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The Financial Accelerator in the Euro Area: New Evidence Using a Mixture VAR Model

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Abstract

We estimate a logit mixture vector autoregressive model describing monetary policy transmission in the euro area over the period 2003Q1–2019Q4 with a special emphasis on credit conditions. With the help of this model, monetary policy transmission can be described as mixture of two states (e.g., a normal state and a crisis state), using an underlying logit model determining the relative weight of these states over time. We show that shocks to the credit spread and shocks to credit standards directly lead to a reduction of real GDP growth, whereas shocks to the quantity of credit are slightly less important in explaining growth fluctuations. The credit spread and — to some extent — credit standards are also the key determinants of the underlying state of the economy in the logit submodel. Together with a more pronounced transmission of monetary policy shocks in the crisis state, this provides further evidence for a financial accelerator in the euro area. Finally, the detrimental effect of credit conditions is also reflected in the labor market.

JEL Codes: E44, E52, E58, G21.

Keywords: Credit growth, credit spread, credit standards, euro area, financial accelerator, mixture VAR, monetary policy transmission.

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1 Introduction

Credit losses borne by banks during the Global Financial Crisis (GFC) increased financial stress in the credit markets (Adrian and Shin 2010).[1] The subsequent impact on the real economy was amplified by the fact that banks in the euro area are important financial intermediaries. Indeed, looking at the ratio of total bank assets to GDP (see Figure A1 in Appendix A) shows that the euro area banks are active in the value creation process.

Driscoll (2004) highlights important consequences of the bank-dependence for the real economy. First, the monetary transmission mechanism also works through the market for bank loans (the "lending channel" of monetary policy). Second, bank failures may amplify recessions. Third, regulatory actions can be a source of monetary policy shocks that is of similar importance as changes in the main refinancing operations (MRO) rate by the European Central Bank (ECB). As a result, banks are a crucial determinant of business cycle fluctuations in the euro area. This is further documented in the results of van der Veer and Hoeberichts (2016) who find that the supply-induced reduction of lending, due to a tightening of lending standards by banks in the euro area during the GFC, has worsened the downturn in the real economy.

Hence, understanding the role of credit conditions is important as these have significant implications for macroeconomic fluctuations. Against this background, our paper addresses the question to what extent changes in the quantity, quality, and risk of credit — that typically occur over the business cycle — act as a financial accelerator (Bernanke et al. 1996) and amplify macroeconomic fluctuations in the euro area during the period 2003Q1–2019Q4.[2] We employ a novel empirical methodology, a mixture vector autoregressive (VAR) model à la Burgard et al. (2019) that assumes the co-existence of two states of the economy (e.g., a normal state and a crisis state) with time-varying weights. In contrast to other classes of non-linear VARs, the regime af-

[1] Bank lending decreased sharply as, for instance, the annual growth rate of loans granted to non-financial corporations fell from 15% in early-2008 to 3% in early-2010.

[2] Note that the starting point of our analysis is restricted by the availability of the ECB's quarterly bank lending survey.

filiation is neither strictly binary, nor binary with a transition period, and based on multiple variables. With the help of this model, monetary policy transmission can be described as mixture of two states using an underlying logit model determining the relative weight of these states over time. Consequently, our approach is well suited to analyze direct effects of shocks to credit quantity, credit quality, and credit risk on the real economy in different states. Moreover, this model is able to identify a financial accelerator effect as monetary policy transmission might differ across states and changes in credit conditions might affect the underlying state weights in the economy.

Indeed, our empirical analysis documents that shocks to the credit spread (i.e., the difference between banks' bond yields and the yield of a German bund zero coupon bond) — which act as a proxy of credit risk — and shocks to credit standards (i.e., a measure based on the ECB's bank lending survey) lead to a reduction of real GDP growth in the euro area, whereas shocks to the quantity of credit (i.e., the growth rate of real loans to non-financial corporations) are slightly less important in explaining growth fluctuations. These direct effects of shocks are more pronounced in the crisis state than in normal times. The ECB responds to shocks in credit standards with loose monetary policy, but does not accommodate shocks to the spread. This might also explain why the detrimental results for the credit spread are more enduring than the ones for credit standards.

In addition, the credit spread and — to some extent — credit standards contribute to the financial accelerator since both variables are key determinants of the underlying state of the economy in the logit mixture VAR model. The "crisis state" is particularly prevalent around the GFC and, to some extent, during the euro area sovereign debt crisis. During crisis times, the transmission of standard monetary policy shocks is more pronounced than during normal times, providing further evidence for the financial accelerator in the euro area.

To ensure that our empirical findings indeed reflect credit conditions, we conduct robustness tests using indicators for stock market volatility and economic policy uncertainty (EPU, Baker et al. 2016) as covariates in the mixture VAR model. We also detect a significant detrimental effect of volatility shocks and policy uncertainty shocks on real GDP growth. However, this effect is quantitatively much smaller than that of the credit spread and credit standards. In addition, the influence of stock market volatility on the state weights is much smaller than that of the two credit variables and the EPU almost plays no role in that regard. Our results are qualitatively robust to using different indicators for the monetary policy stance at the zero lower bound (Wu and Xia 2016; Krippner 2015). Finally, the detrimental effect of credit conditions is also reflected in the labor market.

Our paper contributes to the literature that studies the interaction between bank-credit conditions and the rest of the economy. From a theoretical perspective, there is a long tradition in the literature, beginning with Brunner and Meltzer (1963), that banks may play a special role in the propagation of economic fluctuations. Several contributions, including Bernanke and Gertler (1989), Holmström and Tirole (1997), Kiyotaki and Moore (1997), and Diamond and Rajan (2005), suggest that credit supply and demand are important in explaining the evolution of the business cycle. As an illustration, Gerali et al. (2010) estimate a dynamic stochastic general equilibrium (DSGE) model and find that the largest contribution to the contraction of euro area economic activity in 2008 came from shocks that either pushed up the cost of loans or reduced the amount of credit available to the private sector. The role of banks' loan supply in explaining business cycle fluctuations is further documented by Curdia and Woodford (2010) and Gertler and Karadi (2011). In their models, shocks caused by banks, such as increases in loan losses, an unexpected destruction of bank capital, or changes in the willingness to lend, trigger economic disturbances due to credit frictions. More recently, Ravn (2016) uses a DSGE model in which countercyclical lending standards emerge as an equilibrium outcome and act as an amplifier of shocks to the economy.

Recent empirical evidence for the euro area also underlines the importance of credit standards and loan supply shocks for the business cycle. Altavilla et al. (2019) document that an adverse loan supply shock leads to a prolonged contraction in lending volumes and that this shock is able to explain movements in economic activity over the two latest euro area recessions. Gilchrist and Mojon (2016) aggregate bond-level credit spreads to obtain indices of credit risk and find that disruptions in credit markets lead to significant declines of output and inflation in Germany, France, Italy, and Spain. Bleaney et al. (2016) show that bond spreads in the euro area are correlated with the tightness of credit supply as reported in the ECB's bank lending survey, and that a worsening of bank credit supply is negatively correlated with future real GDP growth.

Other papers study a potentially asymmetric relationship between credit conditions and real economic activity. Akinci and Queralto (2020) show that credit spreads are not only countercyclical, but the strength of their countercyclicality is higher when these are elevated. The results of Xu and de Haan (2018) suggest that the relationship between credit spreads and future employment growth is lower during bubbles and recessions. Finally, Bijsterbosch and Falagiarda (2015) find that the effects of credit supply shocks on the euro area strongly increased at the time the GFC erupted. These more recent findings underscore the need to study the (asymmetric) effects of credit shocks on real economic activity in different states and to understand the determinants of the relative weights of these states. The logit mixture vector autoregressive model is helpful to address both issues in a unified framework.

The remainder of the paper is organized as follows. Section 2 describes the logit mixture VAR model and introduces the dataset. Section 3 shows the baseline empirical results for credit quantity, quality, and risk. Section 4 explores the robustness of the results using (i) indicators for stock market volatility and economic policy uncertainty and (ii) an alternative monetary policy indicator at the zero lower bound. Section 5 documents the effect of credit conditions on the labor market. Section 6 concludes.

2 Econometric Methodology and Data

2.1 Econometric Methodology

The most common approaches to capture regime-dependent non-linearities in macroeconomics are the Markov-switching VAR model proposed by Hamilton (1989, 1990) and the threshold VAR model of Tsay (1998).[3] A general criticism of both model classes is the binary regime affiliation as the economy is assumed to shift between regimes, but is restricted to be located in strictly one regime at a time. A transition period including a mixture of regimes, however, might be a more realistic description of the data. Smooth transition VAR models (Weise 1999, Camacho 2004) aim at filling this gap. Nevertheless, outside of the (possibly long-lasting) transition period, the economy remains rigidly in one state in this class of models, too.

We overcome this shortfall by utilizing a mixture VAR à la Burgard et al. (2019) that assumes the co-existence of two states with time-varying weights.[4] In contrast to other classes of non-linear VAR models, the regime affiliation is neither strictly binary nor binary with a transition period. As a consequence, we are not studying a switch in regime, but the degree of dominance of one state over the other. In addition, we also utilize a submodel — that is simultaneously estimated with the VAR models for both states — to examine and understand the economic reasons for the time-varying weights.

Burgard et al. (2019) extend the models of Fong et al. (2007) and Kalliovirta et al. (2016) by introducing a logit submodel similar to Thompson et al. (1998) to obtain the state weights. Based on their approach, we employ a logit mixture VAR with two states:

$$\begin{aligned} F(y_t|\mathcal{F}_{t-1}) = \quad & \tau_t \quad \cdot \; \Phi\left(\Omega_1^{-\frac{1}{2}}\left(Y_t - \Theta_{0,1} - \Theta_{1,1}Y_{t-1} - \ldots - \Theta_{p_1,1}Y_{t-p_1}\right)\right) \quad + \\ & (1-\tau_t) \quad \cdot \; \Phi\left(\Omega_2^{-\frac{1}{2}}\left(Y_t - \Theta_{0,2} - \Theta_{1,2}Y_{t-1} - \ldots - \Theta_{p_2,2}Y_{t-p_2}\right)\right) \end{aligned} \tag{1}$$

[3] Alessandri and Murmaz (2017) provide a recent application of a threshold VAR for the US in the context of the GFC.

[4] In principle, more than two states could be estimated. Due to the relatively small number of observations, however, this is not feasible in the context of this paper.

Monetary policy transmission is described by two different components, each being a linear Gaussian VAR process with lag order p_1 and p_2, respectively. $\mathcal{F}$ denotes the information set up to time $t-1$ and $\Phi(.)$ is the multivariate cumulative distribution function of independent and identically distributed standard normal random variables. $\Theta_{0,1}$ and $\Theta_{0,2}$ are the n-dimensional vector of intercepts in state 1 and 2. $\Theta_{1,1}, \ldots, \Theta_{p_1,1}$ and $\Theta_{1,2}, \ldots, \Theta_{p_1,2}$ are the $n \times n$ coefficient matrices. Ω_1 and Ω_2 are the $n \times n$ variance covariance matrices. τ_t and $(1-\tau_t)$ are the time-conditional mixture weights for state 1 and 2, which are determined by a concordant logit model:

$$\widehat{\tau_t} = \frac{1}{1 + \exp(-\mathbf{X}'\boldsymbol{\beta})} \tag{2}$$

The variables $\mathbf{X}$ — which may, for example, include a constant, lagged mixture weights, and lagged endogenous variables — are predetermined and, hence, part of the information set $\mathcal{F}_{t-1}$. Consequently, the mixture weights $\widehat{\tau_t}$ are $\mathcal{F}_{t-1}$-measurable. One implication of employing only lagged variables in the submodel is to preclude that monetary policy shocks can change the state weights in period t through their contemporaneous effect on another variable in the VAR that, in turn, might be crucial in determining the state weights. $\boldsymbol{\beta}$ denotes the vector of coefficients in the logit model.

Eqs. (1) and (2) are estimated using an expectation maximization algorithm. The calculation of orthogonalized impulse responses is based on bootstrapping. For each of the 500 bootstrap samples with a horizon of 16 periods and a recursive identification scheme, we obtain the mean of the 500 bootstrapped samples alongside the 16% and 84% quantiles for the corresponding confidence bands. It is worth highlighting that for the calculation of the impulse responses we do not have to assume that the economy remains in a single state as is done in many Markov-switching VAR applications. The overall impulse response function is a continuously varying mixture of the impulse responses for both states, with the weights being determined by the underlying logit model.[5]

[5] Further details on the estimation procedure and the derivation of impulse responses can be found in Burgard et al. (2019).

