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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 a widening of the credit spread and a tightening of credit standards directly lead to a reduction of real GDP growth, whereas shocks to the quantity of credit are 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; the prevalence of the crisis state is more pronounced in times of adverse credit conditions. Together with a stronger 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). 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 B1 in Appendix B) 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 by 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 and for monetary policy transmission. Against this background, our paper addresses the question to what extent changes in various measures of credit market conditions affect real economic activity and amplify the transmission of monetary policy shocks on macroeconomic fluctuations in the euro area during the period 2003Q1–2019Q4.¹ We would interpret such an amplification of shocks as financial accelerator (Bernanke et al. 1996).

We use different credit measures, that is, the quantity, quality, and risk of credit, to capture several dimensions of the credit market. Indeed, the impact of credit conditions on macroeconomic fluctuations might be different depending on whether the

¹Note that the starting point of our analysis is restricted by the availability of the ECB’s quarterly bank lending survey.

reduction in bank lending is due to tight credit supply conditions, weak demand for credit, or both. A correct identification of the underlying source is thus crucial for policymakers to use the appropriate instruments to smooth credit market conditions. Hence, unlike most papers that emphasize separately the demand side and the supply side to proxy credit market conditions, we include both dimensions by considering (i) the quantity of credit, proxied by the growth rate of real loans to non-financial corporations, (ii) the quality of credit, proxied by the ECB's bank lending survey, and (iii) the risk of credit, proxied by the difference between banks' bond yields and the yield of a German bund zero coupon bond. Specifically, the quantity of credit allows to identify credit supply dynamics while the quality of credit reflects both the supply side and the demand side of banks' lending standard decisions.² Lastly, the risk of credit emanating from the financial sector reflects a shock that originates from the supply side of credit (Gilchrist and Mojon, 2016).

In our analysis, we are studying two different themes. First, we want to illustrate the direct effects of credit quantity, quality, and risk on real GDP growth. Second, we aim at identifying those credit indicators which act as a financial accelerator in the sense that the effect of a contractionary interest rate shock is larger during crisis times with adverse credit conditions (co-)driving the prevalence of the crisis state. To reach these objectives, we employ a novel empirical methodology, the mixture vector autoregressive (VAR) model of 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.³ 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

²These lending conditions are related to changes in the net worth of non-financial borrowers but also to the net worth and liquidity of banks.

³In contrast to other classes of non-linear VARs, the regime affiliation is neither strictly binary, nor binary with a transition period, and based on multiple variables.

in credit conditions might affect the underlying state weights in the economy. More precisely, we identify a financial accelerator if (i) the likelihood for the crisis regime increases when credit conditions are worsening (i.e., a decrease in real loan growth, tighter credit standards, or a widening of the credit spread) and (ii) if monetary policy shocks exert a stronger effect in the crisis regime. Hence, our model aims to bring empirical evidence to the theoretical concept by Bernanke et al. (1996). One obvious difference to Bernanke et al. (1996) is that we do not directly test if the financial accelerator appears due to endogenous changes in the agency costs of lending over the business cycle.

Our empirical analysis documents that a widening of the credit spread and a tightening of credit standards lead to a reduction of real GDP growth in the euro area, whereas shocks to the quantity of credit are less important in explaining growth fluctuations. These direct effects of shocks are slightly more pronounced in the crisis state than in normal times. The ECB responds to adverse shocks in credit standards with loose monetary policy, but does not accommodate such 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 are key determinants of the underlying state of the economy in the logit submodel with the crisis state becoming more prevalent in times of adverse credit conditions. During crisis times, the transmission of monetary policy shocks is (slightly) stronger than during normal times, providing 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 adverse volatility 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 also qualitatively robust to using different indicators for the monetary policy stance at the zero lower bound (Wu and Xia 2016; Krippner 2015) and the logit mixture VAR is superior when compared to a linear VAR model and other multi-state VAR models. 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 mar-

kets 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.

Finally, other papers study a potentially asymmetric relationship between credit conditions and real economic activity. Akinci and Queralto (2022) 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. 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 and compares our approach to other classes of VAR models. 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).⁴ 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.⁵ These, however, also have their drawbacks as the transition is based on a single variable or an index with pre-determined weights (see also Section 4.3).

We overcome this shortfall by utilizing the mixture VAR of Burgard et al. (2019) that assumes the co-existence of two states with time-varying weights.⁶ 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 and can include multiple covariates — 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:

$$F(Y_t|\mathcal{F}_{t-1}) = \tau_t \cdot \Phi\left(\Omega_1^{-\frac{1}{2}}\left(Y_t - \Theta_{0,1} - \Theta_{1,1}Y_{t-1} - \dots - \Theta_{p_1,1}Y_{t-p_1}\right)\right) + \\ (1 - \tau_t) \cdot \Phi\left(\Omega_2^{-\frac{1}{2}}\left(Y_t - \Theta_{0,2} - \Theta_{1,2}Y_{t-1} - \dots - \Theta_{p_2,2}Y_{t-p_2}\right)\right) \quad (1)$$

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. Y_t is the vector of endogenous variables, \mathcal{F}_{t-1} denotes the information set up to time $t - 1$ and $\Phi(\cdot)$

⁴Alessandri and Murmaz (2017) provide a recent application of a threshold VAR for the US in the context of the GFC.

⁵Dahlhaus (2017) and Galvão and Owyang (2018) propose smooth transition VAR models with dynamic regimes changes based on financial conditions.

⁶In 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.

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. $\Theta_{1,1}, \dots, \Theta_{p_1,1}$ and $\Theta_{1,2}, \dots, \Theta_{p_1,2}$ 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:

$$\widehat{\tau}_t = \frac{1}{1 + \exp(-\mathbf{X}'\boldsymbol{\beta})} \quad (2)$$

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 and the calculation of orthogonalized impulse responses is based on bootstrapping. Further details on the estimation procedure and the derivation of impulse responses can be found in Burgard et al. (2019) and in Appendix A. 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.

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.⁷ 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.⁸

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 restrictions 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

⁷Note 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 ($\rho = 0.99$).

⁸We 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.

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 B1 in Appendix B). 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 sub-model.⁹ 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. Yet, a caveat is warranted when interpreting our results. We are pushing the methodology of the logit mixture VAR close to its limit. Still, our approach is — to our knowledge — the only one that allows to investigate the direct and indirect role of credit conditions in the monetary policy transmission mechanism with the “small” dataset at hand. Other multi-state VAR models (see also Section 4.3) perform worse with the dataset at hand and are not capable of answering our research question.

⁹Note that we explored further specifications where we excluded core inflation and only kept real GDP growth as key response variable of interest and the composite interest rate indicator as one of the key shock variables of interest. In this setting, we were able to achieve robust convergence when including two of the three credit variables at a time in the main model and the same variables plus real GDP growth alongside the lagged latent variable into the submodel. The general pattern of the results is very similar to the ones in Section 3. In our view, however, an indicator for (core) inflation should be included in a monetary policy transmission model to capture the central bank’s reaction function. This is particularly important for a central bank with an explicit inflation “goal” like the ECB. Hence, in an effort to conserve space we do not report these results (available on request).

Figures B2 and B3 in Appendix B 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.¹⁰ Table B1 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 ($\rho = 0.28$). 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

¹⁰Note that this is equivalent to including a linear trend in the VAR model.

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.¹¹ In the following presentation of the results, we are studying the effect of shocks with a positive sign to all variables of interest: (i) a contractionary monetary policy shock, (ii) an expansion of real loan growth, (iii) a tightening of lending standards, (iv) a widening of the credit spread, (v) an increase in stock market volatility, and (vi) an increase in economic policy uncertainty.

3 Baseline Results

3.1 Weights and Determinants of Crisis State

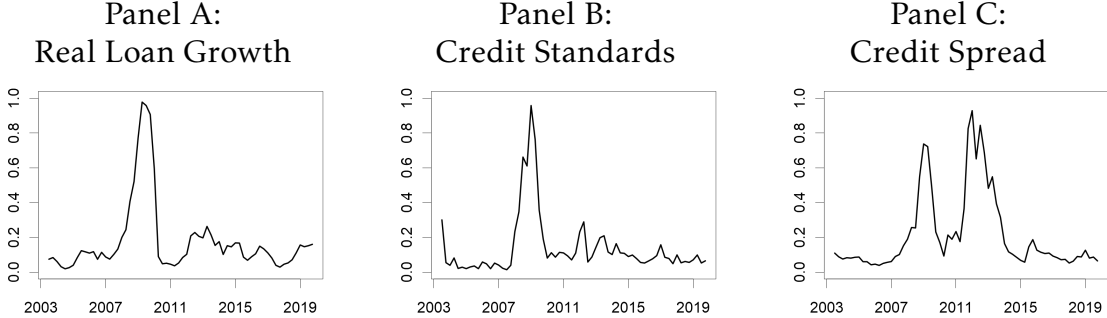
Figure 1 presents the weights of the “crisis” state obtained with the help of the logit submodels.¹² The interpretation as crisis state follows the evolution of the weights in all three specifications. In all panels, a clear peak emerges during the GFC. In addition, the model using the credit spread peaks another time during the euro area sovereign debt crisis in 2011, which also coincides with the peak of the credit spread itself (see also Figure B3 in Appendix B). 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%

¹¹Zero 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).

