetary policy shocks account for over 90 percent of the forecast error variance in interest rates for the United States, while they account for almost 100 percent for the euro area. This contribution goes down at longer horizons for both regions but remains larger in the euro area. For both the United States and the euro area, credit supply shocks explain about twice as much of the policy rate variation as credit demand shocks after two years.

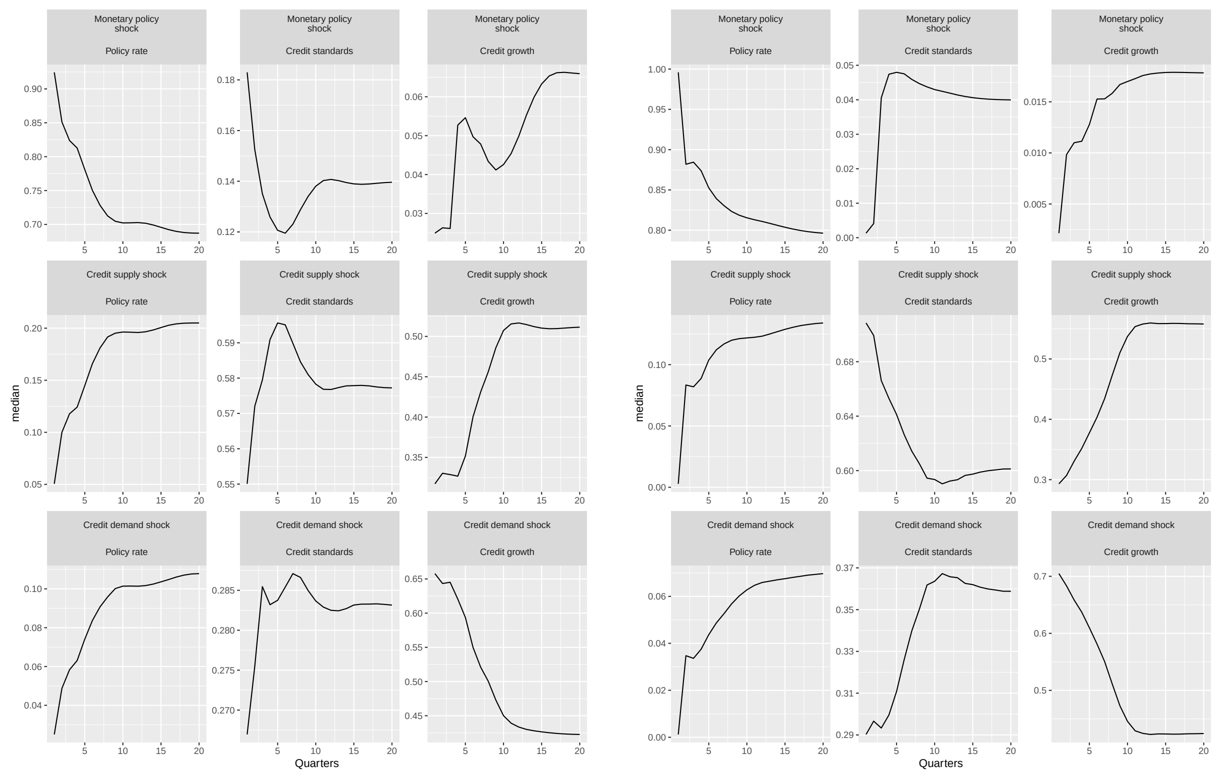
For both countries, credit supply shocks explain the majority (around 60 percent in both cases) of the variation in credit standards. Credit demand shocks come next in terms of sources of variation in credit standards, sitting just under 30 percent in the case of the United States and reaching over 35 percent in the case of the euro area. The remainder of the variation in credit standards is explained by monetary policy shocks. In the case of the United States, the share declines from about 18 percent in the short run to about 14 percent in the long run, while it rises from basically 0 percent in the short run in the euro area to about 4 percent in the long run.

Finally, for both the United States and euro area, variation in credit growth is mostly driven by credit demand and credit supply shocks (in roughly similar proportions), with the importance of monetary policy shocks being very minimal in both economic regions.

Our results are qualitatively in line with the existing literature. For the United States, Lown and Morgan (2006) also find that monetary policy shocks account for only a small share of the error variance in credit standards and credit growth, while credit supply shocks explain nearly two-thirds of credit growth at longer horizons. For the euro area, Peersman (2011) also finds that monetary policy shocks account for just a small fraction of the variation in bank lending growth.

Figure 2. Forecast error variance decomposition of lending rate, credit standards, and credit growth.

(a) United States (b) Euro area



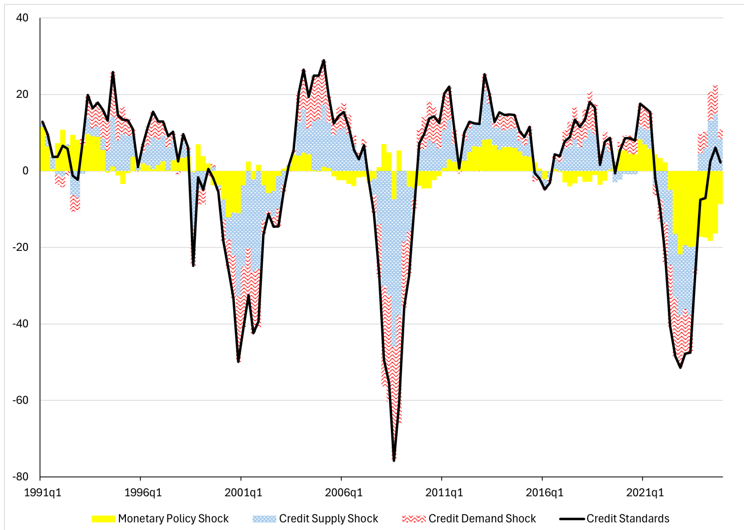

Note: The figure shows the forecast error variance decomposition of for each of the three variables in the SVAR relative to each of the structural shocks based on the estimated SVAR—panel (a) for the United States and panel (b) for the euro area.