2.2 Data

Our data set covers quarterly data for the euro area (changing composition) and the period 2003Q1–2019Q4. The start date coincides with the introduction of the quarterly bank lending survey by the ECB. We estimate several logit mixture VAR models. All of these consist of the three standard monetary policy transmission variables. First, we utilize the growth rate of real GDP (y_t) as the measure of real economic activity. Second, we use the inflation rate (π_t) based on the harmonized index of consumer prices, excluding energy and food. Using a core inflation measure precludes exogenous price movements stemming from these two sources, allowing us to establish a parsimonious model without an exogenous oil price indicator. Third, we make use of a composite indicator of the monetary policy stance (i_t). Until 2008Q3, we use the ECB's MRO rate.[6] After that date, we replace the MRO rate with the shadow interest rate by Wu and Xia (2016), which provides a quantification of all unconventional monetary policy measures in a single shadow interest rate and also allows for negative interest rates. In our view, this is the most parsimonious description of monetary policy in a single variable.[7]

In addition to these three standard variables, we add an indicator for the quantity of credit into the first four-variable logit mixture VAR model. For that purpose, we create a measure of real loans to euro area non-financial corporations ($LOAN_t$) with the help of the harmonized index of consumer prices and employ the growth rate thereof as fourth endogenous variable. The second four-variable model is augmented with a measure of credit standards (CS_t) that is taken from the ECB's bank lending survey of around 140 banks from all euro area countries. This indicator is calculated as the net percentage of banks expecting a tightening in credit standards (as opposed to an easing) in the next quarter. The rationale behind using this variable is to measure the change of non-financial obstacles in credit lending, such as loan-to-value restric-

[6] Note that replacing the MRO rate with the EONIA leaves the results virtually unchanged. This reflects the almost perfect correlation of both variables during the period 2003Q1–2008Q3 ($\rho = 0.99$).

[7] We explore the robustness of our results by using the shadow short rate of Krippner (2015) as alternative indicator of the monetary policy stance at the zero lower bound (i_t^{alt}). The results can be found in Section 4.2.

tions or collateral requirements. Finally, we utilize the credit spread (SPR_t) of euro area banks by Gilchrist and Mojon (2016) as fourth covariate in the third four-variable model. This variable measures the difference between banks' bond yields and the yield of a German bund zero coupon bond of the same maturity and serves as indicator of credit risk. The results of the three baseline four-variable logit mixture VAR models can be found in Section 3.

To ensure that our findings are particularly driven by credit conditions, we conduct two robustness tests. First, we utilize the VSTOXX ($VOLA_t$) as fourth endogenous variable. This model is helpful to compare the effect of shocks in credit standards and risk to that of volatility shocks, particularly in light of the large correlation between these variables (see Table A1 in Appendix A). For similar reasons, we also utilize the economic policy uncertainty (EPU_t) index by Baker et al. (2016) as fourth covariate in the second robustness test. Hereby, we want to disentangle the effects of credit risk from that of economic policy uncertainty. The results of the two robustness tests can be found in Section 4.1.

It has to be emphasized that models with a number of covariates larger than four do not converge in a systematic manner for all combinations of credit, volatility, and uncertainty indicators. This is due to the relatively small number of observations and the demanding nature of a two-state mixture VAR model with a concomitant logit submodel. This is also the reason why we replace real GDP growth with the change in the unemployment rate in our final extension where we test for the impact of credit conditions on the labor market. The results of this extension can be found in Section 5.

Figures A2 and A3 in Appendix A show all variables over the sample period. Following Burgard et al. (2019), we remove the linear trends of all variables before employing these in the mixture VAR model.[8] Table A1 shows the bivariate correlations of the detrended series. Several things are worth highlighting. First, the quantity of credit ($LOAN_t$) is procyclical with respect to real GDP growth ($\rho = 0.28$), giving rise

[8]Note that this is equivalent to including a linear trend in the VAR model.

to the well-known financial accelerator. Second, the quality of credit (CS_t) is countercyclical ($\rho = -0.57$), implying that non-financial obstacles (as indicated by higher values of CS_t) are particularly prevalent in times of low growth and vice versa. Third, a similar countercyclical picture emerges for the credit spread ($\rho = -0.54$). However, there is also a substantial negative correlation between the VSTOXX and real GDP growth ($\rho = -0.45$). This, together with the pronounced positive correlation of CS_t and $VOLA_t$ ($\rho = 0.62$) and SPR_t and $VOLA_t$ ($\rho = 0.64$) underscores the need for some additional analysis to compare the effects of credit shocks and volatility shocks. Finally, the correlations of credit quantity, quality, and risk are even more pronounced when considering the change in the unemployment rate as real macroeconomic indicator (instead of real GDP growth). In the end, however, it remains to be seen if these bivariate contemporaneous relationships hold in a VAR model that also incorporates dynamics in the connections across variables and allows for two different states with time-varying weights.

As a final step, we have to select an appropriate number of lags in the logit mixture VAR model. The selection is based on a battery of specifications with different lag lengths for all four-variable combinations in the VAR model and the concomitant submodel, the latter of which also includes lags of the mixture weights. We choose the final model based on three criteria. First, there should be no autocorrelation left in the residuals of the VAR model at the 5% level. Second, the impulse responses should converge to zero, at least asymptotically. Third, either model should be as parsimonious as possible, that is, redundant (i.e., insignificant) lags should be removed. It turns out that a lag length of two in both states in the main model and one lag of the four variables alongside the lagged dependent variable in the submodel is sufficient to achieve these three goals. Including additional lags in either model only leads to a less sharp identification of the impulse responses due to a loss in the degrees of freedom.

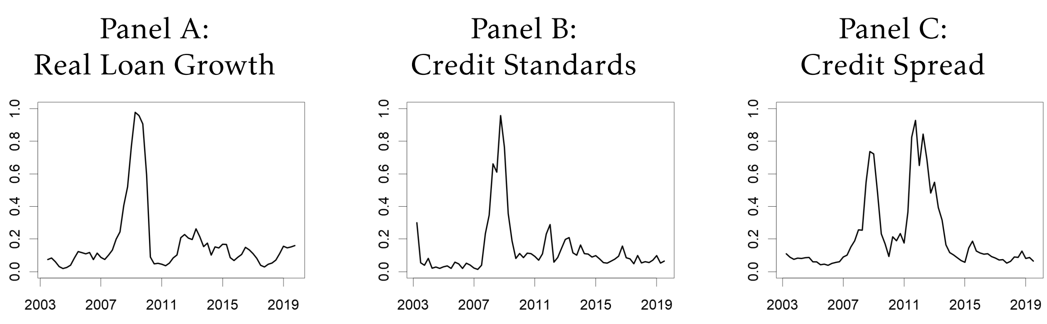
The impulse responses are derived based on the standard ordering in the literature. Real GDP growth (the change in the unemployment rate) is ordered first, followed by core inflation, and the interest rate. The variables real loan growth, credit standards, credit risk, VSTOXX, and economic policy uncertainty are ordered fourth in the respective specifications. This identification scheme implies that monetary policy shocks affect output (unemployment) and prices only with a time lag, whereas monetary policy shocks can affect the credit market, stock market volatility, and policy uncertainty instantaneously.[9]

3 Baseline Results

3.1 Weights and Determinants of Crisis State

Figure 1 presents the weights of the "crisis" state obtained with the help of the logit submodels.[10] The interpretation as crisis state follows the evolution of the weights in all three specifications. In all panels, a clear peak emerges during the GFC. In addition, the model using the credit spread peaks another time during the euro area sovereign debt crisis in 2011. The overall share of the crisis states is 17.7% for real loan growth as indicator of credit conditions, 13.9% for credit standards, and 21.6% for the credit spread. The similarity of all three weight series is also reflected in a noticeable positive correlation.[11]

Figure 1: Weights of Crisis State



Notes: Weights of the crisis states are obtained by estimation of Eq. (2).

[9]Zero restrictions on impact for output and prices after a monetary policy shock are also assumed in other recent papers (e.g., Peersman 2011; Gambacorta et al. 2014).

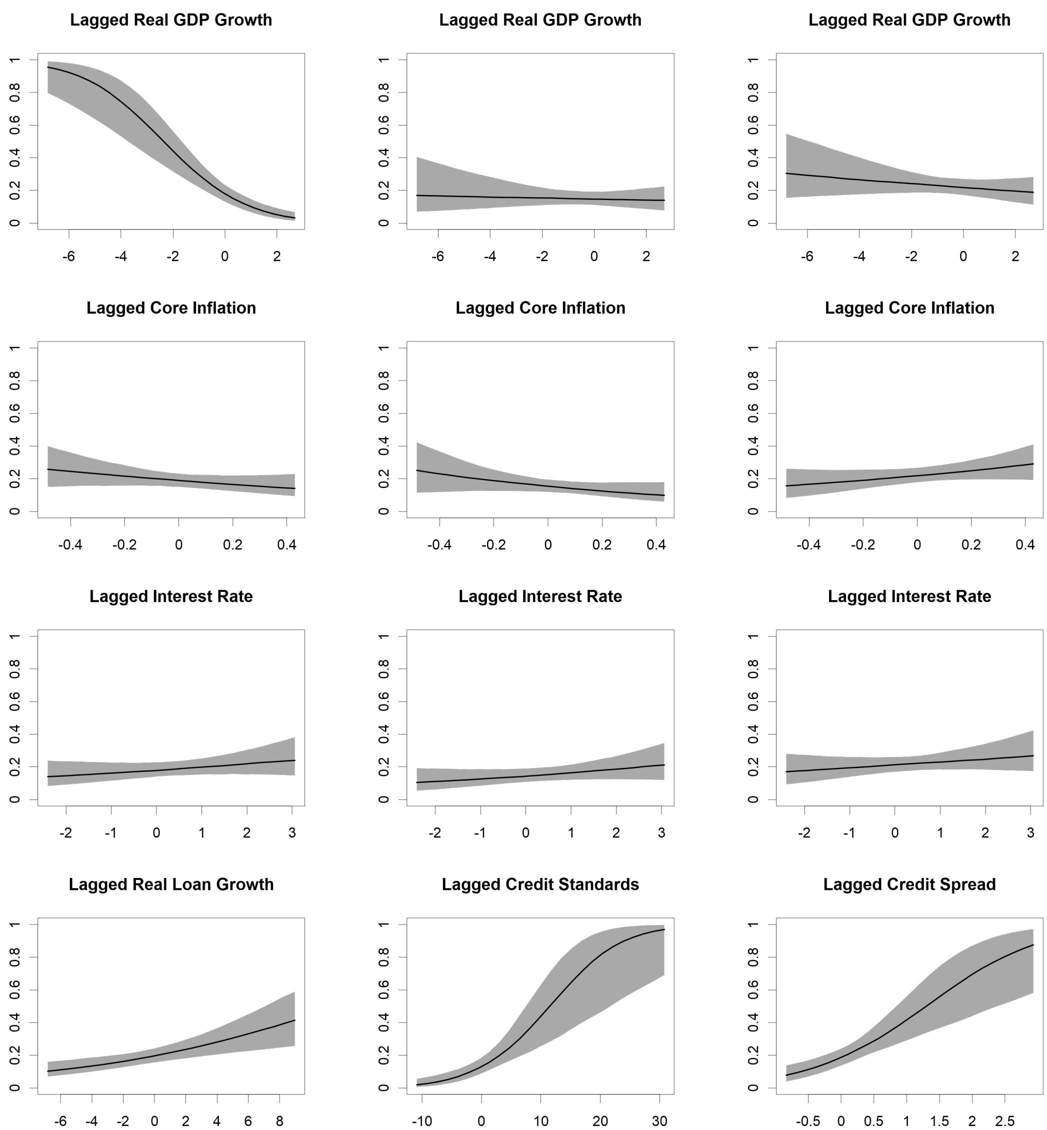
[10]The weights of the "normal" state are 1 minus the weights of the crisis state.

[11]The correlations of the state weight are as follows: Loan growth vs. standards: $\rho = 0.71$; loan growth vs. spread: $\rho = 0.46$; standards vs. spread: $\rho = 0.55$.

Figure 2 shows the predicted probabilities of the logit submodels for the crisis state and for different realized values of lagged real GDP growth, lagged core inflation, the lagged interest rate indicator, and lagged credit conditions. Throughout all three models, lagged inflation and the lagged interest rate are not important as predictor of the crisis state.

Figure 2: Predicted Probabilities

Panel A: Real Loan Growth | Panel B: Credit Standards | Panel C: Credit Spread



Notes: Solid lines show the predicted probabilities of the logit submodels for the crisis state and different realized values of the explanatory variables. Gray-shaded areas indicate 68% confidence bands.