¹²The weights of the “normal” state are 1 minus the weights of the crisis state.

for the credit spread. The similarity of all three weight series is also reflected in a noticeable positive correlation.¹³

Figure 1: Weights of Crisis State



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

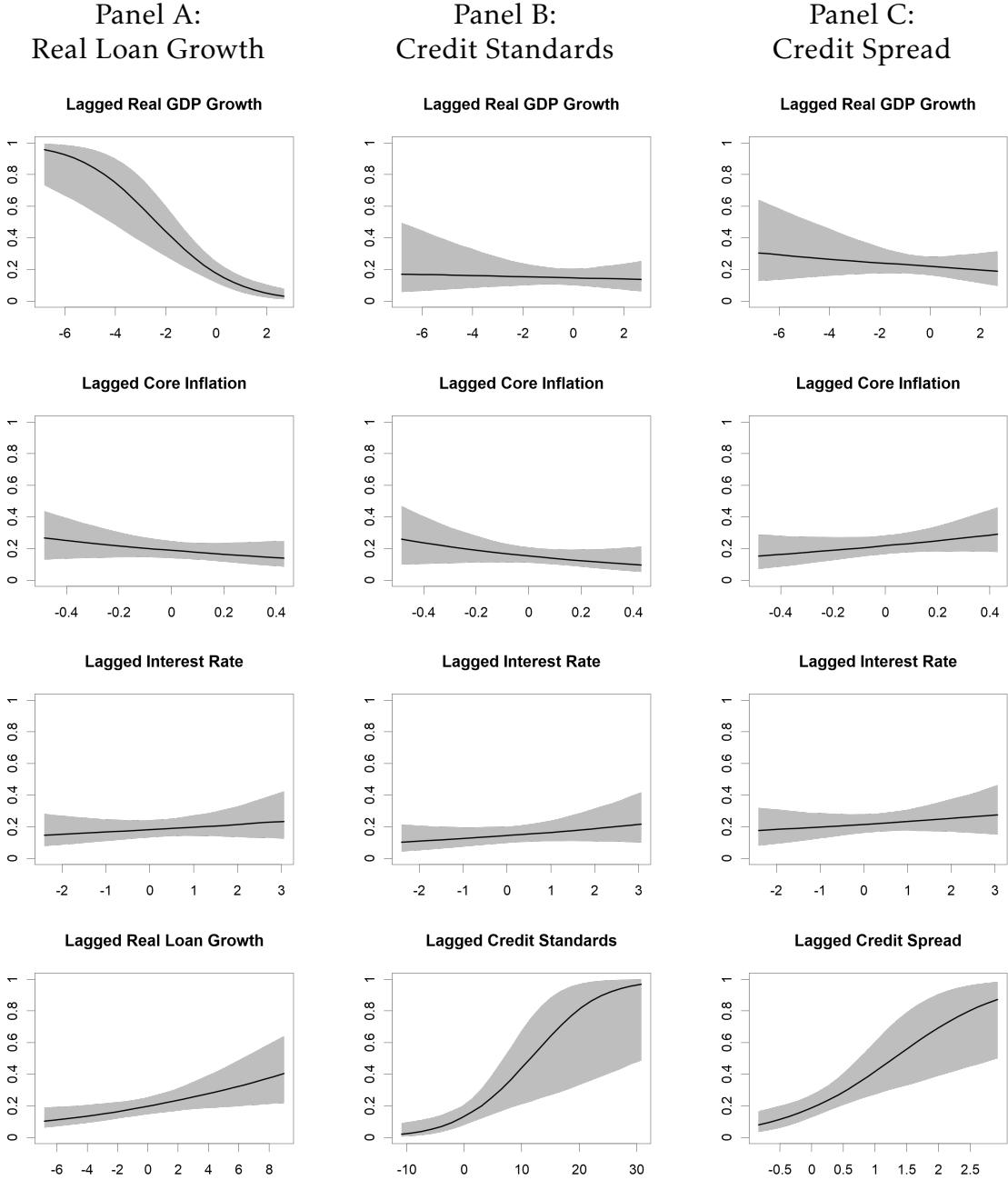
Figure 2 shows the predicted probabilities of the logit submodels for the crisis state and for different realized values of lagged real GDP growth, lagged core inflation, the lagged interest rate indicator, and lagged credit conditions. Throughout all three models, lagged inflation and the lagged interest rate are not important as predictor of the crisis state. 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 40% 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

¹³The 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: $\rho = 0.55$.

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.¹⁴

Figure 2: Predicted Probabilities



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 80% confidence bands.

¹⁴For 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 summarize, credit standards and credit risk are found to be important drivers of the economy's state. Adverse conditions in both variables are increasing the prevalence of the crisis state. Hence, there might be evidence for a financial accelerator in the euro area if the responses to monetary policy shocks are larger in the crisis state. 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.¹⁵

3.2 Impulse Responses for Model with Real Loan Growth

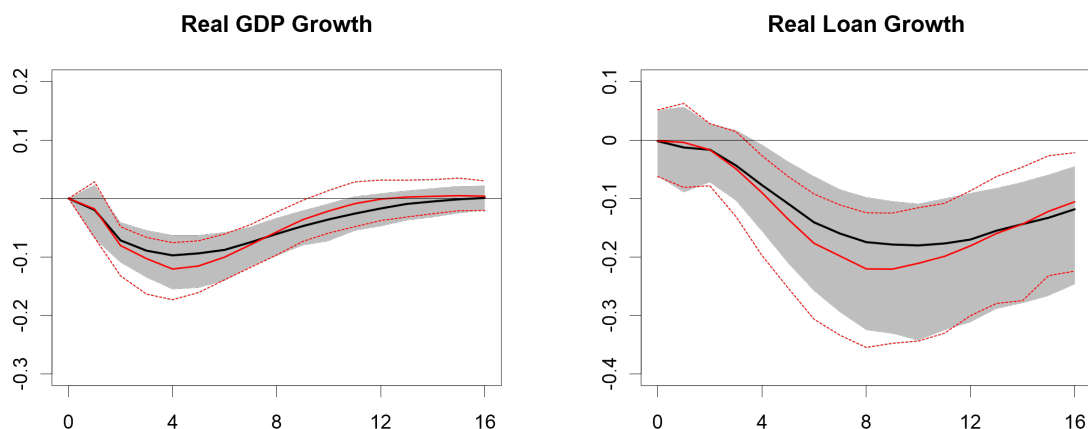
The upper panel of Figure 3 shows selected impulse response functions (IRFs) after a 25 bps interest rate shock when using real loan growth as indicator of credit conditions. To conserve space, the following discussion focuses on real GDP growth and the credit indicator. A contractionary monetary policy 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 (−12.1 bps after four quarters in the crisis state and −9.7 bps after four quarters in the normal state) and real loan growth (crisis: −22.1 bps, 9q; normal: −18.0 bps, 10q). 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, but insignificant effect 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.

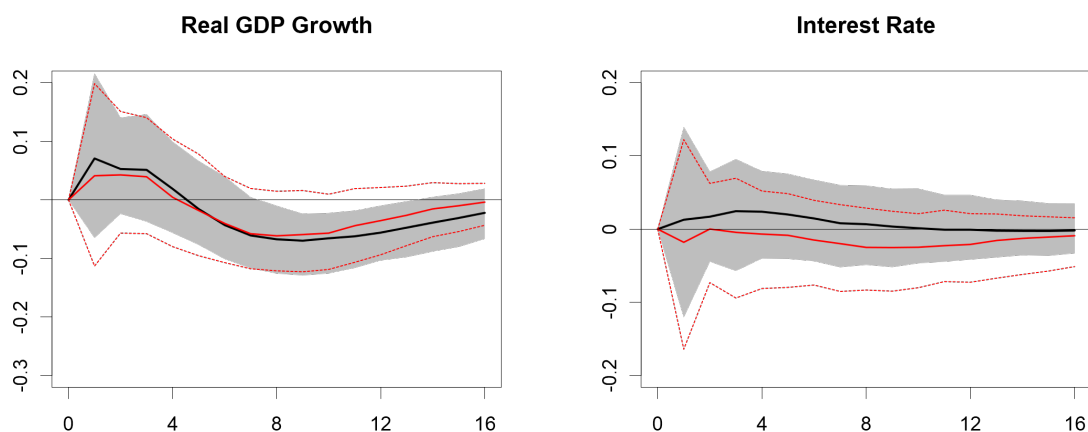
¹⁵Of course, the state-determining process in a smooth transition VAR can also be based on an index. However, such an index requires an ex ante aggregation of the potentially state-determining covariates and a decision about the weights for these (see also Section 4.3).