## 4.3. Historical Decomposition of Credit Standards and Credit Growth

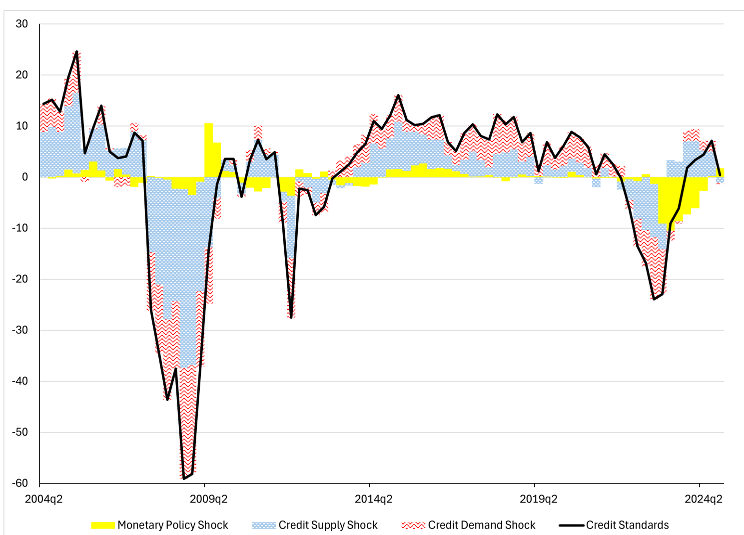
To trace how credit supply, credit demand, and monetary policy shocks drove movements in credit standards and credit growth, we decompose each series using the historical decomposition approach of Burbidge and Harrison (1985). Figures 3 and 4 display the resulting decompositions for credit standards and credit growth in the United States and the euro area. In each panel, the solid black line shows the cumulative effect of all three structural shocks, while the colored bars isolate the individual contributions of credit supply (blue with a rectangular dot pattern), credit demand (red with a wavy line pattern), and monetary policy (solid yellow) shocks.

Figure 3. Historical decomposition of credit standards

(a) United States



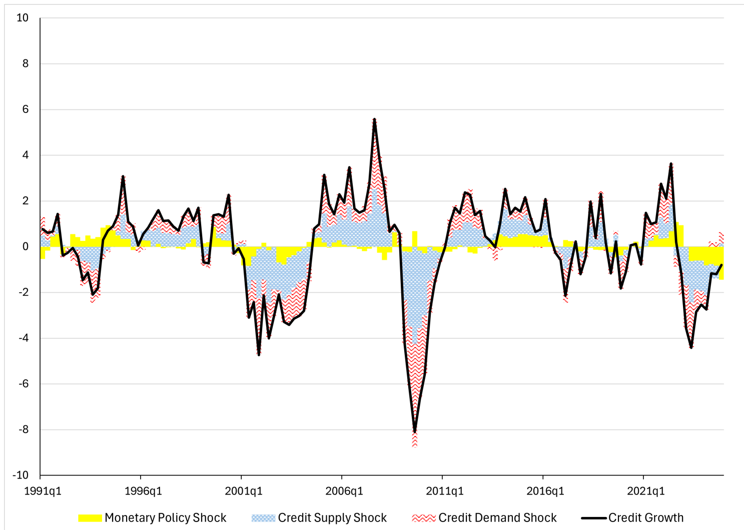

(b) Euro area



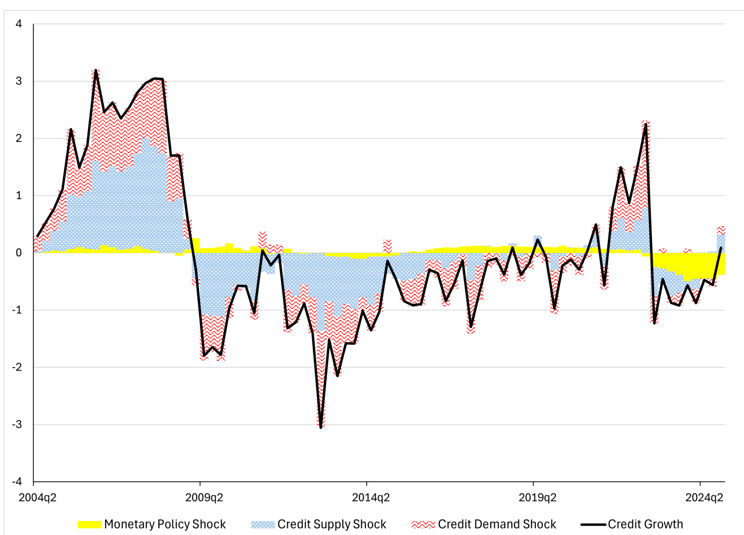

Note: The figure shows the historical decomposition of credit standards based on the three structural shocks identified with the SVAR for the United States in panel (a) and the euro area in panel (b). The results are based on the average of all the structural shocks derived from each draw in the sign restriction part of the identification.

Figure 4. Historical decomposition of credit growth

(a) United States




(b) Euro area




Note: The figure shows the historical decomposition of credit growth based on the three structural shocks identified with the SVAR for the United States in panel (a) and the euro area in panel (b). The results are based on the average of all the structural shocks derived from each draw in the sign restriction part of the identification.

Starting with the result for credit standards in the United States, Figure 3(a) shows that, during the sample period, monetary policy, credit supply, and credit demand shocks were of significant importance in the various peaks and troughs observed. One notable exception, however, is that during the Great Financial Crisis (GFC)—corresponding to the lowest level of credit standards; that large drop in credit standards was almost entirely driven by credit supply and credit demand shocks. Interestingly, in the most recent observations, it is possible to not only see that monetary policy shocks are still a drag on credit standards but also that credit supply and credit demand shocks are contributing to looser standards. This recent period exhibits the starkest difference between the contributions of monetary policy shocks and that of credit supply and credit demand shocks. Also interesting is the fact that the March 2023 turmoil, which lead to the failure of three U.S. banks, had a very short-lived imprint on credit standards. By the fourth quarter of 2023, credit supply shocks were already contributing, on net, to a loosening of bank credit standards.

The results for credit standards in the euro area, shown in Figure 3(b), contrast with those for the United States in terms of the relative importance of all shocks. Unlike for the United States, credit standards in the euro area during the sample considered (which is significantly shorter than that of the United States), were mostly driven by credit supply and credit demand shocks. The only notable exception to this pattern happened recently, as monetary policy shocks were shown to be an important driver of the tightening credit standards after the onset of the ECB's hiking cycle that started in 2022:Q3. Similar to what was observed in the United States, in the recent periods credit supply and credit demand shocks are contributing to a relaxation of credit standards, whereas monetary policy shocks are still a drag on bank lending standards.