When considering real loan growth as indicator of credit conditions (Panel A), lagged real GDP growth is the most important predictor of the crisis state. For small growth rates, the probability of being in the crisis state is 96%, whereas for large values the probability decreases to 3%. Lagged loan growth itself is also of relevance as the likelihood of being in the crisis state increases from 10% for small values up to 41% for large growth rates. Put differently, an overheating market for real loans might be indicative for the economy entering the crisis state in the next quarter. In Panels B and C, however, lagged real GDP growth is of minor relevance as predictor of the crisis state. Here, lagged credit standards in Panel B (2% predicted probability for small values up to 97% for large values) and the lagged spread in Panel C (8%–88%) are the most important predictors. Consequently, the results in Panels B and C confirm the interpretation of a "crisis state" (as opposed to a "recession state") since this state is particularly likely in times of adverse credit conditions. The results in Panel A could also be interpreted as a "recession state" since this state is especially prevalent in times of low real GDP growth rates.[12]

To summarize, credit standards and credit risk are found to be important drivers of the crisis state. This implies that changes in both variables are changing the state of the economy. Put differently, there might be evidence for a financial accelerator in the euro area if the responses to monetary policy shocks differ across states. It also has to be mentioned that multiple variables play a role in determining the regime weights (albeit a small one in Panels B and C), indicating that the focus on a single variable (e.g., as in smooth transition VARs) might oversimplify the state-determining process.

3.2 Impulse Responses for Model with Real Loan Growth

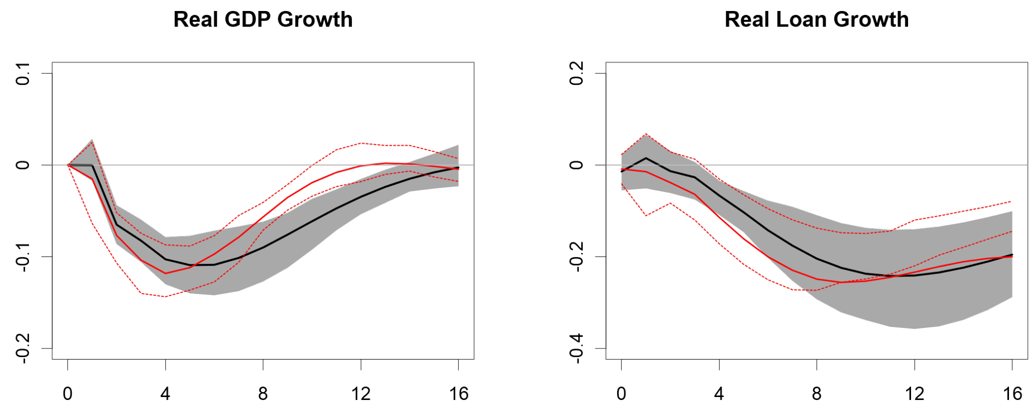
The upper panel of Figure 3 shows selected impulse response functions (IRFs) after a 25 bps interest rate shock when using real loan growth as indicator of credit conditions.

[12] For simplicity reasons, we stick to the notation "crisis state" throughout the rest of the paper, also in light of the much more pronounced empirical results for credit standards and the credit spread (see Sections 3.3 and 3.4).

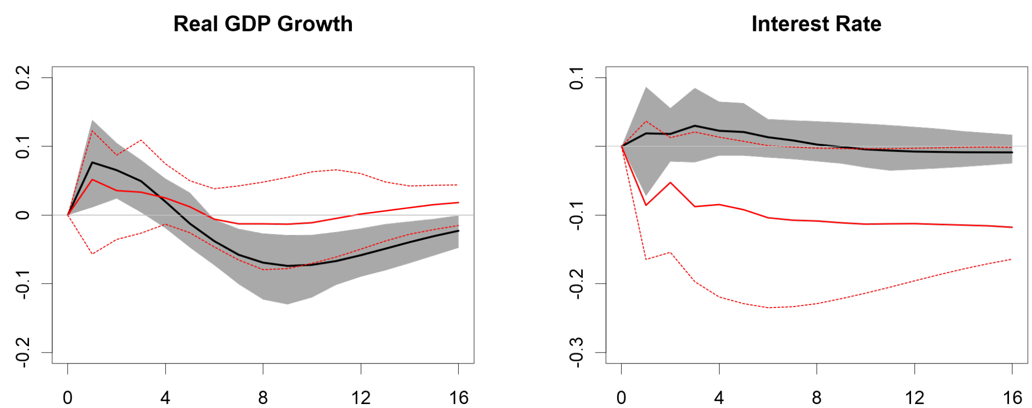
To conserve space, the following discussion focuses on real GDP growth and the credit indicator.[13]

Figure 3: IRFs for Model with Real Loan Growth

Panel A: IRFs for Shocks in the Interest Rate



Panel B: IRFs for Shocks in Real Loan Growth



Notes: Solid black lines show mean impulse responses of a 25 bps shock in the interest rate (upper panel) and a one-pp shock in real loan growth (lower panel) in the normal state. Solid red lines represent the corresponding mean IRFs for the crisis state. Gray-shaded areas (red dashed lines) indicate 68% confidence bands for the normal (crisis) state. Full set of impulse responses is available on request.

A contractionary monetary policy shock leads to a reduction of real GDP growth and real loan growth. The peak results are similar for both states in the case of real GDP growth (–11.8 bps after four quarters in the crisis state and –10.5 bps after five

[13] Core inflation exhibits a theory-consistent significant and prolonged decrease after a contractionary monetary policy shock with an outside lag of four-to-six quarters (also throughout all other specifications).

quarters in the normal state) and real loan growth (crisis: –25.6 bps, 9q; normal: –24.2 bps, 11q). If at all, the response of real GDP growth is more enduring during normal times. Finally, it has to be noted that the IRFs for real loan growth eventually die out when considering a horizon longer than 16 quarters.

The lower panel of Figure 3 shows selected IRFs after a one-pp shock in credit growth. To conserve space, the following discussion of the responses to the credit shock focuses on real GDP growth and the ECB's response. A credit growth shock exerts no significant impact on real GDP growth in the crisis state. During normal times, there is a short-lived positive effect (with a peak of 7.7 bps after one quarter) that eventually turns negative when considering a longer horizon. The latter finding is also in line with the results for the determinants of the state weights (see Panel A of Figure 2) as higher credit growth rates are indicative of a larger weight of the crisis state in the next quarter. Finally, monetary policy does not react in a significant way to credit growth shocks.

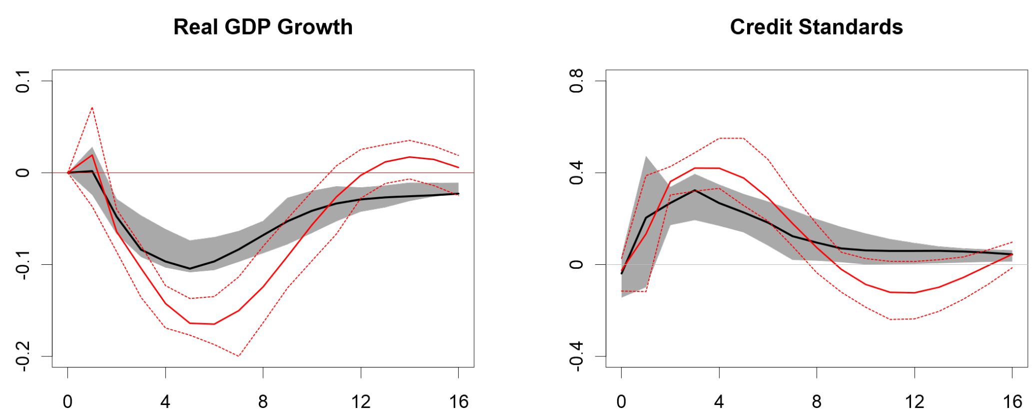
3.3 Impulse Responses for Model with Credit Standards

The upper panel of Figure 4 shows selected IRFs after a 25 bps interest rate shock when using credit standards as indicator of credit conditions. A contractionary monetary policy shock leads to a reduction of real GDP growth and a tightening of credit standards. Here, the peak results are significantly larger in the crisis state for real GDP growth (crisis: –16.5 bps, 6q; normal: –10.5 bps, 5q) and for credit standards (crisis: 42.0 bps, 3q; normal: 32.4 bps, 3q). However, the IRFs are more enduring in the normal state. Taken together with the finding that credit standards are the key determinant of the state weights (see Panel B of Figure 2), these results are indicative of a financial accelerator effect in the euro area.

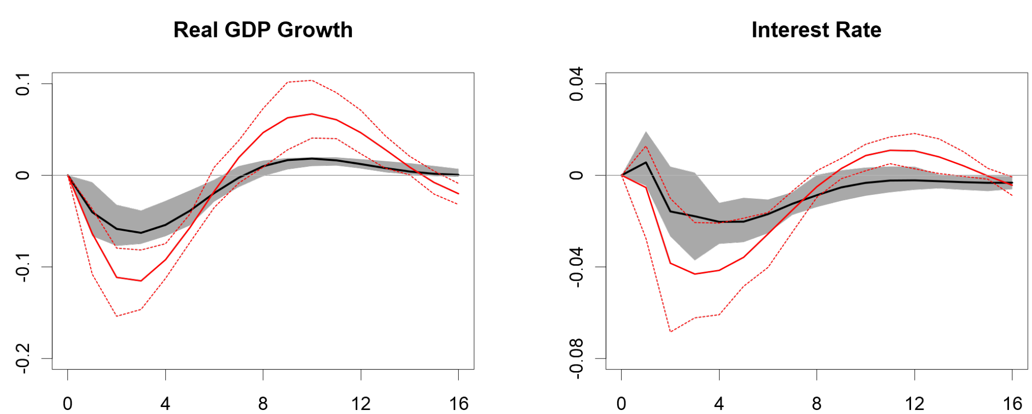
The lower panel of Figure 4 shows selected IRFs after a one-pp shock in credit standards. A shock to credit standards leads to a significant decrease of real GDP growth that is stronger in the crisis state (–11.5 bps, 3q) than in normal times (–6.3 bps, 3q). The effect, however, is short-lived and reverses after roughly eight quarters with the fluctuations being more extreme in the crisis state. The reason for this reversion can be found in the IRFs of the interest rate. The ECB employs an accommodative monetary policy stance after shocks to credit standards, particularly in the crisis state (–4.3 bps, 3q), but also during normal times (–2.0 bps, 4q).

Figure 4: IRFs for Model with Credit Standards

Panel A: IRFs for Shocks in the Interest Rate



Panel B: IRFs for Shocks in Credit Standards



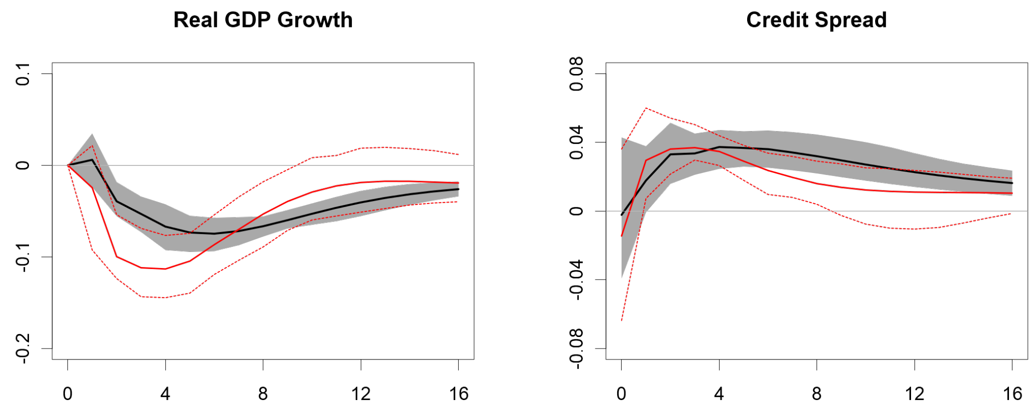
Notes: Solid black lines show mean impulse responses of a 25 bps shock in the interest rate (upper panel) and one-pp shock in credit standards (lower panel) in the normal state. Solid red lines represent the corresponding mean IRFs for the crisis state. Gray-shaded areas (red dashed lines) indicate 68% confidence bands for the normal (crisis) state. Full set of impulse responses is available on request.