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 median 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 median IRFs for the crisis state. Gray-shaded areas (red dashed lines) indicate 80% confidence bands for the normal (crisis) state. Full set of impulse responses is available on request.

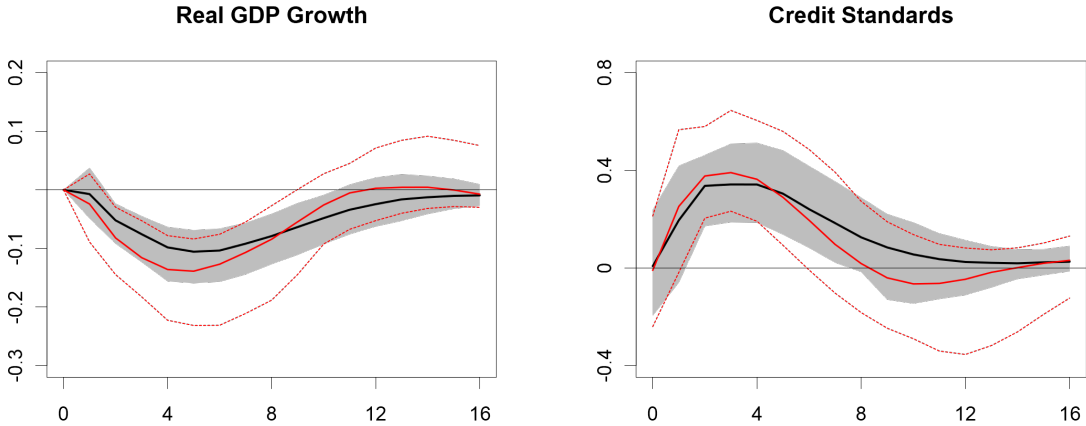
3.3 Impulse Responses for Model with Credit Standards

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 slightly larger in the crisis state for real GDP growth (crisis: -13.9 bps, 5q; normal: -10.6 bps, 5q). For credit standards, the peaks are of similar magnitude (crisis: 39.1 bps, 3q; normal: 34.2 bps, 3q). In both cases,

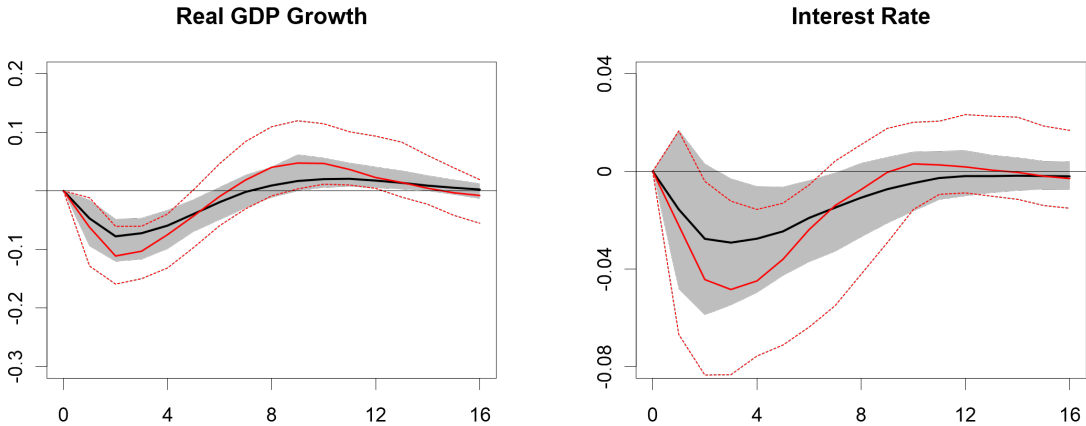
the IRFs are more enduring in the normal state. Taken together with the finding that credit standards are the key determinant of the state weights (see Panel B of Figure 2), these results are indicative of a financial accelerator effect in the euro area.

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 median 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 median IRFs for the crisis state. Gray-shaded areas (red dashed lines) indicate 80% confidence bands for the normal (crisis) state. Full set of impulse responses is available on request.

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 slightly stronger in the crisis state (−11.1 bps, 2q) than in normal times (−7.8 bps, 2q). 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 (−4.8 bps, 3q), but also during normal times (−2.9 bps, 3q).

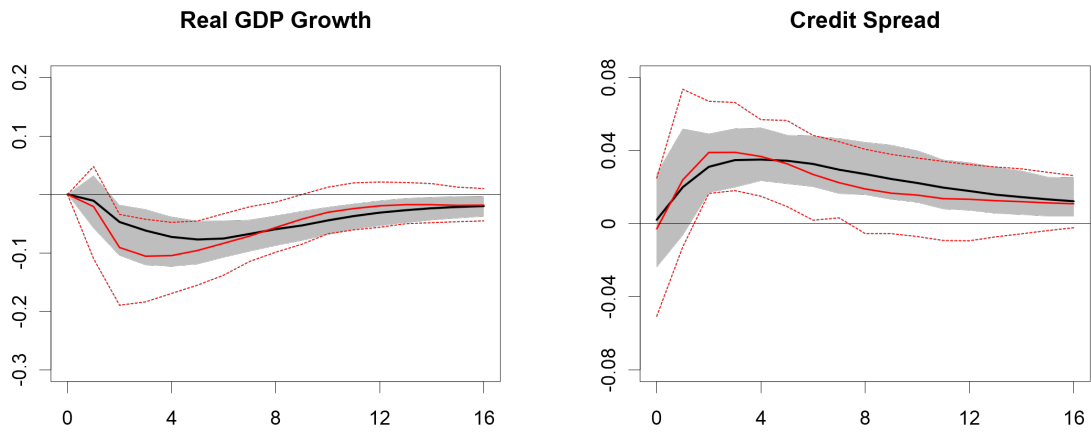
3.4 Impulse Responses for Model with Credit Spread

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. 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 slightly larger in the crisis state for real GDP growth (crisis: −10.6 bps, 3q; normal: −7.7 bps, 5q), but not for the credit spread (crisis: 3.9 bps, 3q; normal: 3.5 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 (slightly) stronger in the crisis state.

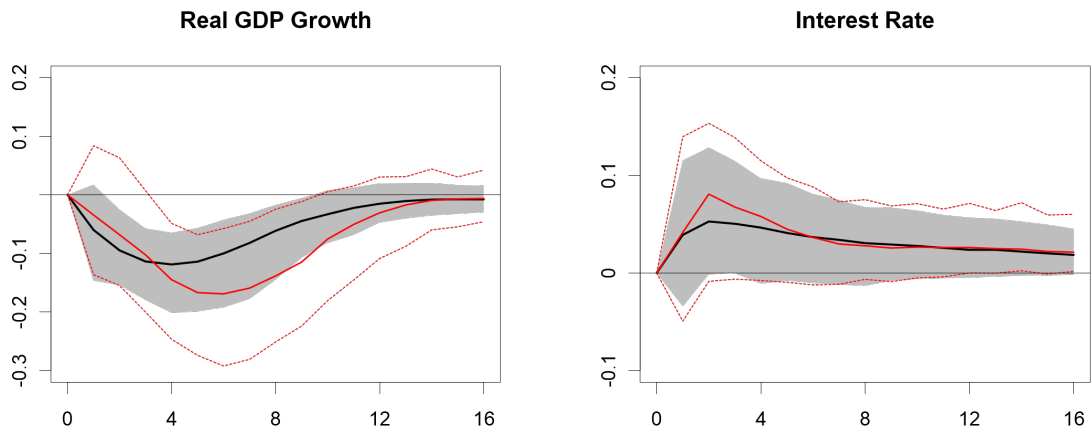
The lower panel of Figure 5 shows selected IRFs after a 25 bps shock in the credit spread. A shock to the credit spread leads to a significant decrease of real GDP growth that is slightly stronger in the crisis state (−16.9 bps, 6q) than in normal times (−11.9 bps, 4q). In contrast to the results for credit standards, the response is persistent and there is no evidence for a reversion. Here, the ECB does not accommodate a worsening of credit conditions. In fact, we even observe a tendency to tighten the interest rate. This makes the accelerating effect of the credit spread even more pronounced compared to that of credit standards.

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 median 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 median IRFs for the crisis state. Gray-shaded areas (red dashed lines) indicate 80% confidence bands for the normal (crisis) state. Full set of impulse responses is available on request.

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 of credit standards and the credit spread are more pronounced in the crisis state than in normal times and the differences across states are statistically significant when considering 68% confidence bands. The ECB responds to credit standard shocks with

loose monetary policy, but does not accommodate shocks to the credit 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 are key determinants of the underlying state of the economy in the logit submodel with the crisis state becoming more prevalent in times of adverse credit conditions. During crisis times, the transmission of monetary policy shocks is (slightly) stronger than during normal times, providing evidence for the financial accelerator in the euro area.¹⁶

Next, for a thorough comparison of the peak effects on real GDP growth (standards, crisis: -11.1 bps; standards, normal: -7.8 bps; spread, crisis: -16.9 bps; spread, normal: -11.9 bps), one needs to consider the (relative) standard deviation of the shock variables (see Table B1 in Appendix B) 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.