We now turn to the results for credit growth—shown in Figure 4.[15] The historical decomposition of credit growth is somewhat in line with the findings of the historical decomposition of credit standards in Figure 3, with the credit standard tightening episodes beginning a few quarters before credit growth starts faltering. However, there are some notable differences. For the United States, Figure 4(a) shows that the credit supply and credit demand shocks were relatively more important than monetary policy shocks—something that is somewhat in contrast with a more even importance of the three shocks in the case of credit standards. Even in the most recent hiking cycle that started in 2022:Q1, monetary policy shocks were only mildly important for the evolution of credit growth. During the March 2023 banking turmoil in the United States, credit growth dipped mainly because of credit demand and credit supply shocks, but these effects were relatively short lived, especially in the case of the effect of credit demand shocks.

For the euro area, as shown in Figure 4(b), credit growth was mostly driven by credit supply and credit demand shocks, with supply shocks being relatively more important during this sample period. Monetary policy shocks only had a meaningful impact on credit growth after 2022:Q3, which is when the ECB started hiking rates in response to the observed high inflation.

[15] Note that in Figure 4 there is no noticeable effect of the COVID-19 pandemic on credit growth because the estimated VAR model included dummy variables for each quarter of the year 2020.

# 5. Quantifying Bank Credit Conditions and Evaluating Their Impact on Macroeconomic Outcomes

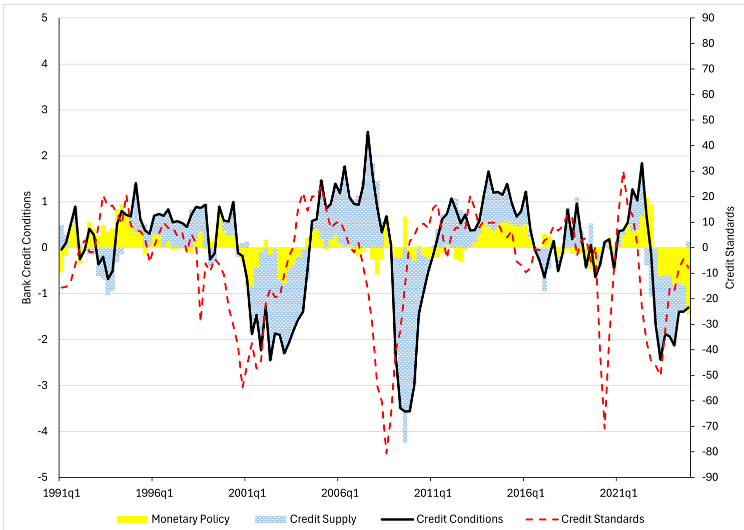
After having discussed the modeling approach and the results, we now present our proposed measure of bank credit conditions and use this proposed measure—and its components—to assess how bank credit conditions affect macroeconomic outcomes.

## 5.1. A Measure of Bank Credit Conditions

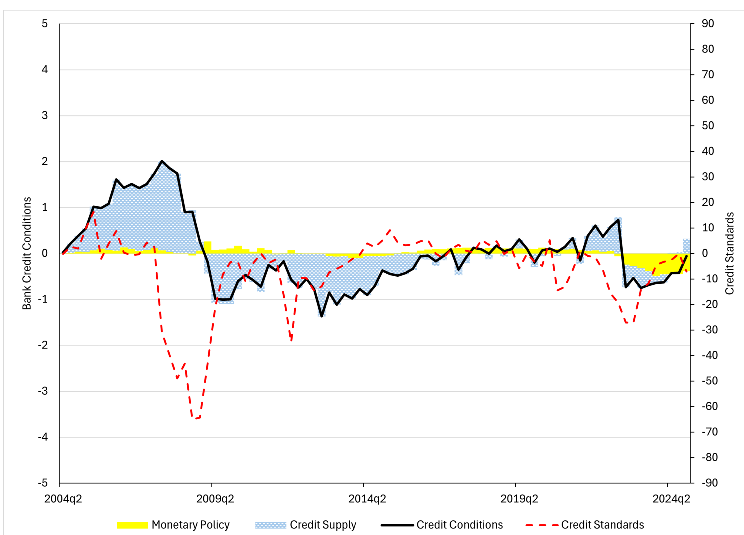
As shown in the previous section, bank credit growth is driven by multiple shocks—specifically, monetary policy, credit supply, and credit demand shocks. A measure of bank credit conditions should ideally capture supply-side developments while holding credit demand constant (or growing in a deterministic and steady manner). With this in mind, we propose using the estimated bank credit growth under the assumption of no demand shocks as a measure of bank credit conditions. This approach, which corresponds to the historical decomposition of credit growth into monetary policy and credit supply shocks only, is illustrated in Figure 5 for both the U.S. and euro-area economies. In the figure, the black solid line reflects overall credit conditions, the solid yellow and blue with white checkered pattern bars represent the contributions of monetary policy and credit supply shocks, and the red dashed line represents the survey-based measure of bank credit standards, respectively.

Figure 5. Bank credit conditions for non-financial corporates in the United States and the euro area

(a) United States




(b) Euro area




Note: The figure shows the proposed measure of bank credit conditions and the survey-based measure of credit standards for NFCs for the United States in panel (a) and for the euro area in panel (b). The measure of bank credit conditions corresponds to the combined effect on credit growth of monetary policy and credit supply shocks as identified by the SVAR model discussed in the paper. The results are based on the average of all the structural shocks derived from each draw in the sign restriction part of the identification.

Figure 5 isolates the effects of monetary policy and credit supply shocks on lending conditions by excluding credit demand shocks. This design enables us to more clearly trace the evolution of supply-side dynamics over time. In the United States, the measure reveals pronounced fluctuations during crisis periods, reflecting rapid adjustments in both policy stances and credit supply conditions. In contrast, the euro area exhibits a more gradual evolution, characterized by a prolonged phase of tight credit even as monetary policy becomes increasingly accommodative. These differing trajectories highlight the distinct structural and institutional dynamics at play, with the U.S. market showing higher volatility and the euro area experiencing more persistent credit constraints.

Our analysis further reveals that relying solely on credit standards—as depicted in Figure 3—to assess changes in credit conditions may lead to an incomplete, or even misleading, narrative. For instance, for both the United States and the euro area, credit standards tend to move before credit conditions change therefore, they do not reflect current bank credit conditions but instead provide some signal about the future state of credit conditions. The estimated SVAR model would also allow us to project credit growth based on a subset of shocks, and this would be more in line with the idea of having a leading indicator of bank credit growth. In Appendix B we provide estimates of expected credit growth in the United States and the euro area given the most recent credit supply and monetary policy shocks.