3.4 Impulse Responses for Model with Credit Spread

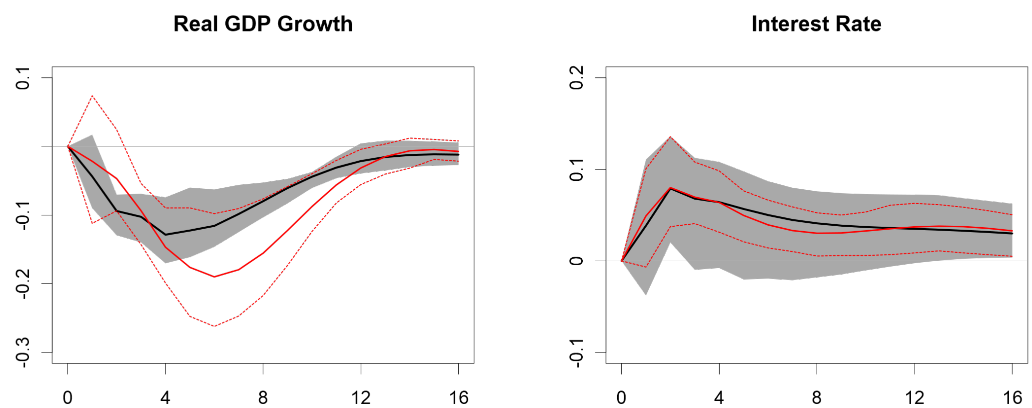
The upper panel of Figure 5 shows selected IRFs after a 25 bps interest rate shock when using the credit spread as indicator of credit conditions.

Figure 5: IRFs for Model with Credit Spread

Panel A: IRFs for Shocks in the Interest Rate



Panel B: IRFs for Shocks in the Credit Spread



Notes: Solid black lines show mean impulse responses of a 25 bps shock in the interest rate (upper panel) and a 25 bps shock in the credit spread (lower panel) in the normal state. Solid red lines represent the corresponding mean IRFs for the crisis state. Gray-shaded areas (red dashed lines) indicate 68% confidence bands for the normal (crisis) state. Full set of impulse responses is available on request.

A contractionary monetary policy shock leads to a reduction of real GDP growth and a widening of the credit spread. Again, the peak results are significantly larger in the crisis state for real GDP growth (crisis: –11.3 bps, 4q; normal: –7.5 bps, 6q), but not for the credit spread (crisis: 3.7 bps, 3q; normal: 3.7 bps, 4q). Similar to the results for the credit standards, there is evidence for a financial accelerator effect since the credit spread is the key determinant of the state weights (see Panel C of Figure 2) and the transmission of monetary policy shocks on real GDP growth is stronger in the crisis state.

The lower panel of Figure 5 shows selected IRFs after a 25 bps shock in the credit spread. A shock to the credit spread leads to a significant decrease of real GDP growth that is stronger in the crisis state (–19.0 bps, 6q) than in normal times (–12.9 bps, 4q). In contrast to the results for credit standards, the response is persistent as it turns insignificant for the first time three years after the shock. Here, the ECB does not accommodate a worsening of credit conditions. In fact, we even observe a tightening of the interest rate, in particular in the crisis state. This makes the accelerating effect of the credit spread even more pronounced compared to that of credit standards.

3.5 Summary and Discussion

Our empirical analysis documents that shocks to the credit spread and shocks to credit standards lead to a significant reduction of real GDP growth, whereas shocks to the quantity of credit are less important in explaining growth fluctuations. These direct effects are more pronounced in the crisis state than in normal times. The ECB responds to credit standard shocks with loose monetary policy, but does not accommodate shocks to the spread. This might also explain why the detrimental results for the credit spread are more enduring than the ones for credit standards.

In addition, the credit spread and credit standards contribute to the financial accelerator since both variables are key determinants of the underlying state of the economy in the logit mixture VAR model. The crisis state is particularly prevalent around the GFC and, to some extent, during the euro area sovereign debt crisis. During crisis times, the transmission of standard monetary policy shocks is more pronounced than during normal times, providing further evidence for the financial accelerator in the euro area.

Finally, for a thorough comparison of the peak effects on real GDP growth (standards, crisis: –11.5 bps; standards, normal: –6.3 bps; spread, crisis: –19.0 bps; spread, normal: –12.9 bps), one needs to consider the (relative) standard deviation of the shock variables (see Table A1 in Appendix A) as a yardstick. When accounting for the larger standard deviation of credit standards (6.95 as opposed to 0.79 for the credit spread) and the different shock sizes in the IRFs (one-pp for credit standards and 25 bps for the credit spread), the peak effect of shocks to credit standards on real GDP growth is (slightly) larger than the one of shocks to the credit spread. Nevertheless, the effects of the latter are much more persistent and not reversed in the four-year horizon under consideration. Accordingly, the strongest results are documented for the credit spread.

4 Robustness Tests

4.1 Volatility and Uncertainty

To ensure that our empirical findings indeed reflect credit conditions, we conduct robustness tests using indicators for stock market volatility and economic policy uncertainty as covariates in the mixture VAR model. As mentioned in Section 2.2, the noticeable bivariate correlations between some of the variables for credit conditions, volatility, and policy uncertainty call for scrutinizing the results. In addition to these data-driven considerations, there is also recent work analyzing the effects of uncertainty and volatility on credit conditions.[14]

4.1.1 Weights and Determinants of Crisis State

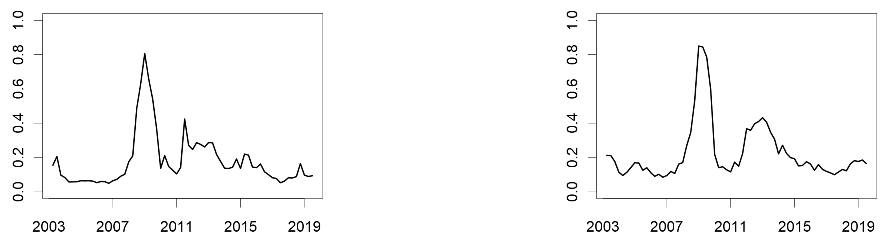
Figure 6 presents the weights of the crisis state obtained with the help of the logit submodels. Similar to Figure 1, we observe a peak during the GFC (albeit a smaller

[14]Firms may choose to invest and borrow less when uncertainty is high (Gilchrist et al. 2014), leading to a lower quantity of credit. Creditors face a similar problem as corporate loans are risky and become less attractive when firms' prospects are more uncertain. Indeed, Alessandri and Bottero (2020) find that high uncertainty reduces a firm's chances of obtaining a new loan. Following this line of thought, Alessandri and Panetta (2015) show that an increase in the EPU of Baker et al. (2016) predicts a tightening in the credit standards reported in the ECB's bank lending survey. Finally, Gissler et al. (2016), Valencia (2016), and Bordo et al. (2016) document a negative relationship between uncertainty and bank lending in the US.

one) and another noticeable increase during the euro area sovereign debt crisis in 2011. In general, the crisis weight series in this robustness correlate more strongly with credit quantity than with credit standards or the credit spread.[15] The overall share of the crisis state is 17.9% for the VSTOXX and 22.7% for the EPU.

Figure 6: Weights of Crisis State

Panel A: VSTOXX | Panel B: EPU



Notes: Weights of the crisis states are obtained by estimation of Eq. (2).

Figure 7 shows the predicted probabilities of the logit submodels for the crisis state and for different realized values of lagged real GDP growth and the lagged VSTOXX/EPU.[16] When using the EPU as additional indicator in the mixture VAR (Panel B), lagged real GDP growth is the most important predictor of the crisis state. For small growth rates, the probability of being in the crisis state is 85%, whereas for large values the probability decreases to 8%. The predicted probabilities for policy uncertainty do not vary that much for different values of this variable (26%–19%). In Panel A, real GDP growth is also the most important driver (59%–9%). In addition, variation in the VSTOXX is helpful in explaining the economy's state in the next period (10%–43%). Nevertheless, the effect of the VSTOXX is much less pronounced when compared to credit standards and the credit spread (see Figure 2). Hence, we can conclude that credit conditions (standards and the spread) are the key drivers of the state of the economy, whereas volatility and policy uncertainty are not. Moreover, we can rule out that the financial accelerator effect documented for credit standards and the

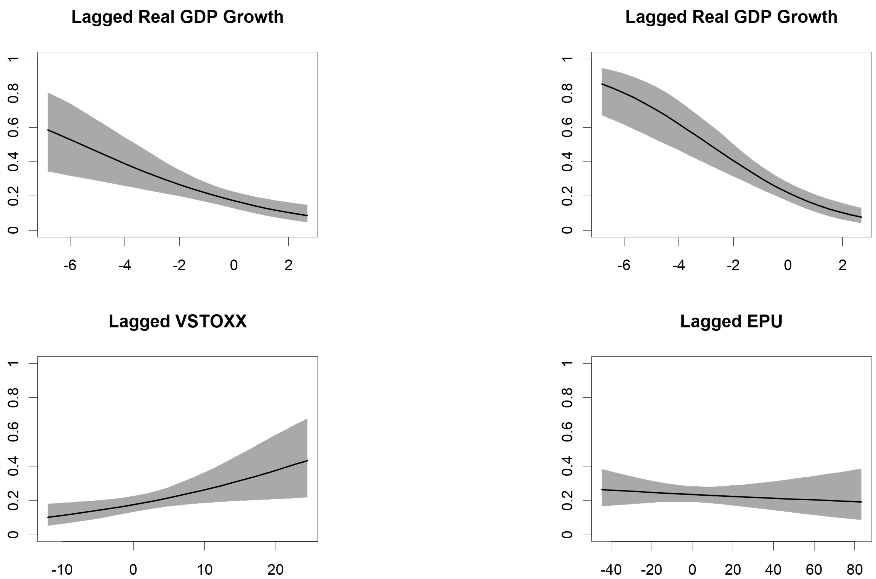
[15] The correlations of the state weights are as follows: VSTOXX (EPU) vs. loan growth: $\rho = 0.88$ ($\rho = 0.92$); VSTOXX (EPU) vs. standards: $\rho = 0.73$ ($\rho = 0.58$); VSTOXX (EPU) vs. spread: $\rho = 0.72$ ($\rho = 0.56$).

[16] Similar to Figure 2, lagged inflation and the lagged interest rate are not important as predictors of the crisis state and, consequently, not shown in Figure 7.

credit spread is confounded by financial market volatility or economic policy uncertainty.

Figure 7: Predicted Probabilities

Panel A: VSTOXX   Panel B: EPU



Notes: Solid lines show the predicted probabilities of the logit submodels for the crisis state and different realized values of selected explanatory variables. Gray-shaded areas indicate 68% confidence bands. Full set of predicted probabilities is available on request.

4.1.2 Impulse Responses

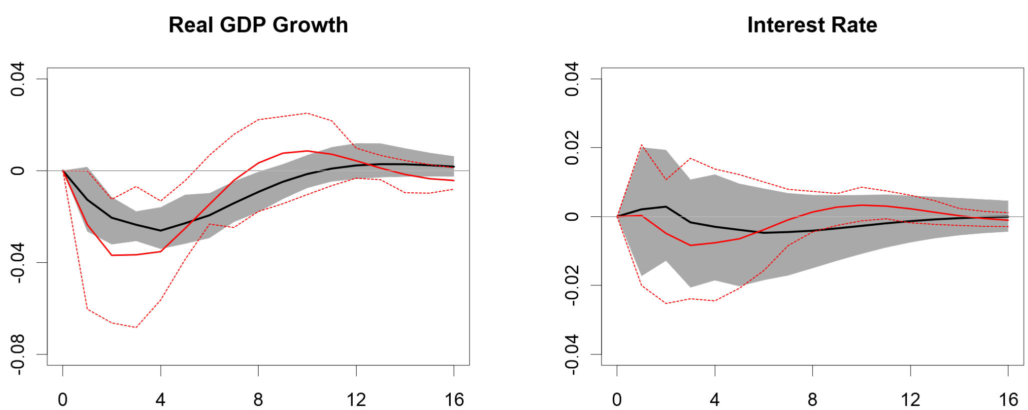
The results in the previous subsection already ruled out an accelerating effect of stock market volatility, and even more so for the EPU, when it comes to the transmission of monetary policy shocks on real GDP growth. Hence, in an effort to conserve space, the following discussion focuses on the direct effect of volatility shocks and policy uncertainty shocks.[17]

Figure 8 shows selected IRFs after a one-pp shock in the VSTOXX. A shock to the VSTOXX leads to a significant decrease of real GDP growth that is stronger in the crisis state (–3.7 bps, 2q) than in normal times (–2.6 bps, 4q). In addition, we find no significant response of the ECB to volality shocks in both states. Hence, there is some

[17] Volatility increases in both states after a contractionary monetary policy shock with the peak response being stronger but less enduring in the crisis state. Similarly, policy uncertainty increases significantly after the same type of shock, but without a distinct difference across states.

evidence for a direct effect of volatility shocks on output but this is much smaller than for credit standards and the credit spread. This also holds when accounting for the larger standard deviation of the VSTOXX (8.16) as compared to the ones of credit standards (6.95) and the credit spread (0.79) as well as the different shock sizes in the IRFs (one-pp for the VSTOXX, one-pp for credit standards, and 25 bps for the credit spread).