Finally, Figures B1–B3 in Appendix C show selected cumulative impulse response functions (CIRFs) of real GDP growth after shocks in the interest rate, real loan growth, credit standards, and the credit spread. These confirm that shocks to the interest rate exert a (slightly) stronger impact on real GDP growth in the crisis state when employing credit standards and the credit spread as indicators of credit conditions. Shocks to the credit spread have a persistent negative effect on real GDP growth that is (slightly) more pronounced in the crisis state. A similar pattern is found for shocks to credit standards during the first two years after the shock; thereafter, the CIRFs are similar in both states. This reversion tendency in the crisis state is also the reason why the

¹⁶Again, the difference across states are statistically significant when considering 68% confidence bands for the models with credit standards and the credit spread.

cumulative effect is the strongest for the credit spread, even when taking differences in the standard deviations of the shock variables into account.

4 Robustness Tests

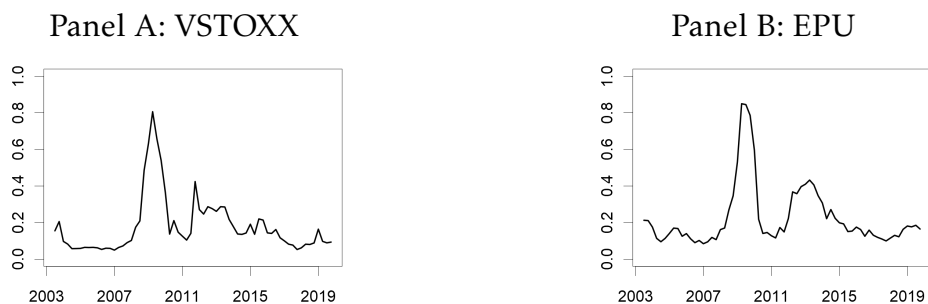
4.1 Volatility and Uncertainty

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.¹⁷

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.

Figure 6: Weights of Crisis State

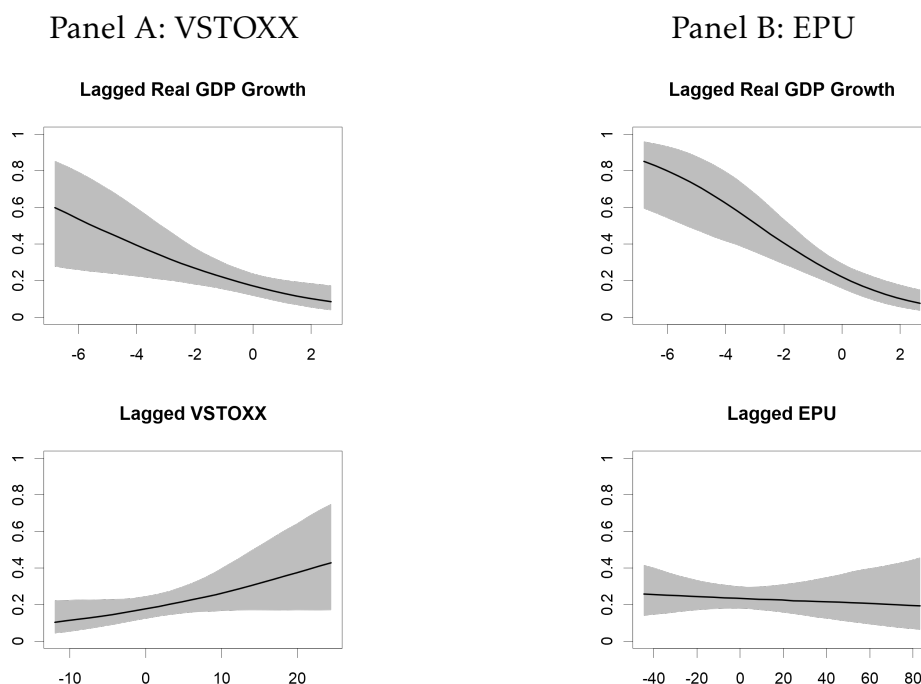


Notes: Weights of the crisis states are obtained by estimation of Eq. (2).

¹⁷Firms 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.

Similar to Figure 1, we observe a peak during the GFC (albeit a smaller 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.¹⁸ The overall share of the crisis state is 17.9% for the VSTOXX and 22.7% for the EPU.

Figure 7: Predicted Probabilities



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 80% confidence bands. Full set of predicted probabilities is available on request.

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.¹⁹ 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 uncer-

¹⁸The 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: $\rho = 0.72$ ($\rho = 0.56$).

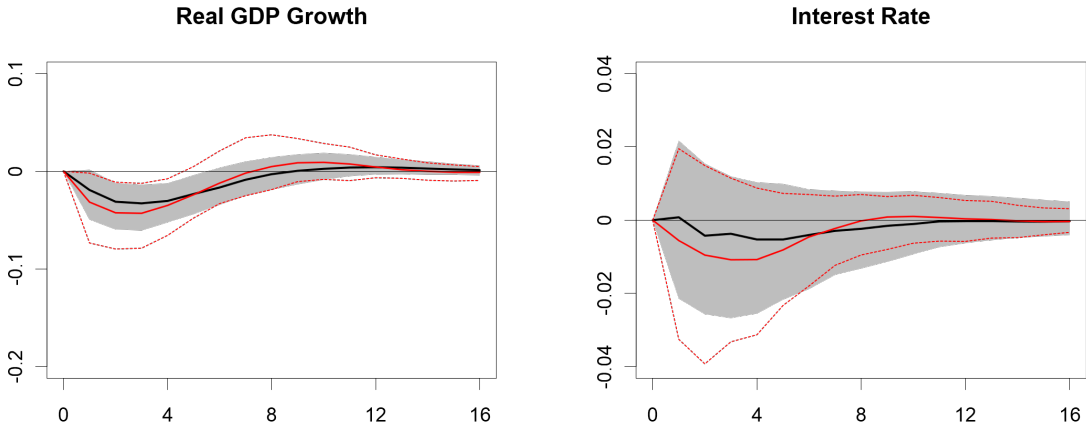
¹⁹Similar to Figure 2, lagged inflation and the lagged interest rate are not important as predictors of the crisis state and, consequently, not shown in Figure 7.

tainty 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 (60%–8%). 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. Accordingly, we can rule out that the financial accelerator effect documented for credit standards and the credit spread is confounded by financial market volatility or economic policy uncertainty.

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.

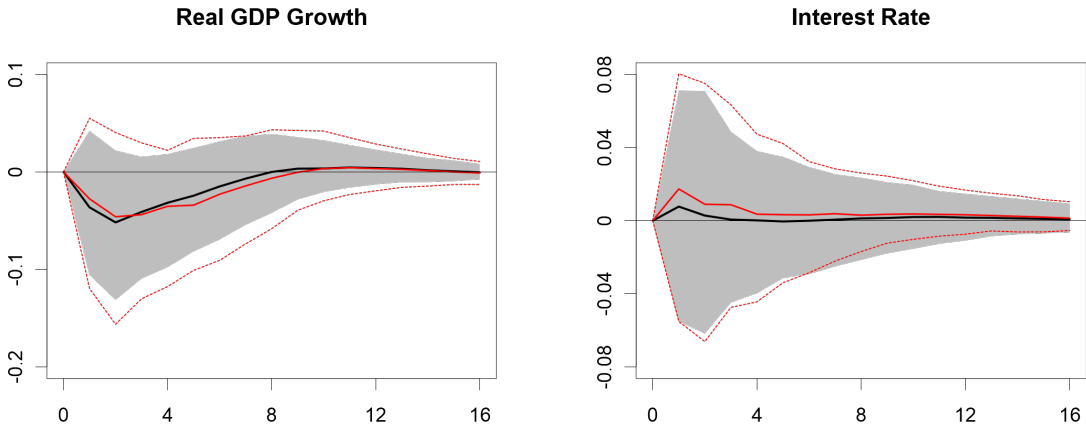
Figure 8: IRFs for Shocks in the VSTOXX



Notes: Solid black lines show median impulse responses of a one-pp shock in the VSTOXX in the normal state. Solid red lines represent the corresponding median IRFs for the crisis state. Gray-shaded areas (red dashed lines) indicate 80% confidence bands for the normal (crisis) state. Full set of impulse responses is available on request.

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 similar in both states (crisis: -4.3 bps, 3q; normal: -3.3 bps, 3q). In addition, we find no significant response of the ECB to volatility shocks in both states. Hence, there is some 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 9: IRFs for Shocks in the EPU



Notes: Solid black lines show median impulse responses of a ten-unit shock in the EPU in the normal state. Solid red lines represent the corresponding median IRFs for the crisis state. Gray-shaded areas (red dashed lines) indicate 80% 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 decrease of real GDP growth that is of similar strength in the peak responses in both states (crisis: -5.2 bps, 2q; normal: -4.6 bps, 2q), but not significant. In addition, we find no significant response of the interest rate. Even when abstracting from the lack of significance, the peak responses on output are 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).