## 5.2. Macroeconomic Effects of Bank Credit Conditions

So far we have only provided a measure of bank credit conditions, but we have not yet shown whether such a measure contains information about future macroeconomic outcomes, which is ultimately why there should be interest in measuring bank credit conditions. In this subsection we use the proposed measure of bank credit conditions and its components to assess the effects of bank credit conditions on real GDP, real gross capital fixed formation (GFCF), employment, and consumer prices. For this analysis we estimate the following model:

$$\ln(Y_{t+h}) - \ln(Y_{t-1}) = \alpha + \beta X_t + \gamma \text{Controls}_t + \delta \text{GFC}_t + \omega \text{Pandemic}_t^h + \varepsilon_t. \tag{8}$$

The dependent variable is the $h$-quarter-ahead growth of variable $Y$, which can refer to real GDP, real GFCF, employment, and consumer prices. Specifically, it is expressed as the difference in the natural logarithm of the variable between time $t+h$ and $t-1$. The main control variable $X$ will be either the proposed bank credit conditions measure or the two components that comprise this variable (the part due to monetary policy shocks and the part due to credit supply shocks). The remaining control variables include lags of one-quarter growth rate of variable $Y$ and lags of changes in the policy rate. The variable GFC is a dummy variable that takes the value 1 between 2007:Q4 and 2008:Q4 and 0 for all other quarters; the variable pandemic$^h$ is a dummy variable that takes the value 1 in the quarters for which the dependent variable includes either of the following quarters: 2020:Q2 and 2020:Q3.[16] Parameter $h$ takes values 0, 3, and 7, which correspond to 1-quarter-ahead, 4-quarter ahead, and 8-quarter-ahead changes in the dependent variable. The estimations results are shown in Table 1 for the United States and in Table 2 for the euro area.

Starting with the results for the United States, shown in Table 1, it can be seen that the effects of bank lending conditions on each of the dependent variables vary across dependent variables and different time horizons. In the case of the one-quarter changes, bank lending conditions does not have a statistically significant effect on real GFCF and consumer prices.

[16]The pandemic variable tries to account for the high volatility in most major macroeconomic variables in quarters 2020:Q2 and 2020:Q3 due to the effect of the shutdown and reopening of the economy in response to the COVID-19 pandemic.

Table 1. Estimated effects of bank credit conditions on select macroeconomic variables - United States

**Panel A: 1-quarter change**

| | Real GDP | | Real GFCF | | Employment | | CPI | |
|---|---|---|---|---|---|---|---|---|
| Bank lending conditions | 0.03 | | 0.00 | | 0.01 | | 0.02 | |
| | (1.17) | | (0.06) | | (0.37) | | (0.82) | |
| Bank lending conditions - credit supply | | 0.01 | | -0.02 | | -0.01 | | 0.02 |
| | | (0.29) | | (0.25) | | (0.84) | | (0.61) |
| Bank lending conditions - monetary policy | | 0.13 | | 0.10 | | 0.09 | | 0.05 |
| | | (1.87)* | | (0.47) | | (2.19)** | | (0.64) |
| $R^2$ | 0.14 | 0.15 | 0.33 | 0.33 | 0.76 | 0.77 | 0.21 | 0.21 |
| $N$ | 136 | 136 | 135 | 135 | 136 | 136 | 136 | 136 |

**Panel B: 4-quarter change**

| | Real GDP | | Real GFCF | | Employment | | CPI | |
|---|---|---|---|---|---|---|---|---|
| Bank lending conditions | 0.06 | | -0.39 | | 0.44 | | 0.08 | |
| | (0.47) | | (0.98) | | (2.24)** | | (0.67) | |
| Bank lending conditions - credit supply | | -0.02 | | -0.60 | | 0.32 | | 0.07 |
| | | (0.14) | | (1.53) | | (1.77)* | | (0.53) |
| Bank lending conditions - monetary policy | | 0.43 | | 0.56 | | 1.08 | | 0.13 |
| | | (1.96)* | | (0.53) | | (3.22)*** | | (0.36) |
| $R^2$ | 0.07 | 0.09 | 0.25 | 0.26 | 0.39 | 0.43 | 0.19 | 0.19 |
| $N$ | 133 | 133 | 132 | 132 | 133 | 133 | 133 | 133 |

**Panel C: 8-quarter change**

| | Real GDP | | Real GFCF | | Employment | | CPI | |
|---|---|---|---|---|---|---|---|---|
| Bank lending conditions | -0.35 | | -2.20 | | 0.46 | | -0.20 | |
| | (1.34) | | (1.37) | | (0.95) | | (0.89) | |
| Bank lending conditions - credit supply | | -0.52 | | -2.90 | | 0.19 | | -0.27 |
| | | (1.24) | | (1.72)* | | (0.43) | | (1.30) |
| Bank lending conditions - monetary policy | | 0.72 | | 1.56 | | 2.49 | | 0.32 |
| | | (1.11) | | (0.89) | | (4.89)*** | | (0.53) |
| $R^2$ | 0.06 | 0.10 | 0.20 | 0.25 | 0.15 | 0.25 | 0.16 | 0.17 |
| $N$ | 129 | 129 | 128 | 128 | 129 | 129 | 129 | 129 |

*Note:* The table shows the estimation results for equation (8) for values of $h = 0,\ 3,$ and 7, corresponding to 1-quarter-ahead, 4-quarter-ahead, and 8-quarter-ahead changes of the independent variables. All results include 4 lags for the growth of real GDP, real GFCF, employment, and consumer prices, as well as 4 lags of changes in the effective federal funds rate. Serial correlation and heteroskedasticity robust standard errors are shown in parentheses. $*$, $**$, $***$ denote statistical significance at 10%, 5%, and 1% confidence, respectively.

For real GDP and employment, the combined effect of bank lending conditions is not statistically significant, but it is positive and statistically significant when only the component of bank lending conditions pertaining to monetary policy shocks is considered.

The results for four- and eight-quarter changes are qualitatively similar. The effect of bank lending conditions is not always statistically significant, but in some cases, regardless of whether the bank lending conditions effect is statistically significant or not, the effect of bank lending conditions pertaining to monetary policy shocks is. These results for the U.S. economy suggest that whether banks are willing to lend only matters if that effect comes from monetary policy shocks—but not much from bank-originated credit supply shocks. The lack of an effect from credit supply shocks may be due to firms, especially larger ones, having access to other sources of funding other than bank credit.