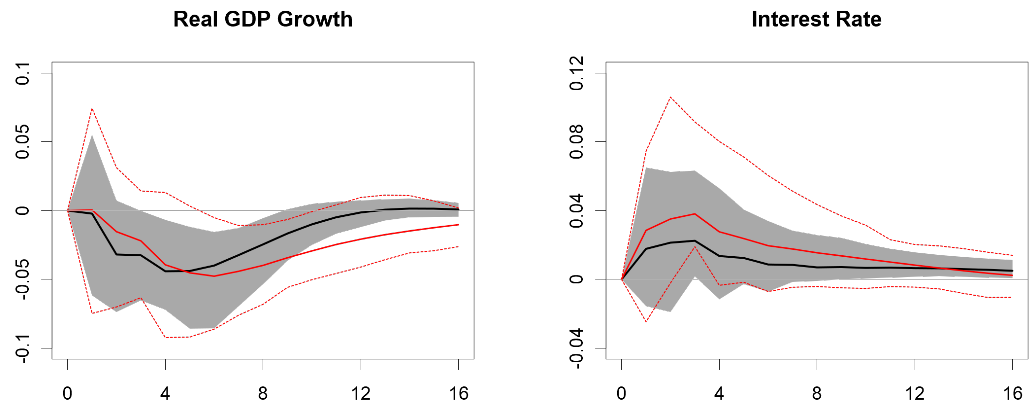
Figure 8: IRFs for Shocks in the VSTOXX



Notes: Solid black lines show mean impulse responses of a one-pp shock in the VSTOXX in the normal state. Solid red lines represent the corresponding mean IRFs for the crisis state. Gray-shaded areas (red dashed lines) indicate 68% confidence bands for the normal (crisis) state. Full set of impulse responses is available on request.

Figure 9 shows selected IRFs after a ten-unit shock in the EPU. A shock to the EPU leads to a significant decrease of real GDP growth that is of similar strength in the peak responses in both states (crisis: –4.8 bps, 6q; normal: –4.4 bps, 4q), but more enduring in normal times. In addition, we find mild evidence for a tightening of the interest rate, in particular in the crisis state. Hence, there is also some evidence for a direct effect of policy uncertainty shocks on output but this is, again, much smaller than for credit standards and the credit spread. This also holds when accounting for the larger standard deviation of the EPU (25.41) as compared to the ones of credit standards (6.95) and the credit spread (0.79) as well as the different shock sizes in the IRFs (ten-unit for the EPU, one-pp for credit standards, and 25 bps for the credit spread).

Figure 9: IRFs for Shocks in the EPU



Notes: Solid black lines show mean impulse responses of a ten-unit shock in the EPU in the normal state. Solid red lines represent the corresponding mean IRFs for the crisis state. Gray-shaded areas (red dashed lines) indicate 68% confidence bands for the normal (crisis) state. Full set of impulse responses is available on request.

To summarize, we detect a significant detrimental effect of volatility shocks and policy uncertainty shocks on real GDP growth. However, this effect is quantitatively much smaller than that of credit spreads and credit risk. In addition, the influence of stock market volatility on the state weights is much smaller than that of the two credit variables and the EPU almost plays no role in that regard. Thus, we are confident that our results indeed reflect credit conditions and not financial market volatility or policy uncertainty.

4.2 Alternative Shadow Short Rate

The shadow rate by Wu and Xia (2016) has been subject to criticism (e.g., Krippner 2020). Hence, we explore the robustness of our results by using the shadow short rate (Krippner 2015) as alternative indicator of the monetary policy stance at the zero lower bound. Indeed, there are some differences visible in both composite indicators when inspecting the time series plots (see Figure A2 in Appendix A) and the bivariate correlations to the other variables in the VAR system (see Table A1 in Appendix A). Figures B1–B7 in Appendix B show the results of this robustness test. To facilitate the comparison across monetary policy indicators, the left panel in Figures B1–B7 replicates some of the baseline results from Section 3.

As indicated by Figure B1, the state weights are very similar for both monetary policy indicators in the models for real loan growth ($\rho = 0.99$) and the credit spread ($\rho = 0.95$). This is also confirmed by the corresponding predicted probabilities of the logit submodels in Figures B2 and B4. However, the state weights of the model for credit standards differ — to some extent — from the baseline results. Although the peak for the crisis state is still found around the GFC and the correlation to the baseline weights is substantial ($\rho = 0.72$), the overall share of the crisis states is now larger with 19.2% as compared to the baseline model (13.9%). The differences also become evident when looking at the predicted probabilities of the logit submodels (Figure B3). Although credit standards are still a noticeable driver of the crisis state with probabilities varying between 14% and 46%, real GDP growth is clearly more important (94%–3%) when employing the shadow short rate as indicator of the monetary policy stance. Consequently, we have to tone down our conclusion from Section 3. The credit spread and — only to some extent — credit standards are the key determinants of the underlying state of the economy in the logit submodel.

Figures B5–B7 show the responses of real GDP growth to monetary policy shocks and shocks in credit conditions. The response of output is qualitatively similar for all three credit indicators when employing the shadow short rate by Krippner (2015) as compared to the baseline results. However, the peak effects are quantitatively larger in both states (often by 50% or more), indicating the our baseline results provide a rather conservative picture of the effects of monetary policy on real GDP growth. Comparing the shocks to credit conditions across monetary policy indicators does not reveal much of a difference for credit standards and the credit spread. However, shocks to real loan growth exert a more significant effect on output when using the short shadow rate by Krippner (2015). Consequently, we can conclude that shocks to the quantity of credit are only slightly less important in explaining growth fluctuations as compared to the other two credit indicators.

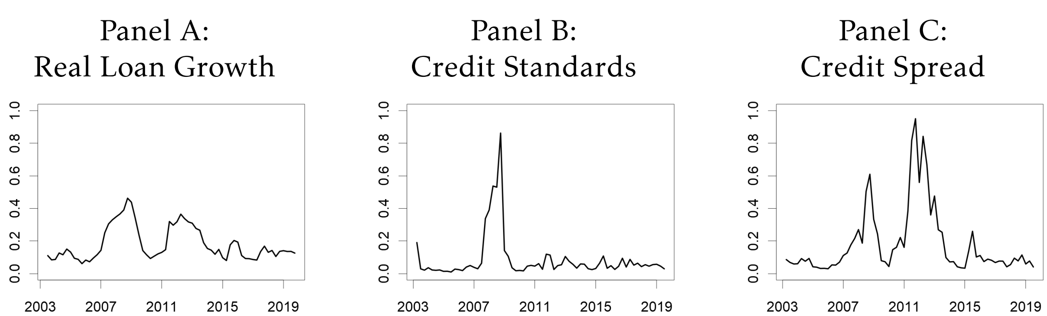
5 Extension: Impact on Unemployment

Several studies document a significant relationship between credit risk and (un-) employment. For instance, Gilchrist et al. (2009) and Gilchrist and Zakrajsek (2012) show that credit spreads help predicting US employment. For the euro area, Gilchrist and Mojon (2016) suggest that higher credit spreads lead to significant increases in unemployment. To provide further evidence for the impact of credit conditions on the labor market, we include the change in the unemployment rate as indicator of real economic activity (instead of real GDP growth) into the mixture VAR. Similar to Section 3, we employ the shadow rate by Wu and Xia (2016) as indicator of the monetary policy stance at the zero lower bound.

5.1 Weights of Crisis State

Figure 10 presents the weights of the crisis state obtained with the help of the logit submodels.

Figure 10: Weights of Crisis State



Notes: Weights of the crisis states are obtained by estimation of Eq. (2).

The evolution of the time series in Panels B and C are very similar to the corresponding panels of Figure 1. We observe a peak during the GFC and another noticeable increase during the euro area sovereign debt crisis in 2011 in the case of the credit spread. Indeed, the correlations to the weights in the baseline series are very pronounced (standards: $\rho = 0.86$; spread: $\rho = 0.96$). This is also reflected in the predicted probabilities (not shown, but available on request) for credit standards (1%–93%) and the credit spread (5%–93%), which are almost the same as in the baseline specifications (see Panels B and C of Figure 2). The weights in Panel A, however, indicate that the unemployment rate is no substitute for real GDP growth when determining the state weights in the specification using real loan growth as indicator of credit conditions. This specification does not exhibit a pronounced peak in the crisis state during the GFC or the euro area sovereign debt crisis.

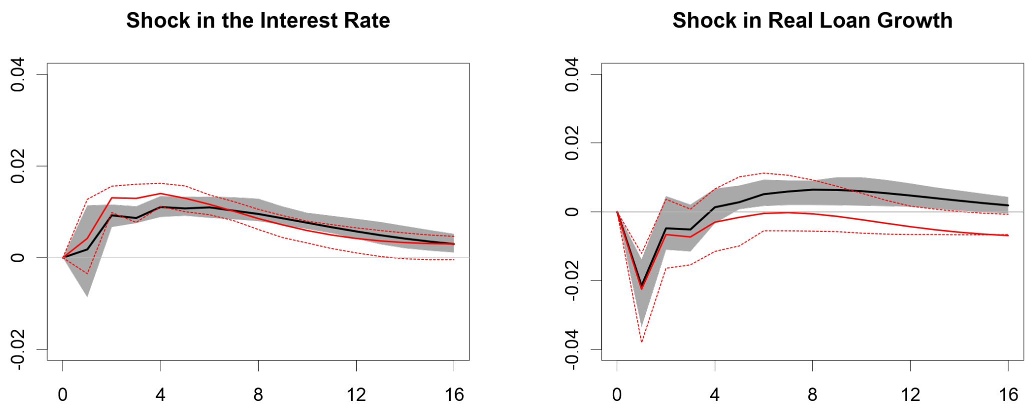
5.2 Impulse Responses

The left panel of Figure 11 shows the response of the change in the unemployment rate after a 25 bps interest rate shock. A contractionary monetary policy shock leads to an increase in the unemployment rate, irrespective of the indicator used for credit conditions. The peak effects are 1.4–2.0 bps for the crisis state and 1.0–1.3 bps during normal times. The effects are enduring for all three credit variables, in particular in the normal state, but eventually die out when considering a horizon longer than four years. Similar to the baseline specifications, we find significantly stronger peak effects in the crisis state. Taken together with the finding that credit standards and the credit spread are the key determinants of the state weights, these results are indicative of an financial accelerator effect on the labor market, too.

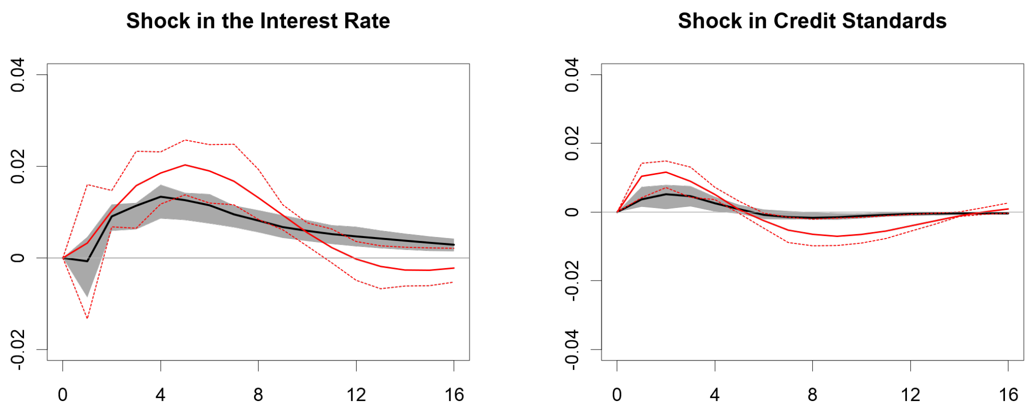
The right panel of Figure 11 shows the response of the change in the unemployment rate to a one-pp shock in real loan growth (upper right panel), a one-pp shock in credit standards (middle right panel), and a 25 bps shock in the credit spread (lower right panel). Loan growth shocks lead to a short-lived reduction of the unemployment rate with similar peak effect in both states (crisis: –2.3 bps, 1q; normal: –2.1 bps, 1q) and some reversion tendency in the normal state. Shocks to credit standards lead to a short-lived increase of the unemployment rate with a stronger peak effect in the crisis state (crisis: 1.2 bps, 2q; normal: 0.5 bps, 2q). Here, a reversion tendency can be found in the crisis state. Finally, shocks to the credit spread lead to a persistent increase in the unemployment rate in both states with the same peak effect of 2.2 bps after one quarter.