To summarize, we detect a detrimental effect of volatility shocks on real GDP growth. However, this effect is quantitatively much smaller than that of credit standards and credit risk.²⁰ 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 B2 in Appendix B) and the bivariate correlations to the other variables in the VAR system (see Table B1 in Appendix B). Figures D1–D7 in Appendix D show the results of this robustness test. To facilitate the comparison across monetary policy indicators, the left panel in Figures D1–D7 replicates some of the baseline results from Section 3.

As indicated by Figure D1, 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 D2 and D4. 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 D3).

²⁰Note that CIRFs (not shown, but available on request) confirm the stronger effect of credit standards and the credit spread.

Although credit standards are still a noticeable driver of the crisis state with probabilities varying between 13% and 47%, real GDP growth is clearly more important (95%–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 D5–D7 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, indicating that our baseline results provide a conservative picture of the effects of monetary policy on real GDP growth. This holds in particular for differences across states as these are now significant for credit standards and the credit spread when using 80% confidence bands (instead of the 68% bands as in the summary of the baseline results in Section 3.5). Comparing the shocks to credit conditions across monetary policy indicators does not reveal much of a difference except for the credit spread where the IRFs now show a similar pattern across states. Hence, we are confident that our results are not driven by a particular choice of a monetary policy indicator at the zero-lower bound of interest rates.

4.3 Comparison to Other VAR Models

4.3.1 Comparison to Linear VAR Models

Obviously, a single-state VAR does not allow for an identification of multiple states and the drivers thereof. Beyond that, one crucial advantage of the logit mixture VAR model is the potential gain in efficiency compared to a standard linear VAR model. The economy is not forced into a single state and, accordingly, the impulse responses might be identified in a sharper fashion, in particular when these differ across states. Figure E1–E3 in Appendix E show the median impulse response for a linear VAR (right

panels) with the left panels replicating some of the baseline results from Section 3 to facilitate a comparison between the two classes of models.

We find two crucial differences when studying the effect of monetary policy shocks on real GDP growth. First, as expected, the confidence bands of the crisis state and normal state impulse responses of the mixture VAR model (left panels) are more narrow than the ones of the linear VAR (right panels). Second, output is found to initially increase after a monetary policy shock in the linear VAR, which is at odds with macroeconomic theory and raises doubt on the proper identification in a single-state VAR model. The impulse responses of the mixture VAR model, in contrast, turn negative right away and become significantly negative after a short outside lag of monetary policy and, hence, are in line with our theoretical expectations.

The effect of shocks in credit conditions on real GDP growth also differ across the two types of models, at least for shocks to real loan growth and shocks to the credit spread. Whereas the general pattern is the same across both types of models, the confidence bands are, again, more narrow in the case of the mixture VAR model.

4.3.2 Comparison to Other Multi-State VAR Models

Next, we compare the performance of our logit mixture VAR model to that of a standard Markov-switching VAR (MSVAR) and a standard logistic smooth transition VAR (LSTVAR) model with the same set of variables and the same set of lags. In the MSVAR, the regime affiliation is generated by a discrete-state homogenous Markov chain and does not depend on the explicit specification of state-determining or transition variables. In the case of the LSTVAR, however, we have to define a transition variable. To overcome the criticism of having just a single transmission variable, we extract the first principal component of the four endogenous variables in each VAR system. This is still restrictive in the sense that the (arbitrary) aggregation takes place *ex ante* and the underlying weights are not created during the estimation of the actual two-state VAR model as in the case of the mixture VAR model. Figure E4 in Appendix E shows

the weights of the crisis states of the logit mixture VAR model (in black) against the non-dominant states of the MSVAR (in blue) and the LSTVAR (in red).

The blue lines shows an almost perfect binary distinction of regimes for the MSVAR (except for some short time periods). In particular during episodes of small increases in the crisis states of the logit mixture VAR model, the weight for the corresponding state in the MSVAR quickly reaches the maximum value of one.²¹ In all three panels, we also observe some delayed signals in the MSVAR when it comes to indicate a “crisis regime.” This is because the MSVAR relies on a first-order Markov chain in the state-determination and new information cannot enter the system via (abrupt) changes in the state-determining variables.

The red line in Panel A indicates a too early detection of the “crisis regime” for the LSTVAR. The non-dominant regime appears to capture the build-up of the GFC and the euro area sovereign debt crisis instead of the crises themselves. In Panels B and C, the non-dominant regimes merely fluctuate around equally weighted states. This is due to the low values for the estimated smoothness parameter γ (0.13 for credit standards; 0.12 for the credit spread).²² All three correlations with the crisis regime of the logit mixture VAR are negative.²³ But even when interpreting the dominant states of Panels B and C as “crisis regimes,” these never reach the clear distinction of states found in the logit mixture VAR model.

The key advantages of the logit mixture VAR model can be summarized as follows: (i) the usage of external information in the state-determining model (in contrast to the MSVAR), (ii) coming from potentially multiple variables without pre-determined weights (in contrast to both other non-linear VARs), (iii) together with employing the lagged latent variable in the submodel, which allows for some degree of persistence in the state weights (in contrast to the LSTVAR). This combination allows for a non-binary distinction of regimes, a smooth development of the state weights over time,

²¹The correlation in the weights of the MSVAR model compared to the logit mixture VAR are $\rho = 0.23$ (real loan growth), $\rho = 0.60$ (credit standards), and $\rho = 0.50$ (credit spread).

²²Note that we tried to overcome this issue by an extensive grid search for the starting values in the optimization algorithm and by manually imposing a starting value of $\gamma = 1$.

²³The correlation in the weights compared to the logit mixture VAR are $\rho = -0.17$ (real loan growth), $\rho = -0.74$ (credit standards), and $\rho = -0.90$ (credit spread).

and yet a prompt response to changes in the macroeconomic environment beyond what is captured by a single variable or a composite indicator.

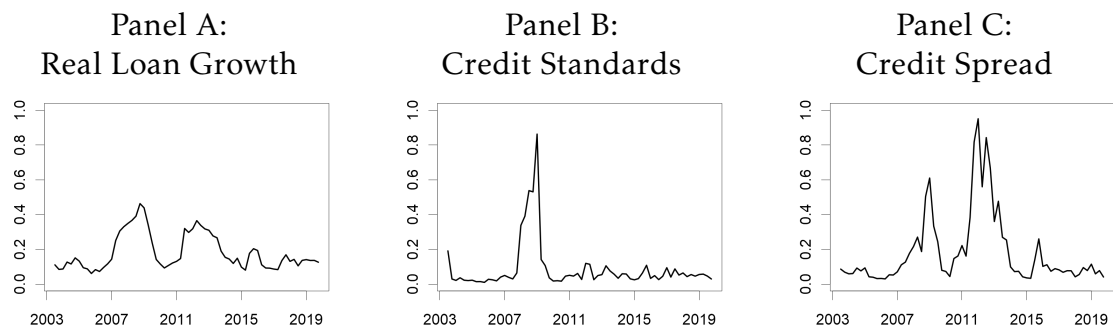
5 Extension: Impact on Unemployment

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) find 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. 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%–92%), 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.

Figure 10: Weights of Crisis State



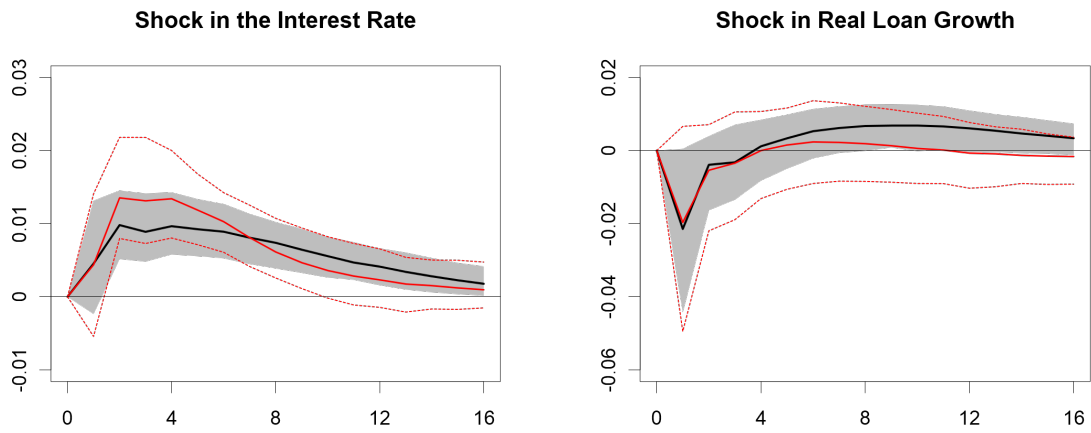
Notes: Weights of the crisis states are obtained by estimation of Eq. (2).