Turning now to the euro-area results, which are shown in Table 2, a similar pattern of heterogeneous effects across variables and at different time horizons as that observed for the United States emerges. However, in contrast to the results for the U.S. economy, bank lending conditions shows a statistically significant effect for several cases and for the horizons of one quarter and four quarters. When looking at the separate effect of bank lending conditions from credit supply shocks and from monetary policy shocks, the results are very different from those for the United States. In the case of the euro area, the credit supply part of bank lending conditions is statistically significant in many more instances, while the monetary policy shock part of bank lending conditions is only statistically significant in a couple of cases. The stark difference in results with respect to the United States suggests that for the euro area, bank lending is much more important, as the euro-area economy is much more reliant on bank credit than the U.S. economy.

Taken together, the results in Tables 1 and 2 show that the proposed measure of bank

Table 2. Estimated effects of bank credit conditions on select macroeconomic variables - euro area

**Panel A: 1-quarter change**

| | Real GDP | | Real GFCF | | Employment | | HCPI | |
|---|---|---|---|---|---|---|---|---|
| Bank lending conditions | 0.16 | | 1.03 | | 0.16 | | 0.14 | |
| | (2.44)** | | (3.69)*** | | (2.54)** | | (1.77)* | |
| Bank lending conditions - credit supply | | 0.19 | | 1.04 | | 0.19 | | 0.14 |
| | | (2.74)*** | | (4.52)*** | | (2.70)*** | | (1.87)* |
| Bank lending conditions - monetary policy | | -0.18 | | 0.94 | | -0.07 | | 0.17 |
| | | (0.41) | | (0.39) | | (0.54) | | (0.33) |
| $R^2$ | 0.18 | 0.18 | 0.17 | 0.17 | 0.23 | 0.24 | 0.24 | 0.24 |
| $N$ | 83 | 83 | 82 | 82 | 83 | 83 | 83 | 83 |

**Panel B: 4-quarter change**

| | Real GDP | | Real GFCF | | Employment | | HCPI | |
|---|---|---|---|---|---|---|---|---|
| Bank lending conditions | 0.71 | | 1.91 | | 0.56 | | 0.78 | |
| | (5.00)*** | | (4.78)*** | | (4.20)*** | | (2.03)** | |
| Bank lending conditions - credit supply | | 0.62 | | 1.74 | | 0.66 | | 0.66 |
| | | (4.08)*** | | (4.40)*** | | (3.82)*** | | (2.00)** |
| Bank lending conditions - monetary policy | | 2.01 | | 4.30 | | -0.45 | | 2.36 |
| | | (3.10)*** | | (1.12) | | (0.70) | | (1.30) |
| $R^2$ | 0.20 | 0.21 | 0.19 | 0.20 | 0.39 | 0.41 | 0.37 | 0.38 |
| $N$ | 80 | 80 | 79 | 79 | 80 | 80 | 80 | 80 |

**Panel C: 8-quarter change**

| | Real GDP | | Real GFCF | | Employment | | HCPI | |
|---|---|---|---|---|---|---|---|---|
| Bank lending conditions | 0.03 | | 0.07 | | 0.75 | | 1.36 | |
| | (0.04) | | (0.05) | | (2.58)*** | | (1.61) | |
| Bank lending conditions - credit supply | | -0.10 | | 0.10 | | 0.99 | | 0.80 |
| | | (0.16) | | (0.07) | | (3.40)*** | | (1.33) |
| Bank lending conditions - monetary policy | | 3.02 | | -0.73 | | -3.77 | | 13.07 |
| | | (0.92) | | (0.06) | | (1.83)* | | (2.70)*** |
| $R^2$ | 0.01 | 0.02 | 0.00 | 0.00 | 0.22 | 0.27 | 0.21 | 0.27 |
| $N$ | 76 | 76 | 75 | 75 | 76 | 76 | 76 | 76 |

*Note:* The table shows the estimation results for equation (8) for values of $h = 0,\ 3,$ and 7, corresponding to 1-quarter-ahead, 4-quarter-ahead, and 8-quarter-ahead changes of the independent variables. All results include 2 lags for the growth of real GDP, real GFCF, employment, and consumer prices, as well as 2 lags changes in the ECB's overnight deposit rate. Serial correlation and heteroskedasticity robust standard errors are shown in parentheses. $*$, $**$, $***$ denote statistical significance at 10%, 5%, and 1% confidence, respectively.

lending conditions contains important information about future macroeconomic outcomes at short- and medium-term horizons. Our results also show that understanding the source of variation in bank lending conditions is important, as the effects of monetary policy–induced variations can be different from credit supply–induced variations.

## 6. Concluding Remarks

In this paper, we use a three-variable SVAR model identified with external instruments and sign restrictions to extract information about bank credit supply conditions from central bank lending survey data. This approach allows us to construct a measure of bank credit conditions that is comparable over time and across countries. Our measure captures credit growth under the assumption that only monetary policy and credit supply shocks are at play. Applying this methodology to U.S. commercial and industrial lending data and euro-area bank lending to NFCs, we find that, historically, credit supply shocks have been the dominant driver of bank credit conditions. However, in recent periods, large negative monetary policy shocks have played a central role in tightening bank credit conditions.

Using the proposed measure of bank credit conditions, we find that credit supply–driven changes in credit conditions in the euro area have strong effects on real economic activity. However, in the United States, while we detect an impact on employment growth, we find no significant evidence of effects on GDP, GFCF, or consumer price growth. Notably, in contrast to the euro area, changes in U.S. bank credit conditions are primarily driven by monetary policy shocks, with no evidence of credit supply-driven changes influencing macroeconomic variables.

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# Appendix

## A. Data Description

Table A1 lists all the data used in the empirical analysis and respective sources. With the exception of the "Credit supply impulse" variable, which is based in the work of Bassett et al. (2014) and is updated by the Federal Reserve Board staff using bank confidential data, all other data are publicly available.

## B. Additional Results

### B.1. The Bassett et al. (2014) Measure of Credit Impulse Indicator and the Identified Monetary Policy, Credit Supply, and Credit Demand Shocks

The credit impulse measure of Bassett et al. (2014) is a weighted average of bank's individual responses to the SLOOS after controlling for bank-specific and aggregate macroeconomic factors that could be related to credit demand conditions.[17] Put differently, the credit impulse indicator is a measure of credit standards net of demand factors. To see how the monetary policy, credit supply, and credit demand shocks identified with the SVAR model described in section 2.2, we regress the credit impulse variable on the three shocks, both

[17] As noted earlier, Cavallo et al. (2024) use the Bassett et al. (2014) as starting point and incorporate some changes to the original methodology to produce a measure of credit supply that is not correlated with previous shocks and better separates credit supply and credit demand effects on credit standards. While the Cavallo et al. (2024) may have better properties than the original measured based on the Bassett et al. (2014)'s work, we chose to use Bassett et al. (2014) as our benchmark due to its seminal contributions to this literature and to ensure comparability with a broad range of studies in this area.