Figure 11: IRFs of the Unemployment Rate

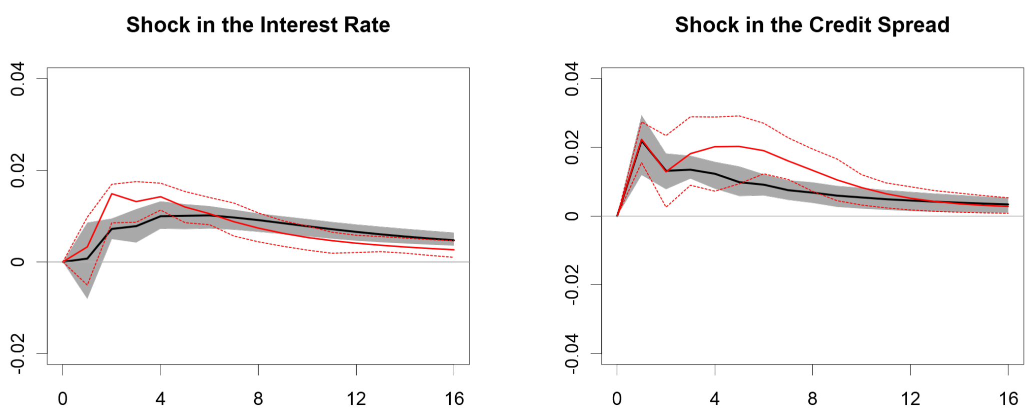
Panel A: Model with Real Loan Growth



Panel B: Model with Credit Standards



Panel C: Model with the Credit Spread



Notes: Solid lines show mean impulse responses of the change in the unemployment rate in the normal state to a 25 bps shock in the interest rate (left panel), a one-pp shock in real loan growth (upper right panel), a one-pp shock in credit standards (middle right panel), and a 25 bps shock in the credit spread (lower right panel). Solid red lines represent the corresponding mean IRFs for the crisis state. Gray-shaded areas (red dashed lines) indicate 68% confidence bands for the normal (crisis) state. Full set of impulse responses is available on request.

Consequently, the direct effect of credit shocks on real GDP growth and the financial accelerator effect are replicated when using the change in the unemployment rate as indicator of real economic activity. The direct effects are most pronounced for the credit spread, followed by credit standards. The accelerating effect can be found in a similar way for both variables. The quantity of credit matters least.

6 Conclusions

In this paper, we estimate a logit mixture vector autoregressive model describing monetary policy transmission in the euro area over the period 2003Q1–2019Q4 with a special emphasis on credit conditions. This type of model allows us to differentiate between different states of the economy (e.g., a normal state and a crisis state) with the time-varying state weights being determined by an underlying logit model. Hence, our approach is well suited to analyze direct effects of shocks to credit quantity, credit quality, and credit risk on the real economy in different states. Moreover, this model is able to identify a financial accelerator effect as monetary policy transmission might differ across states and changes in credit conditions might affect the underlying state weights in the economy.

We show that shocks to the credit spread and shocks to credit standards lead to a reduction of real GDP growth in the euro area, whereas shocks to the quantity of credit are slightly less important in explaining growth fluctuations. In addition, the credit spread and — to some extent — credit standards contribute to the financial accelerator in the euro area. Both variables are key determinants of the underlying state of the economy in the logit submodel and, during crisis times, the transmission of standard monetary policy shocks is more pronounced than during normal times. As part of our robustness tests, we document that our empirical findings indeed reflect credit conditions and that these are not confounded by stock market volatility and economic policy uncertainty. Our results are qualitatively robust to using different indicators for the monetary policy stance at the zero lower bound (Wu and Xia 2016;

Krippner 2015). Finally, the detrimental effect of credit conditions is also reflected in the labor market.

Our findings have several implications for policymakers. These highlight the importance of monitoring and assessing credit developments to ensure the effectiveness of ECB monetary policy. The relevance of credit shocks for economic fluctuations in the euro area underlines the need for macroprudential policies, which could involve the use of regular stress testing and countercyclical policies. As a case in point, the Basel III agreement constitutes a good progress in this regard as it requires countercyclical capital buffers.

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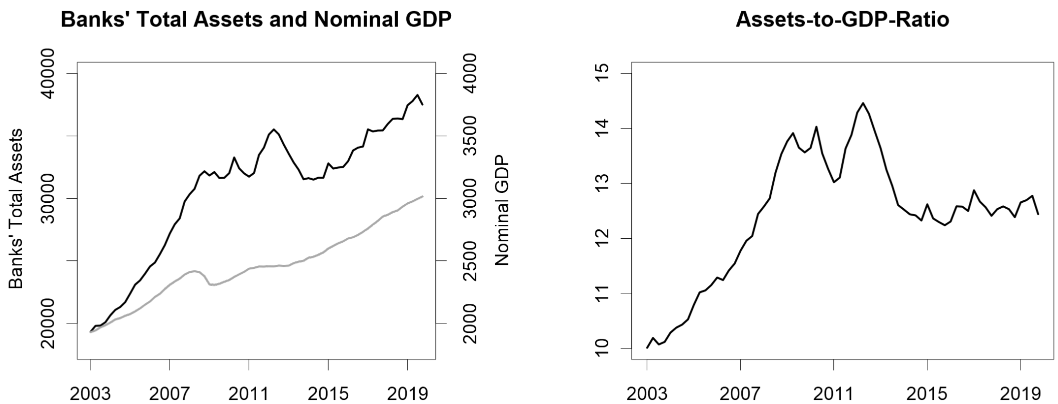
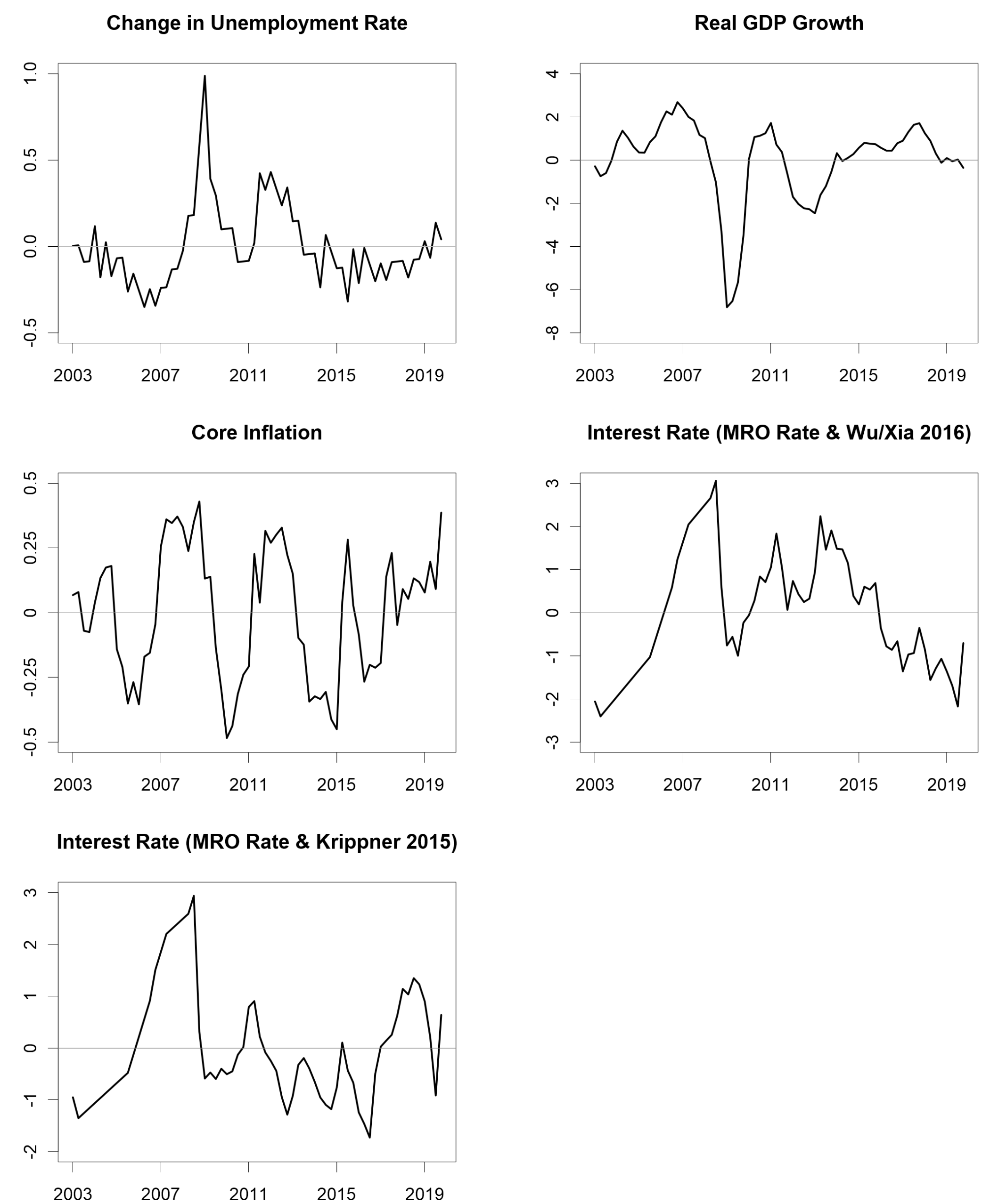
Appendix A: Background on Dataset

Figure A1: Banks' Assets and Nominal GDP in the Euro Area



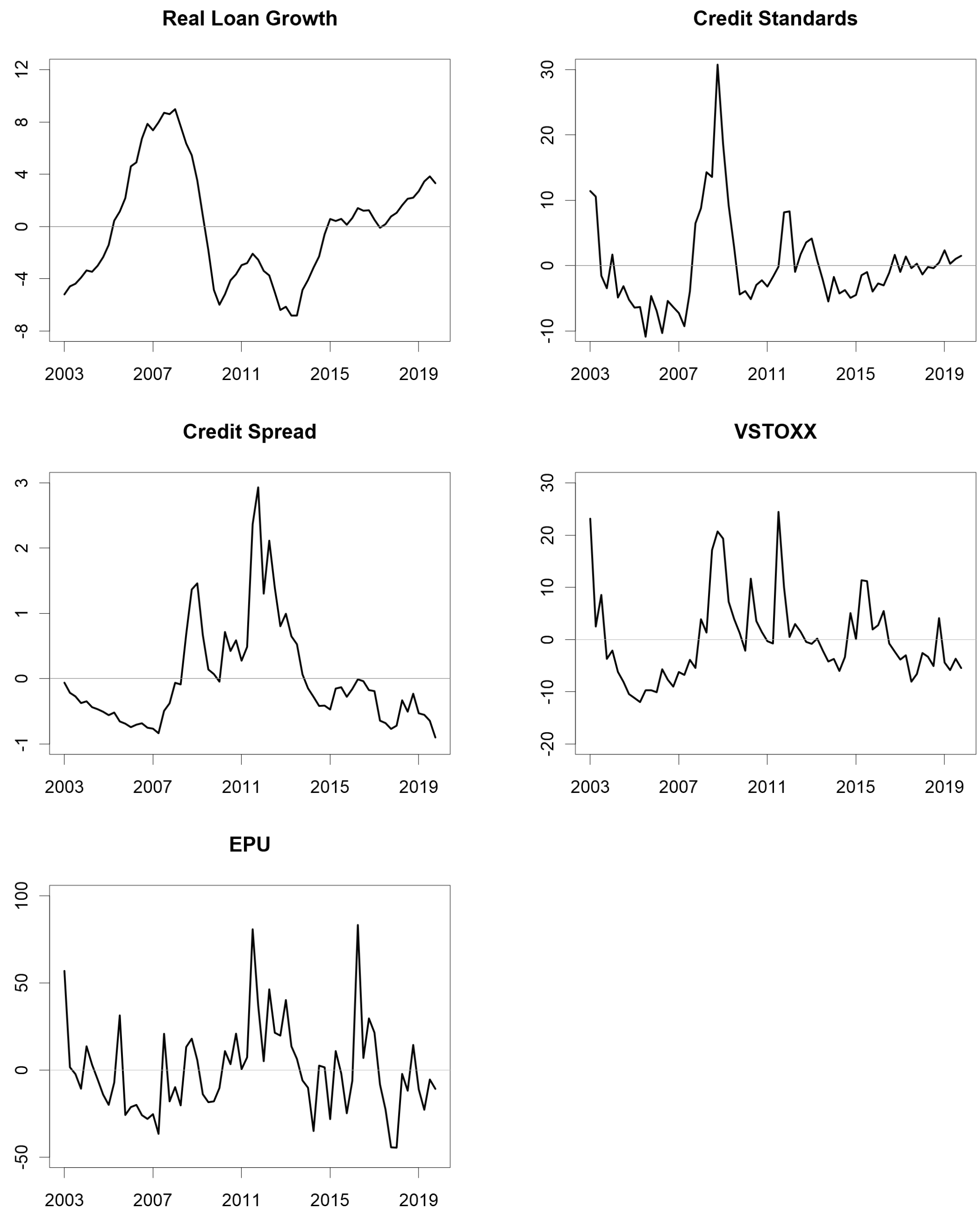
Source: ECB/Eurostat. End-of-quarter banks' total assets (black line in left panel, left y-axis) and quarterly nominal GDP (gray line in left panel, right y-axis) are measured in billions of euros.