5.2 Impulse Responses

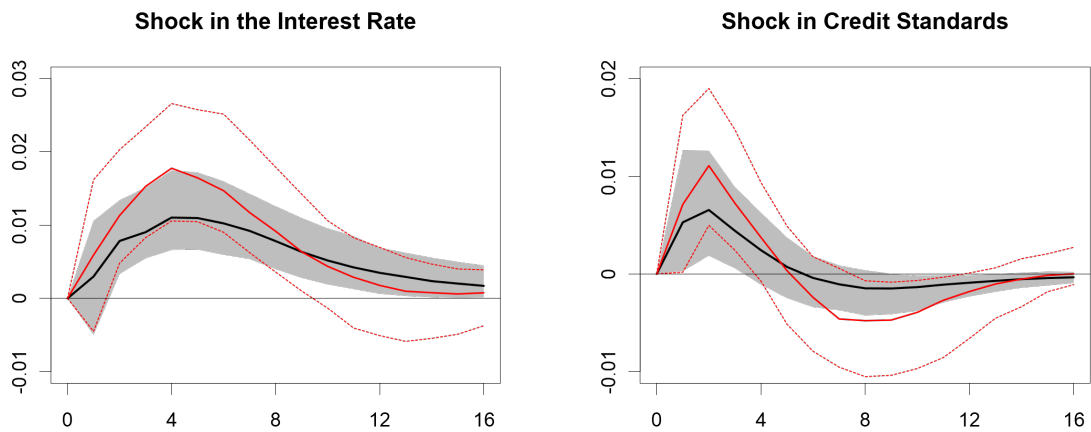
The left panel of Figure 11 shows the response of the change in the unemployment rate after a 25 bps interest rate shock. A contractionary monetary policy shock leads to an increase in the unemployment rate, irrespective of the indicator used for credit conditions. The peak effects are 1.3–1.8 bps for the crisis state and 1.0–1.1 bps during normal times. The effects are enduring for all three credit variables, in particular in the normal state, but eventually die out. We find significantly stronger peak effects in the crisis state for credit standards and the credit spread, but not for real loan growth. 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 a financial accelerator effect on the labor market, too.

Figure 11: IRFs of the Unemployment Rate

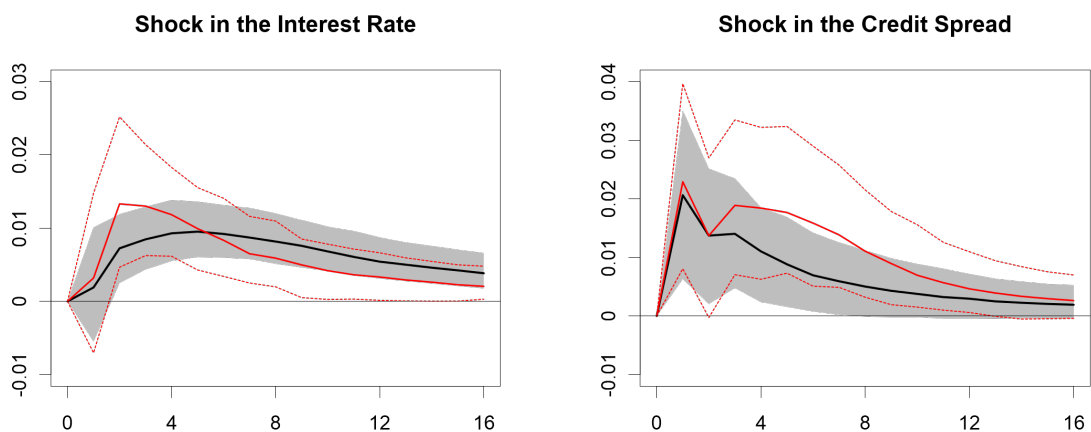
Panel A: Model with Real Loan Growth



Panel B: Model with Credit Standards



Panel C: Model with the Credit Spread



Notes: Solid lines show median 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 median IRFs for the crisis state. Gray-shaded areas (red dashed lines) indicate 80% confidence bands for the normal (crisis) state. Full set of impulse responses is available on request.

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, but insignificant reduction of the unemployment rate with similar peak effects in both states (crisis: -2.0 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 (slightly) stronger peak effect in the crisis state (crisis: 1.1 bps, 2q; normal: 0.7 bps, 2q). Here, a reversion tendency can be found in both states. Finally, shocks to the credit spread lead to an increase in the unemployment rate in both states with a peak effect of 2.3 bps (crisis) and 2.1 bps (normal) after one quarter, with the detrimental effect being more persistent in the crisis state.

Consequently, the direct effects 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 (i) if the likelihood for the crisis regime increases when credit conditions are worsening and (ii) if monetary policy shocks exert a stronger effect in the crisis regime.

We show that a widening of the credit spread and a tightening of credit standards lead to a reduction of real GDP growth in the euro area, whereas shocks to the quantity of credit are less important in explaining growth fluctuations. In addition, the credit spread and — to some extent — credit standards contribute to a financial accelerator in the euro area. Both variables are key determinants of the underlying state of the economy in the logit submodel with adverse credit conditions increasing the prevalence of the crisis state. During crisis times, the transmission of 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) and the logit mixture VAR is superior when compared to a linear VAR model and other multi-state VAR models. 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: Details of Estimation Procedure

In the following, we provide further information on the estimation procedure for the general case of K regimes and the generation of the impulse response functions (see also Burgard et al., 2019).

Expectation Maximization Algorithm

We use an expectation maximization (EM) algorithm for the parameter estimation. Starting from Eq. (1) in Section 2.1, we define $Z_t = (Z_{t,1}, \dots, Z_{t,K})^\top, \forall t = 1, \dots, T$ as the component affiliation of Y_t :

$$Z_{t,i} = \begin{cases} 1 & \text{if } Y_t \text{ comes from the } i^{\text{th}} \text{ component; } 1 \leq i \leq K \\ 0 & \text{otherwise.} \end{cases} \quad (\text{A1})$$

The conditional log-likelihood function at time t is then given by:

$$l_t = \sum_{k=1}^K Z_{t,k} \log(\alpha_k) - \frac{1}{2} \sum_{k=1}^K Z_{t,k} \log |\Omega_k| - \frac{1}{2} \sum_{k=1}^K Z_{t,k} (e_{kt}^\top \Omega_k^{-1} e_{kt}) \quad (\text{A2})$$

where

$$\begin{aligned} e_{kt} &= Y_t - \Theta_{k0} - \Theta_{k1} Y_{t-1} - \Theta_{k2} Y_{t-2} - \dots - \Theta_{kp_k} Y_{t-p_k} \\ &= Y_t - \tilde{\Theta}_k X_{kt} \\ \tilde{\Theta}_k &= [\Theta_{k0}, \Theta_{k1}, \dots, \Theta_{kp_k}] \\ X_{kt} &= (1, Y_{t-1}^\top, Y_{t-2}^\top, \dots, Y_{t-p_k}^\top) \end{aligned}$$

for $k = 1, \dots, K$. The log-likelihood is then given by:

$$l = \sum_{t=p+1}^T l_t = \sum_{t=p+1}^T \left(\sum_{k=1}^K Z_{t,k} \log(\alpha_k) - \frac{1}{2} \sum_{k=1}^K Z_{t,k} \log |\Omega_k| - \frac{1}{2} \sum_{k=1}^K Z_{t,k} (e_{kt}^\top \Omega_k^{-1} e_{kt}) \right) \quad (\text{A3})$$

Expectation Step

Since we cannot directly observe the vectors Z_1, \dots, Z_K , these are replaced by their conditional expectation on the matrix of parameters $\widetilde{\Theta}$ and the observed vectors Y_1, \dots, Y_T . Defining $\alpha_{t,k} = E(Z_{t,k} | \widetilde{\Theta}, Y_1, \dots, Y_T)$ with $t = 0, \dots, T$ and $k = 1, \dots, K$ to be the conditional expectation of the k^{th} component of Z_t , we obtain the mixture weights,

$$\alpha_{t,k} = \frac{\alpha_k |\Omega_k|^{\frac{1}{2}} e^{-\frac{1}{2} e_{kt}^\top \Omega_k^{-1} e_{kt}}}{\sum_{k=1}^K \alpha_k |\Omega_k|^{\frac{1}{2}} e^{-\frac{1}{2} e_{kt}^\top \Omega_k^{-1} e_{kt}}}, \quad \forall k = 1, \dots, K. \quad (\text{A4})$$

We employ the mixture weights obtained in Eq. (A4) as dependent variables in a (multinomial) logit model. The explanatory variables of the multinomial logit model are denoted by the vector ζ and the γ_j 's are the estimated parameters, where we set $\gamma_1 = 0$ for identification reasons. The expected mixture weights are then the predictions of the submodel given ζ :

$$\widehat{\tau}_{t,k} = \frac{e^{\zeta_t^\top \gamma_k}}{\sum_{j=1}^K e^{\zeta_t^\top \gamma_j}} \quad (\text{A5})$$

In the empirical application, we restrict the description of the economy to a mixture of two states and, accordingly, estimate a binary logit model as submodel, which simplifies to Eq. (2) in Section 2.1.