Table A1. Data and Sources

| **U.S. model data and ancillary U.S. data** | | | |
|---|---|---|---|
| Series | Official name | Source | Time Range |
| C&I loans credit growth | Commercial and Industrial Loans, All Commercial Banks, seasonally adjusted | H.8 Assets and Liabilities of Commercial Banks in the United States, Federal Reserve Board | 1990Q1 - 2024Q4 |
| Interest rate | Effective Federal Funds Rate | St. Louis Fred Database | 1990Q1 - 2024Q4 |
| Credit Standards | Net Percentage of Domestic Banks Tightening Standards for Commercial and Industrial Loans to Large and Middle-Market Firms | Senior Loan Officer Opinion Survey on Bank Lending Practices, Federal Reserve Board | 1990Q1 - 2024Q4 |
| | Net Percentage of Domestic Banks Tightening Standards for Commercial and Industrial Loans to Small-Market Firms | Senior Loan Officer Opinion Survey on Bank Lending Practices, Federal Reserve Board | 1990Q1 - 2024Q4 |
| High-frequency monetary policy instrument | N/A | Miranda-Agrippino and Ricco (2021) | 1991Q1-2009Q4 |
| Credit supply impulse | N/A | Bassett et al. (2014) | 1990Q1-2023Q1 |
| **Euro area model data and ancillary euro area data** | | | |
| Series | Official name | Source | Time Range |
| NFC credit growth | Loans vis-a-vis euro area NFCs reported by MFIs in the euro area (stocks), Euro area (changing composition), seasonally adjusted | ECB Data Portal | 2003Q1 - 2024Q4 |
| Interest rate | EONIA | ECB Data Portal | 2003Q1 - 2019Q3 |
| | Euro short-term rate | ECB Data Portal | 2019:Q4 - 2024Q4 |
| Credit Standards | Net Percentage of Banks Reporting a Tightening of Credit Standards | Euro Area Bank Lending Survey, European Central Bank | 2003Q1 - 2024Q4 |
| High-frequency monetary policy instrument | N/A | Altavilla et al. (2019) | 1991Q1-2023Q2 |

Note: The table lists all the data used in the paper and respective official names and sources, when applicable.

contemporaneous and lagged one quarter, and on a one-quarter lag of the credit impulse variable. The results of this analysis are shown in Table B1.

Table B1. The Relation Between the Bassett et al. (2014) Credit Impulse Indicator and the Identified Monetary Policy, Credit Supply, and Credit Demand Shocks

| | Credit Impulse | | | |
|---|---|---|---|---|
| Monetary Policy Shock | -4.79 | -5.49 | -5.82 | -5.95 |
| | (4.27)*** | (6.90)*** | (6.24)*** | (8.19)*** |
| Credit Supply Shock | 12.23 | 11.54 | 12.44 | 11.79 |
| | (5.10)*** | (5.56)*** | (6.21)*** | (6.18)*** |
| Credit Demand Shock | -1.05 | -0.72 | -1.45 | -1.18 |
| | (0.69) | (0.49) | (1.02) | (0.88) |
| Credit Impulse$_{t-1}$ | | 0.37 | | 0.30 |
| | | (7.20)*** | | (3.84)*** |
| Monetary Policy Shock$_{t-1}$ | | | -0.87 | 0.44 |
| | | | (0.91) | (0.47) |
| Credit Supply Shock$_{t-1}$ | | | 6.65 | 2.89 |
| | | | (6.04)*** | (1.80)* |
| Credit Demand Shock$_{t-1}$ | | | -3.79 | -3.42 |
| | | | (2.67)*** | (2.53)** |
| Constant | 0.45 | 0.39 | 0.46 | 0.37 |
| | (0.28) | (0.38) | (0.34) | (0.34) |
| $R^2$ | 0.33 | 0.46 | 0.44 | 0.50 |
| $N$ | 132 | 131 | 132 | 131 |

Note: The table shows regression results between the Bassett et al. (2014) credit impulse indicator and the three structural shocks — monetary policy, credit supply, and credit demand — identified with the model described in section 2.2. For consistency with the rest of the paper, we changed the sign of the credit impulse variable, such that a positive value represents loosening of credit conditions, while a negative value represents tightening of credit conditions. Heteroskedasticity and serial correlation robust standard errors are in parentheses. *, **, *** denote 10%, 5%, and 1% statistical significance, respectively.

The results in the first column show that only the monetary policy and credit supply shocks have a statistically significant effect on the credit impulse measure. This result is quite reassuring, because it suggests that, compared to an alternative measure of credit supply that is supposed to strip out demand factors, our identified shocks represent what they are supposed to represent. Notably, these three variables collectively explain more than 30% of the variation of the credit impulse variable.

The second column's results, which add the one-quarter lag of the dependent variable, show that the results pertaining to the effect of the structural shocks are robust to including past information of the dependent variable. The results in the third and fourth columns, while very much in line with those of the first two columns, also suggest that the credit impulse measure may still contain some residual information from past credit demand shocks.

In the next table, we show the results of regressing the Bassett et al. (2014) credit impulse indicator on each one of the three structural shocks identified with the model described in section 2.2.

Table B2. The Effect of the Bassett et al. (2014) Credit Impulse Indicator on the Identified Monetary Policy, Credit Supply, and Credit Demand Shocks

| | MP shock | | CS shock | | CD shock | |
|---|---|---|---|---|---|---|
| Credit Impulse | -0.01 | -0.02 | 0.02 | 0.02 | -0.00 | -0.00 |
| | (2.85)*** | (3.45)*** | (5.87)*** | (5.38)*** | (0.99) | (0.84) |
| Credit Impulse$_{t-1}$ | | 0.01 | | -0.01 | | -0.00 |
| | | (1.65)* | | (1.32) | | (0.11) |
| Constant | 0.02 | 0.03 | -0.01 | -0.01 | -0.01 | -0.00 |
| | (0.36) | (0.50) | (0.26) | (0.22) | (0.16) | (0.07) |
| $R^2$ | 0.07 | 0.11 | 0.27 | 0.29 | 0.01 | 0.01 |
| $N$ | 132 | 131 | 132 | 131 | 132 | 131 |

Note: The table shows regression results between the three structural shocks — monetary policy, credit supply, and credit demand — identified with the model described in section 2.2 and the Bassett et al. (2014) credit impulse indicator. For consistency with the rest of the paper, we changed the sign of the credit impulse variable, such that a positive value represents loosening of credit conditions, while a negative value represents tightening of credit conditions. Heteroskedasticity and serial correlation robust standard errors are in parentheses. *, **, *** denote 10%, 5%, and 1% statistical significance, respectively.