Figure A2: Macroeconomic Data for the Euro Area



Source: ECB/Eurostat as well as Wu and Xia (2016) and Krippner (2015) as parts of the composite interest rate indicators. All variables are linearly detrended.

Figure A3: Credit Conditions, Volatility, and Uncertainty in the Euro Area



Source: ECB/Eurostat, Gilchrist and Mojon (2016) for the credit spread, STOXX Limited for the VSTOXX, and Baker et al. (2016) for the EPU. All variables are linearly detrended.

Table A1: Correlation Matrix and Standard Deviations

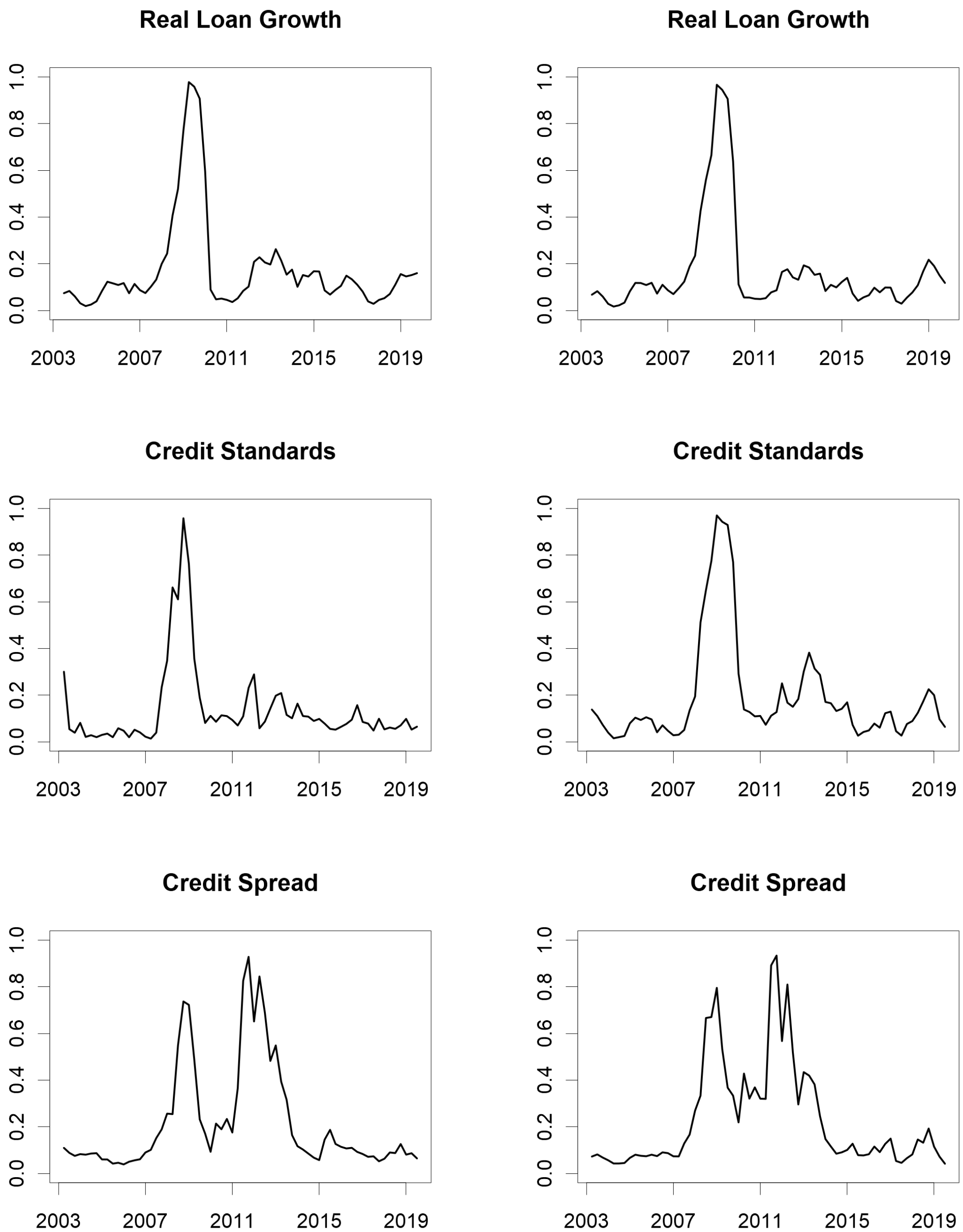
	u_t	y_t	π_t	i_t	i_t^{alt}	$LOAN_t$	CS_t	SPR_t	$VOLA_t$	EPU_t	Std. Dev.
Change in Unemp. Rate (u_t)	1										0.23
Real GDP Growth (y_t)	−0.80	1									1.88
Core Inflation (π_t)	0.29	−0.15	1								0.25
MRO Rate & Wu/Xia (2016) (i_t)	0.04	0.08	0.11	1							1.38
MRO Rate & Krippner (2015) (i_t^{alt})	−0.15	0.30	0.45	0.53	1						1.11
Real Loan Growth ($LOAN_t$)	−0.21	0.28	0.35	0.24	0.71	1					4.34
Credit Standards (CS_t)	0.70	−0.57	0.52	0.06	0.14	0.12	1				6.95
Credit Spread Banks (SPR_t)	0.74	−0.54	0.23	0.25	−0.15	−0.37	0.48	1			0.79
VSTOXX ($VOLA_t$)	0.59	−0.45	0.19	0.12	−0.06	−0.12	0.62	0.64	1		8.16
EPU (EPU_t)	0.37	−0.19	0.06	−0.02	−0.27	−0.31	0.23	0.61	0.55	1	25.41

Notes: All variables are linearly detrended.

Appendix B: Results using the Shadow Short Rate

Figure B1: Weights of Crisis State

Panel A: MRO Rate & Wu/Xia (2016)	Panel B: MRO Rate & Krippner (2015)

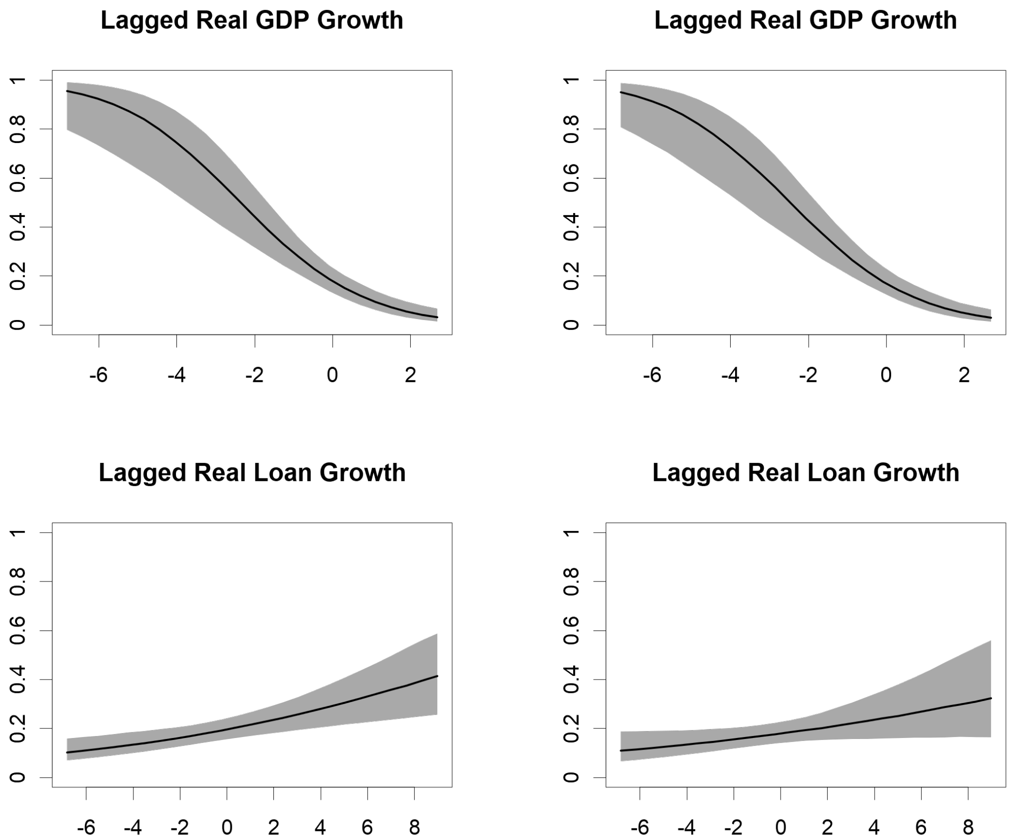


Notes: Weights of the crisis states are obtained by estimation of Eq. (2).

Figure B2: Predicted Probabilities: Model with Real Loan Growth

Panel A: MRO Rate & Wu/Xia (2016)

Panel B: MRO Rate & Krippner (2015)

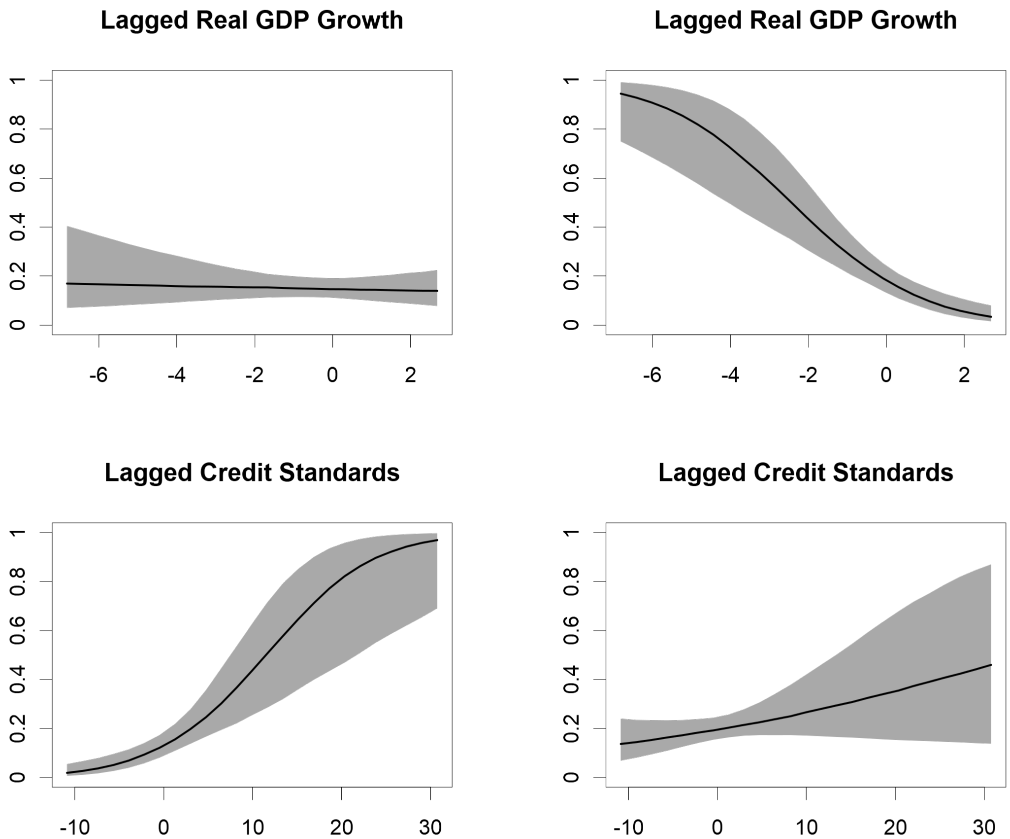


Notes: Solid lines show the predicted probabilities of the logit submodels for the crisis state and different realized values of selected explanatory variables. Gray-shaded areas indicate 68% confidence bands.