Maximization Step

Given the expected values for Z , we can obtain estimates for the α_k 's, the parameter matrices $\widetilde{\Theta}_k$, and the variance-covariance matrices Ω_k by maximizing the log-likelihood function l in Eq. (A3) with respect to each variable. This yields the follow-

ing estimates:

$$\widehat{\alpha}_k = \frac{1}{T-p} \sum_{t=p+1}^T \widehat{\tau}_{t,k} \quad (\text{A6})$$

$$\widehat{\Theta}_k^\top = \left(\sum_{t=p+1}^T \widehat{\tau}_{t,k} X_{kt} X_{kt}^\top \right)^{-1} \left(\sum_{t=p+1}^T \widehat{\tau}_{t,k} X_{kt} Y_t^\top \right) \quad (\text{A7})$$

$$\widehat{\Omega}_k = \frac{\sum_{t=p+1}^T \widehat{\tau}_{t,k} \widehat{e}_{kt} \widehat{e}_{kt}^\top}{\sum_{t=p+1}^T \widehat{\tau}_{t,k}} \quad (\text{A8})$$

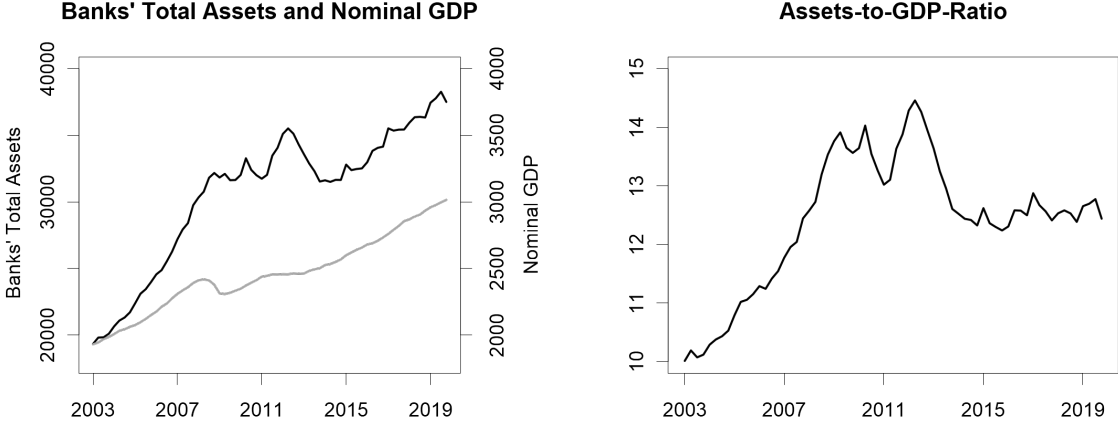
Both, the expectation step and the maximization step are repeated until convergence is achieved.

Calculation of Impulse Response Functions

The calculation of impulse response functions is done using the following six steps. First, we use the original sample and calculate the estimates $\widehat{\tau}_{t,k}$, $\widehat{\Theta}_k$, and $\widehat{\Omega}_k$ using Eqs. (A6)–(A8). Second, we use the original regime-dependent error terms e_{k1}, \dots, e_{kt} and calculate regime-independent errors $\mathbf{e}_t = \sum_{k=1}^K \widehat{\tau}_{t,k} \cdot e_{kt}$ using the state weights. Third, we center \mathbf{e}_t for each variable to obtain the centered errors $\mathbf{e}_{t,n}^* = \mathbf{e}_{t,n} - \frac{1}{T} \sum_{t=1}^T \mathbf{e}_{t,n}$ with $\mathbf{e}_{t,n}$ denoting the error term for variable n at time t . Fourth, we randomly draw 250 bootstrap samples using the centered errors $\widehat{\mathbf{e}}_{t,n}^*$. Fifth, we calculate the orthogonalized impulse responses for each of the 250 bootstrap samples with a horizon of 16 quarters and the identification scheme described at the end of Section 2.2. Finally, we obtain the impulse response functions by calculating the median over the 250 bootstrapped samples for each horizon. The corresponding confidence bands are calculated using the 10% and 90% quantile of the distribution over the 250 bootstrapped samples for each horizon.