Starting with the contemporaneous effect of the credit impulse indicator, the results in Table B2 show once again that the credit impulse variable only correlated with the monetary policy and credit supply shocks and not with the credit demand shock. For the cases of the credit supply and credit demand shocks, the lagged value of the credit impulse variable is both close to zero and not statistically significant. Somewhat surprisingly, the lagged value of the credit impulse variable has a statistically significant effect on the monetary policy shock. However, after inspecting the data more closely, this result is entirely driven by two outlier observations, one related with the failure of Long-Term Capital Management in 1998 and the other related with the 2007-2008 Great Financial Crisis.

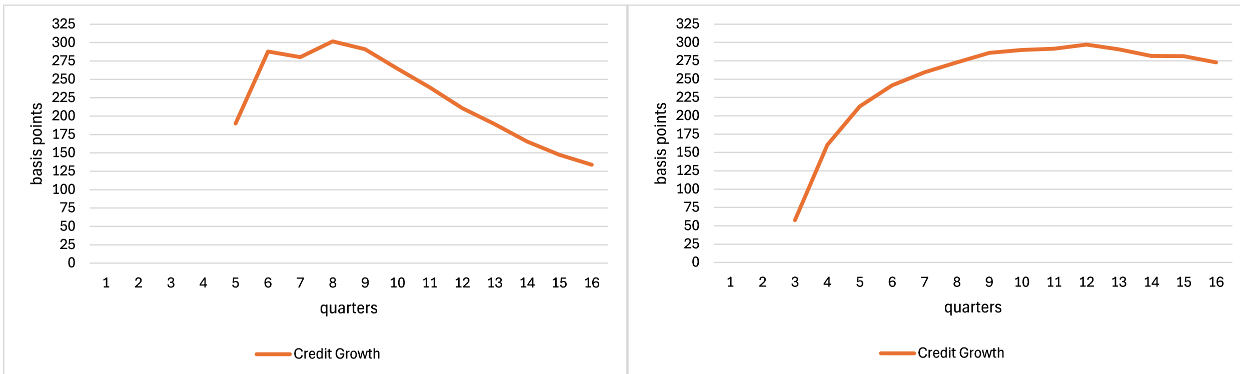
Overall, based on the results in Tables B1 and B2, we conclude that the structural shocks we identify with the SVAR model of section 2.2 are consistent with the credit impulse measure of Bassett et al. (2014). The shocks that we identify have the advantage of separating monetary policy from credit supply, seem to better separate the effects of credit demand shocks on current credit conditions, and only require using publicly available data.

## B.2. Comparing the Effects of Monetary Policy and Credit Supply Shocks for Credit Growth

The SVAR model presented in section 2.2 also allows to estimate the relative effects of variables of interest. For example, it allows to estimate the relative effect of a monetary policy and credit supply shocks on credit standards or credit growth. The case of the relative effect on credit growth is of particular interest because it allows to understand if monetary policy is having the desired effect on credit growth or whether bank's willingness to lend (credit supply shock) is making the effects either smaller or larger than those desired by the central bank. Figure B1 shows how much interest rates would have to rise (in basis points) to offset the effect of a one standard deviation expansionary credit supply shock on credit standards and on credit growth for the United States and the euro area. Because the effects of the shocks vary over time, we show how the estimated trade off over different time horizons. However, because for some cases the initial effects are somewhat noisy and volatile (see Figure 1), and, in some cases with the opposite sign of what is observed at longer horizons, we show the effects starting at different horizons.

Figure B1. Estimated Equivalence Between Monetary Policy and Credit Supply Shocks for Credit Growth.

(a) United States (b) Euro area




Note: The Figure shows the estimated increase in interest rates (monetary policy shock) that is necessary to offset the effect of a one standard deviation credit supply shock on credit growth, for the United States (panel a) and the euro area (panel b). The two charts start at different periods because the series are somewhat noisy in the first few quarters. These calculations are based on the median of the cumulative impulse responses of credit growth to a monetary policy shock and a credit supply shock.

Figure B1 illustrates the monetary policy response required to counteract a one-standard deviation credit supply shock in both the United States and the euro area. In both regions, this response peaks at approximately 300 basis points (bps). However, the timing and persistence of this effect differ notably between the two economies. For the United States, the peak effect occurs after 8 quarters but then tapers off significantly. By the 16-quarter mark, the required monetary policy adjustment has diminished to less than half of its 8-quarter value. In contrast, the euro area experiences a more delayed but persistent effect. The peak response is observed after 12 quarters and maintains its strength over a longer period, showing little decline even at 16-quarter horizon.

We can use the results from Figure B1, combined with our series of identified credit supply shocks, to estimate the equivalent interest rate increase that would match the negative credit supply shock due to the Silicon Valley Bank (SVB) failure in March 2023 and the subsequent banking stress. When we combine the identified credit supply shocks in 2023Q1 and 2023Q2, we get a combined credit supply shock close to two and a half standard deviations. Applying this to the results from Figure 2, which are based on a one standard deviation credit supply shock, we can extrapolate the impact of the SVB failure. The equivalent effect would be a a little over 725 bps in interest rates, considering the peak effect that is observed after 8 quarter in the united States. The same result would apply to the euro area in case it was hit by a negative credit supply shock similar to that caused by the failure of SVB.[18] This comparison provides a tangible perspective on the magnitude of the SVB failure's impact on credit supply, equating it to a substantial monetary policy tightening in both the US and potentially in the euro area.

These results are in line with previous findings showing that negative credit supply shocks (possibly arising from acute distress in the banking sector) are very difficult to offset and can even have very long lasting effects (see, for example, Reinhart and Rogoff (2009) or Reinhart and Rogoff (2014)). In this case we are just looking at credit to firms, and other type of credit are likely more important for short-term GDP growth. However, to the extent that banks' credit to firms is financing some of firms' investments, negative credit supply shocks can stunt firms' investment and with that future productivity growth, and ultimately future GDP growth.