Figure B3: Predicted Probabilities: Model with Credit Standards

Panel A: MRO Rate & Wu/Xia (2016)

Panel B: MRO Rate & Krippner (2015)

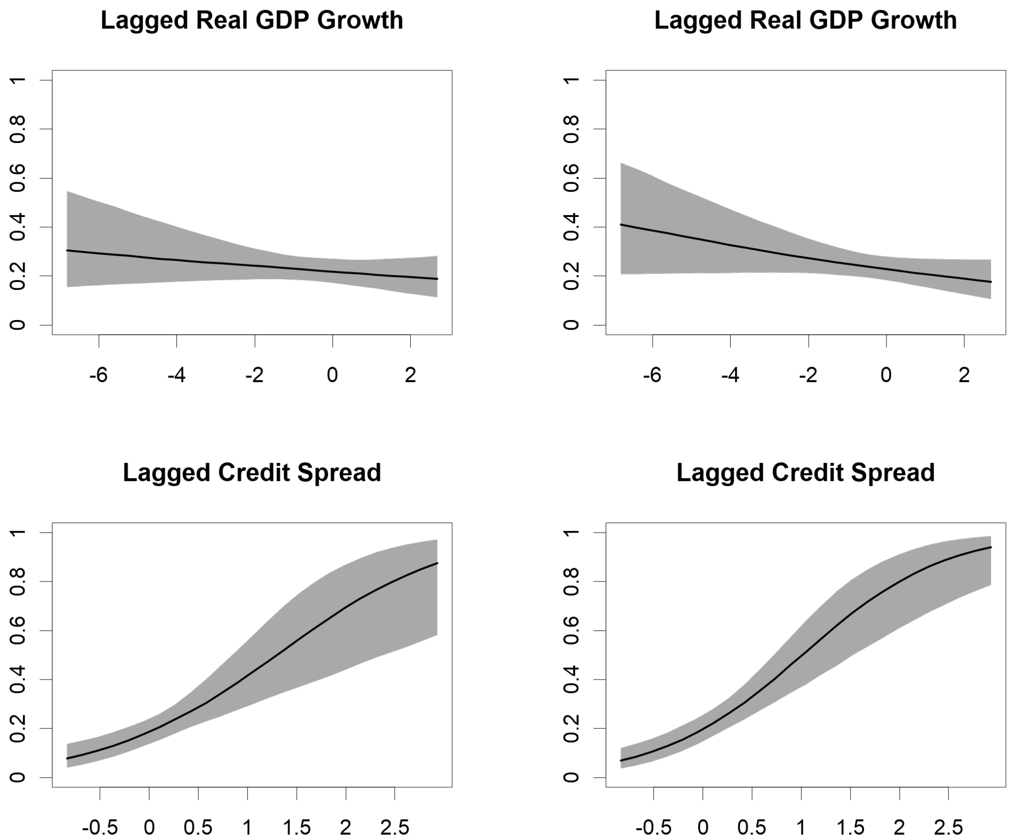


Notes: Solid lines show the predicted probabilities of the logit submodels for the crisis state and different realized values of selected explanatory variables. Gray-shaded areas indicate 68% confidence bands.

Figure B4: Predicted Probabilities: Model with Credit Spread

Panel A:
MRO Rate & Wu/Xia (2016)

Panel B:
MRO Rate & Krippner (2015)

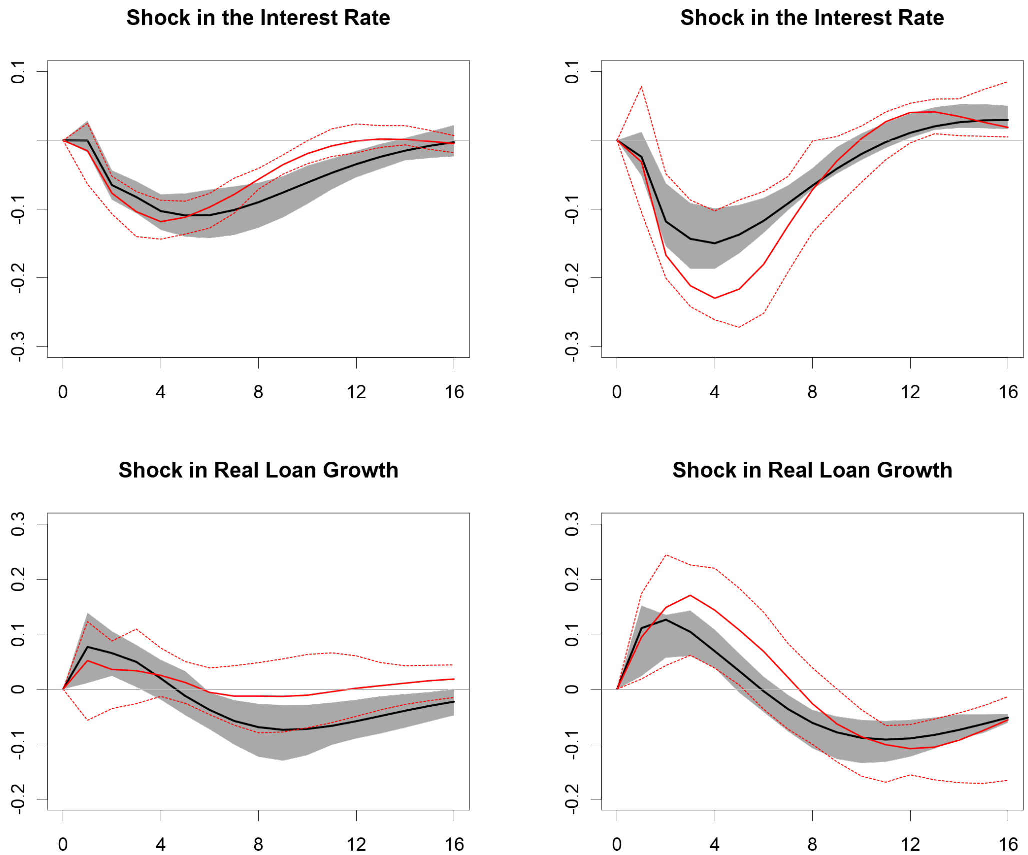


Notes: Solid lines show the predicted probabilities of the logit submodels for the crisis state and different realized values of selected explanatory variables. Gray-shaded areas indicate 68% confidence bands.

Figure B5: IRFs of Real GDP Growth for Model with Real Loan Growth

Panel A:
MRO Rate & Wu/Xia (2016)

Panel B:
MRO Rate & Krippner (2015)

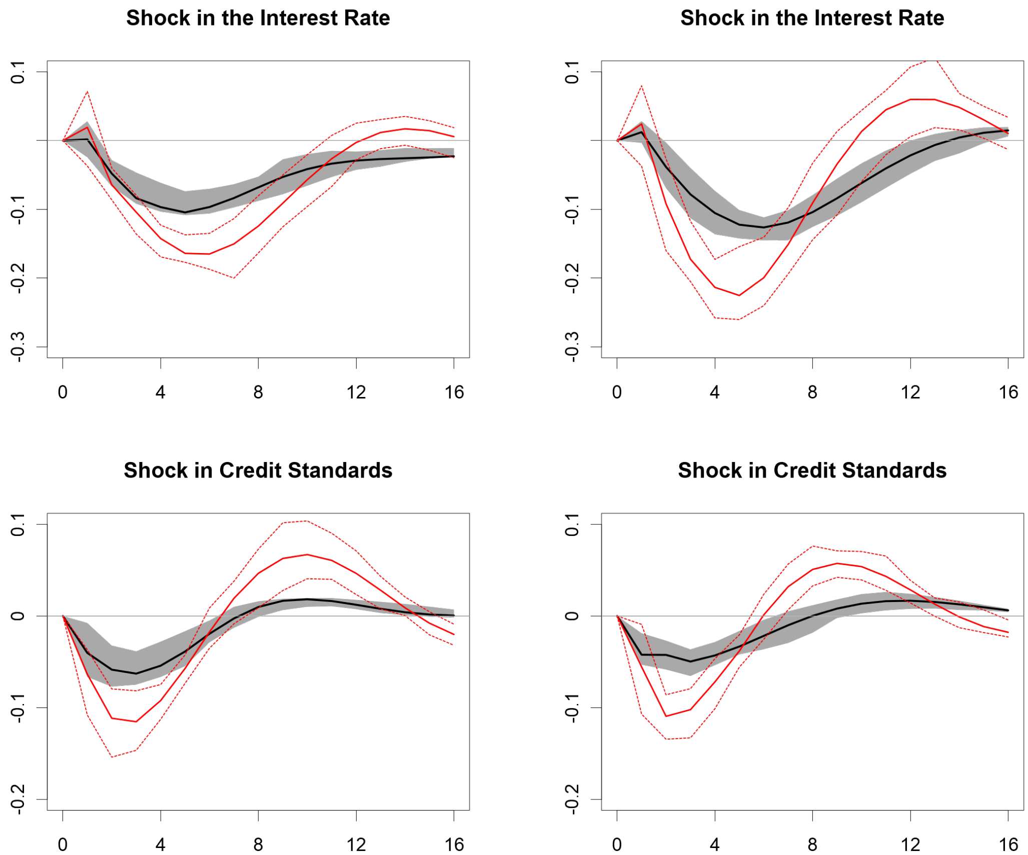


Notes: Solid black lines show mean impulse responses of real GDP growth to a 25 bps shock in the interest rate (upper panel) and a one-pp shock in real loan growth (lower panel) in the normal state. Solid red lines represent the corresponding mean IRFs for the crisis state. Gray-shaded areas (red dashed lines) indicate 68% confidence bands for the normal (crisis) state. Full set of impulse responses is available on request.

Figure B6: IRFs of Real GDP Growth for Model with Credit Standards

Panel A: MRO Rate & Wu/Xia (2016)

Panel B: MRO Rate & Krippner (2015)

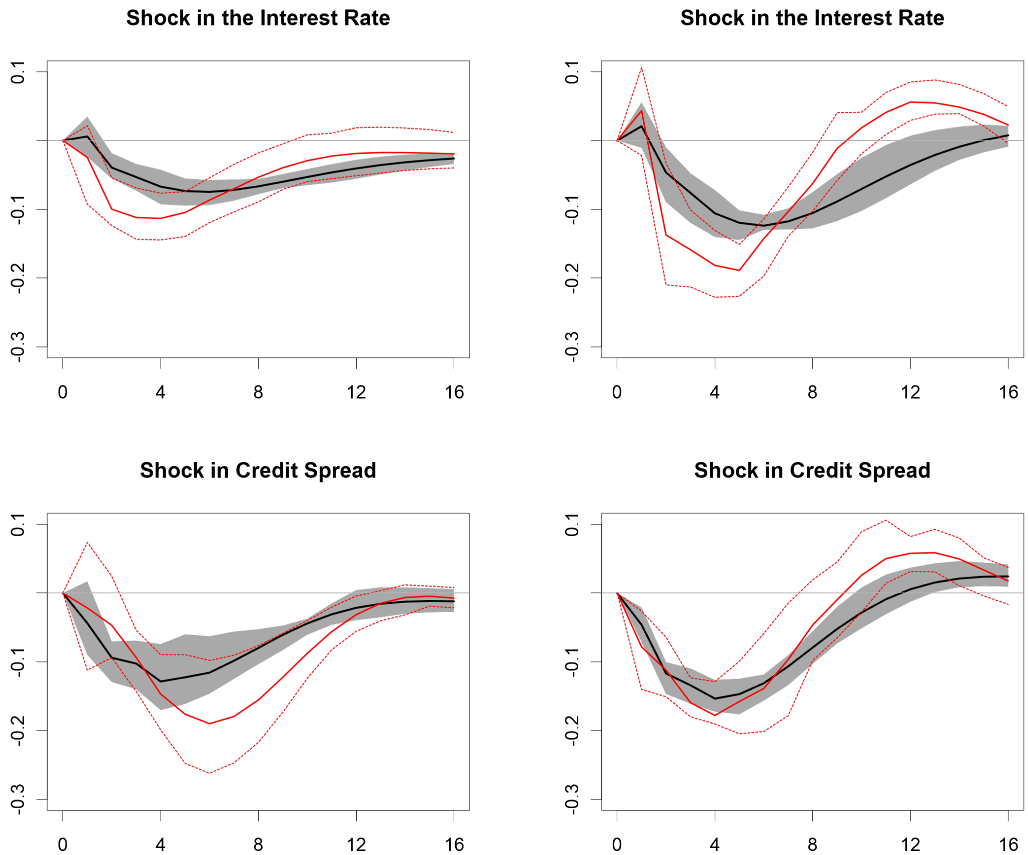


Notes: Solid black lines show mean impulse responses of real GDP growth to a 25 bps shock in the interest rate (upper panel) and one-pp shock in credit standards (lower panel) in the normal state. Solid red lines represent the corresponding mean IRFs for the crisis state. Gray-shaded areas (red dashed lines) indicate 68% confidence bands for the normal (crisis) state. Full set of impulse responses is available on request.

Figure B7: IRFs of Real GDP Growth for Model with Credit Spread

Panel A:
MRO Rate & Wu/Xia (2016)

Panel B:
MRO Rate & Krippner (2015)



Notes: Solid black lines show mean impulse responses of real GDP growth to a 25 bps shock in the interest rate (upper panel) and a 25 bps shock in the credit spread (lower panel) in the normal state. Solid red lines represent the corresponding mean IRFs for the crisis state. Gray-shaded areas (red dashed lines) indicate 68% confidence bands for the normal (crisis) state. Full set of impulse responses is available on request.