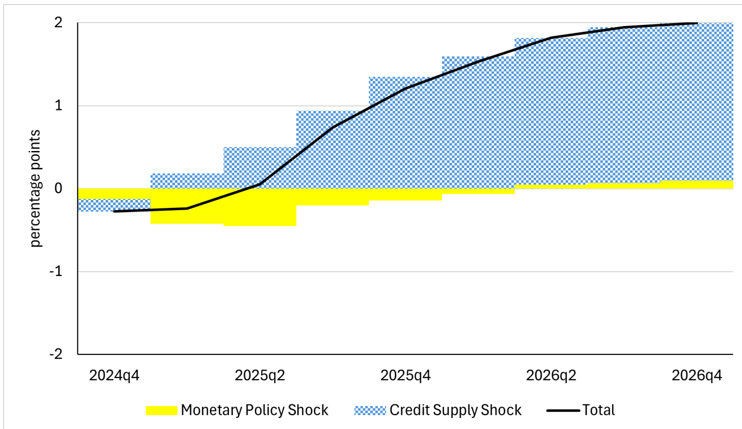
[18]It is important to note that neither the Fed or the ECB target the growth of bank credit to firms.

## B.3. Projecting Bank Credit Growth from Estimated Credit Supply and Monetary Policy Shocks

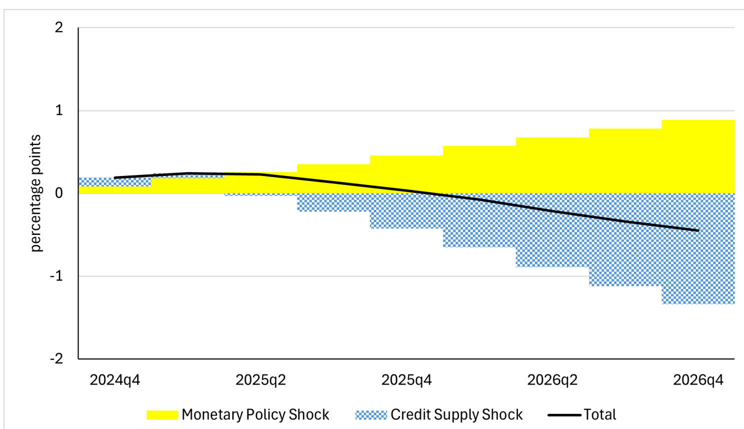
While the main goal of the paper is to provide a measure of current bank credit conditions, the SVAR model can also be used to project expected credit growth given the recently observed credit supply and monetary policy shocks. In Figure B2 we show the projected credit growth in the next two years given the estimated monetary policy and credit supply shocks from 2024:Q1 to 2024:Q4.

Figure B2. Projected bank credit growth for NFCs in the United States and the euro area

(a) United States




(b) Euro area



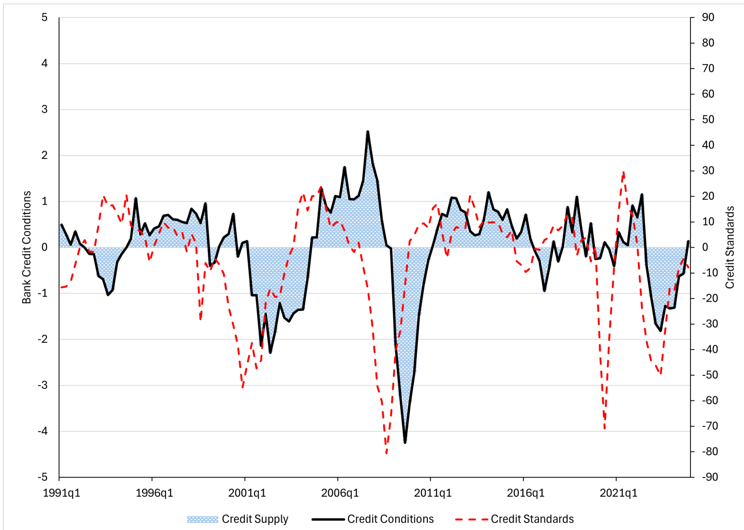

Note: The Figure shows the projected bank credit growth for firms based on the most recent four monetary policy and credit supply shocks for the United States in panel a) and for the euro area in panel b). This measure combines the estimated impulse response functions and identified monetary policy and credit supply shocks to project the level of credit conditions given the most recent four shocks. The results are based on the average of all the structural shocks derived from each draw in the sign restriction part of the identification.

The results in Figure B2 suggest that recent monetary policy shocks in the United States are still constraining credit growth, though their impact will diminish over time, as shown in panel (a). Conversely, recent credit supply shocks are fostering credit growth. The net effect of these opposing forces indicates that credit conditions should begin to support overall credit growth from the second half of 2025 onward. The situation in the euro area presents a different picture, as shown in panel (b). Recent monetary policy shocks are supporting credit growth, while the impact of recent credit supply shocks are muted for now but will start to weigh on credit growth a year from now.

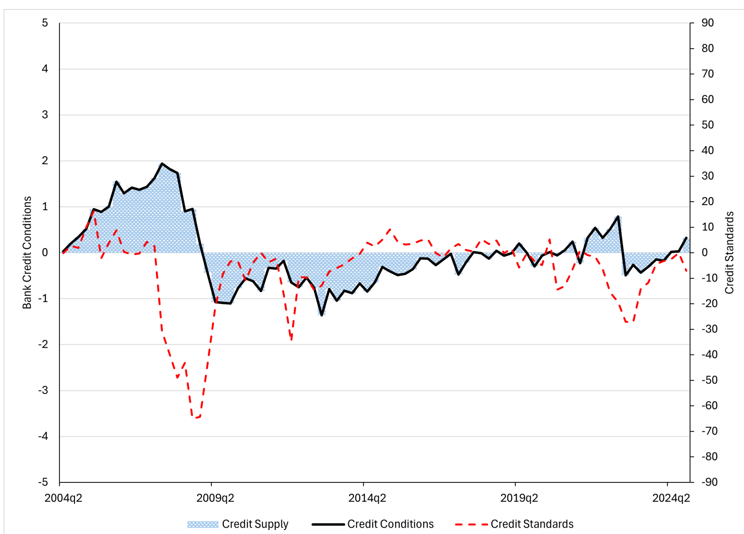
## C. Alternative measure of bank credit conditions

Figure B3. Alternative bank credit conditions for NFCs in the United States and the euro area

(a) United States




(b) Euro area




Note: The Figure shows estimates of bank credit conditions for NFCs for the United States in panel a) and for the euro area in panel b). This measure corresponds to the effect of credit supply shocks as identified by the SVAR model discussed in the paper on credit growth. The results are based on the average of all the structural shocks derived from each draw in the sign restriction part of the identification.