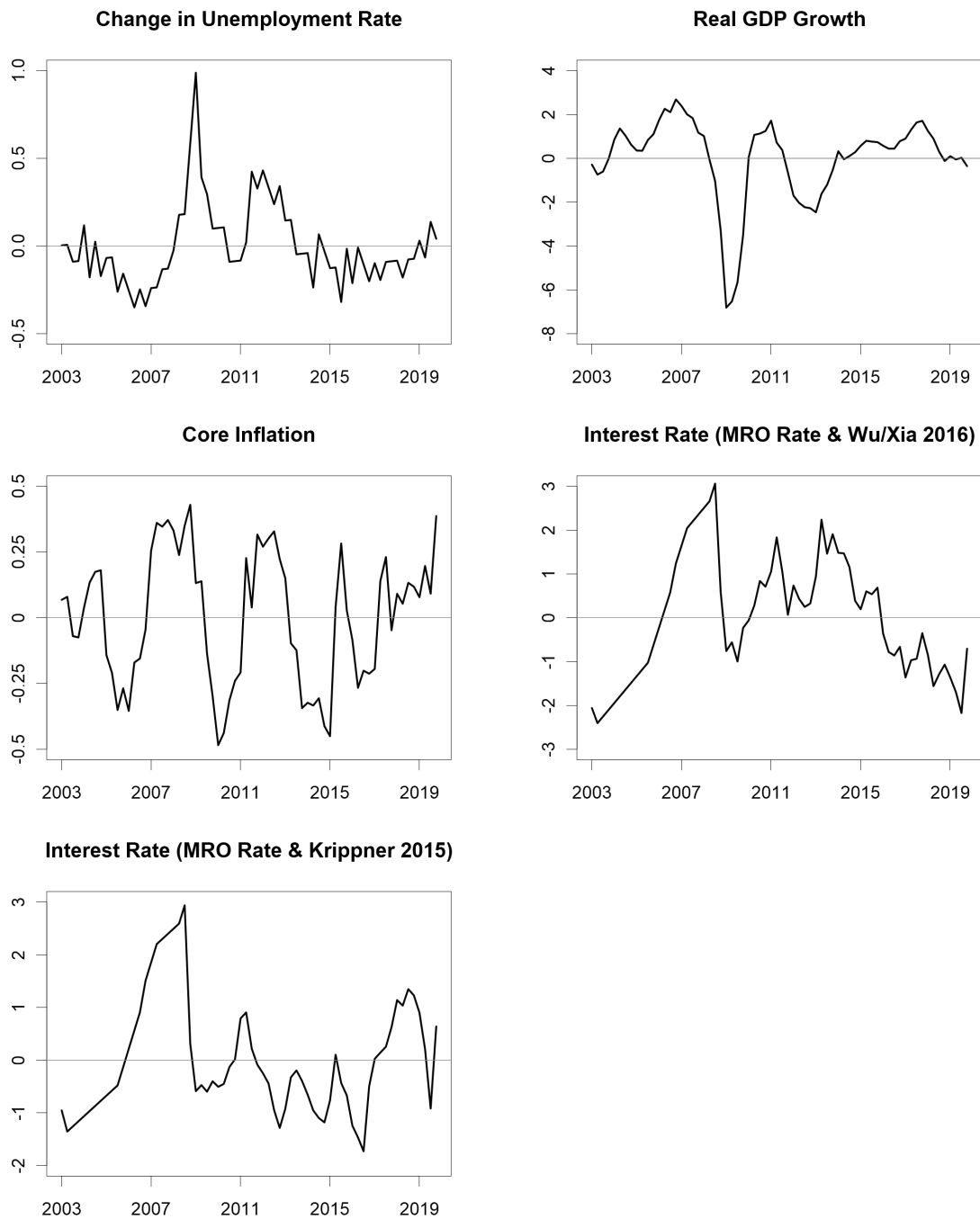
Appendix B: Background on Dataset

Figure B1: Banks' Assets and Nominal GDP in the Euro Area



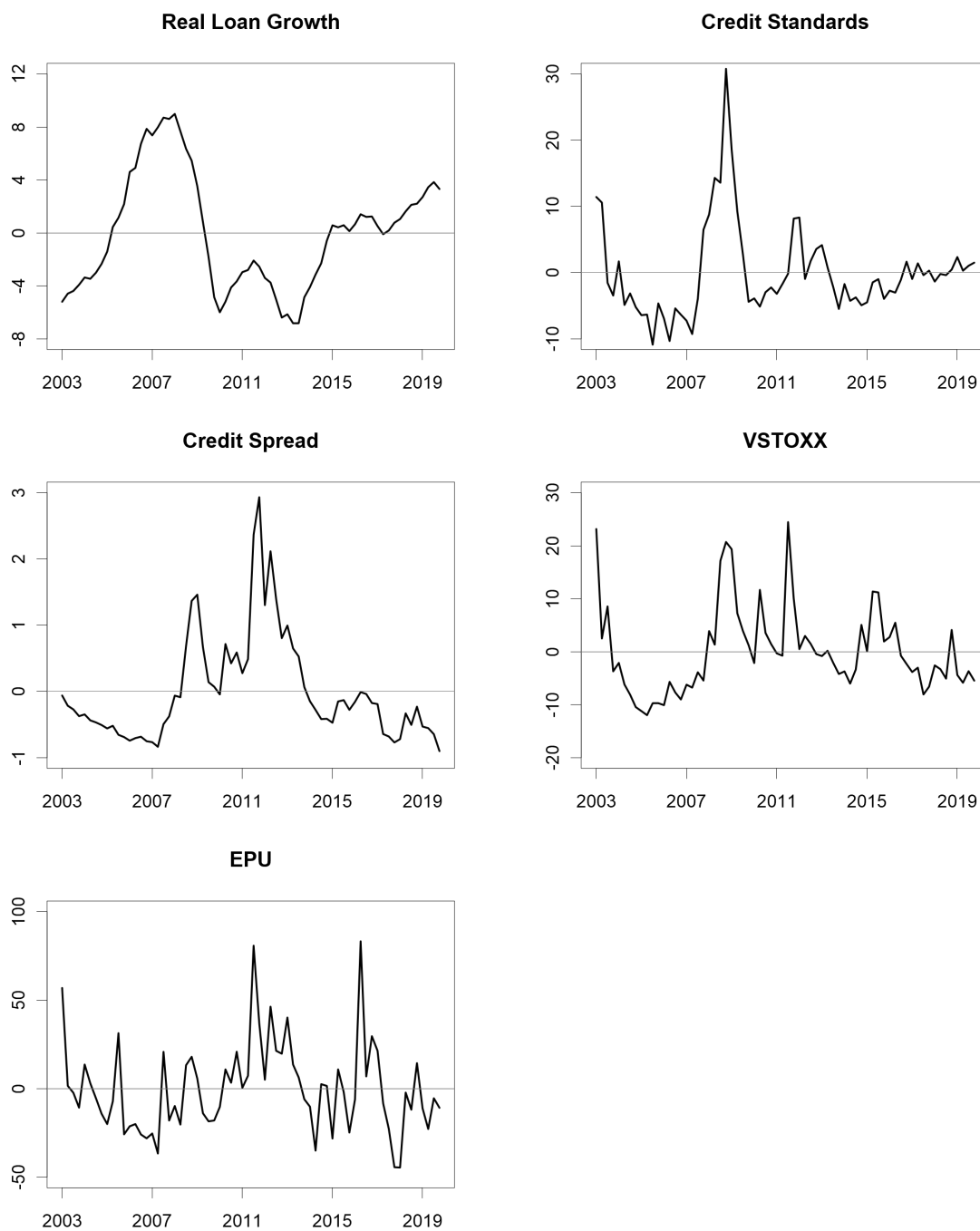
Source: ECB/Eurostat. End-of-quarter banks' total assets (black line in left panel, left y-axis) and quarterly nominal GDP (gray line in left panel, right y-axis) are measured in billions of euros.

Figure B2: 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 B3: 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.

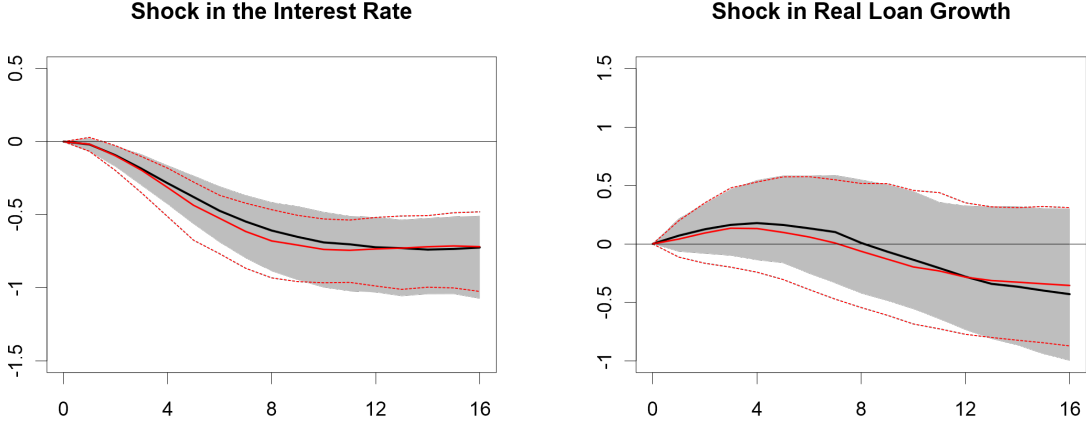
Table B1: Correlation Matrix and Standard Deviations

	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.

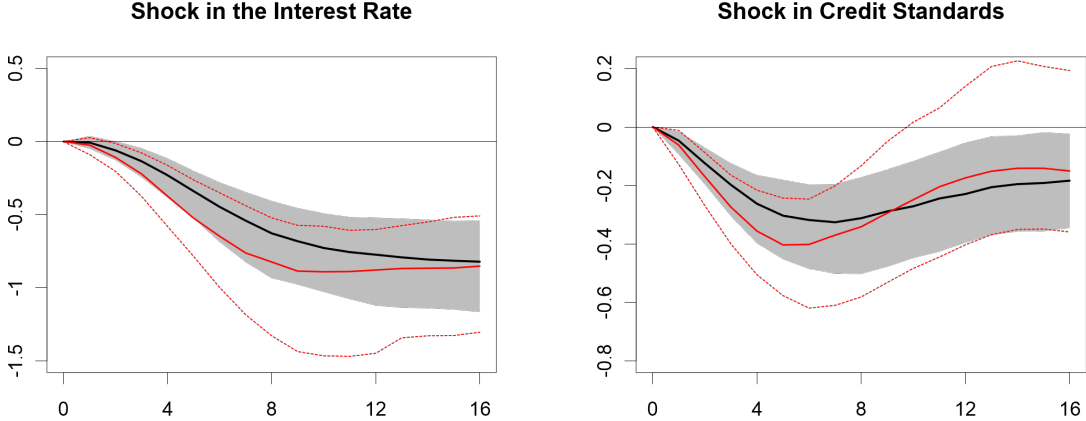
Appendix C: Cumulative Impulse Responses

Figure B1: CIRFs of Real GDP Growth for Model with Real Loan Growth



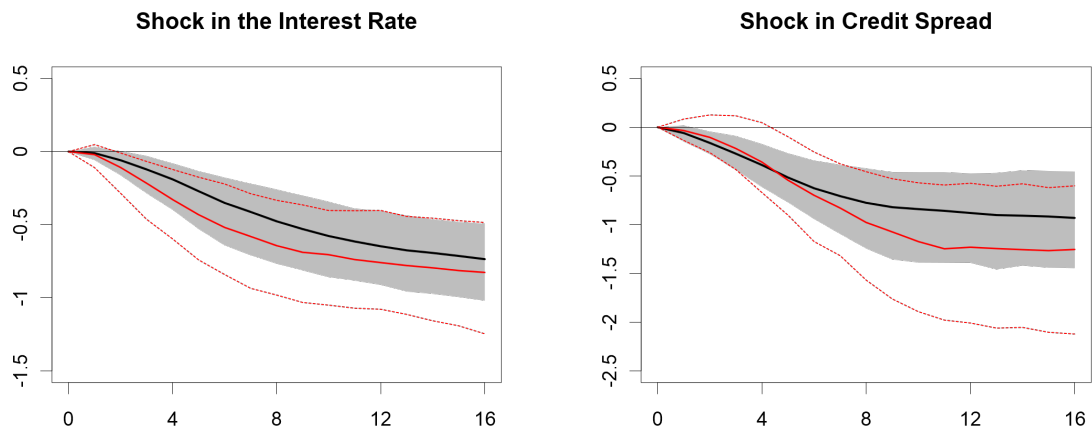
Notes: Solid black lines show median cumulative impulse responses of real GDP growth to a 25 bps shock in the interest rate (left panel) and one-pp shock in real loan growth (right panel) in the normal state. Solid red lines represent the corresponding median cumulative IRFs for the crisis state. Gray-shaded areas (red dashed lines) indicate 80% confidence bands for the normal (crisis) state. Full set of impulse responses is available on request.

Figure B2: CIRFs of Real GDP Growth for Model with Credit Standards



Notes: Solid black lines show median cumulative impulse responses of real GDP growth to a 25 bps shock in the interest rate (left panel) and one-pp shock in credit standards (right panel) in the normal state. Solid red lines represent the corresponding median cumulative IRFs for the crisis state. Gray-shaded areas (red dashed lines) indicate 80% confidence bands for the normal (crisis) state. Full set of impulse responses is available on request.

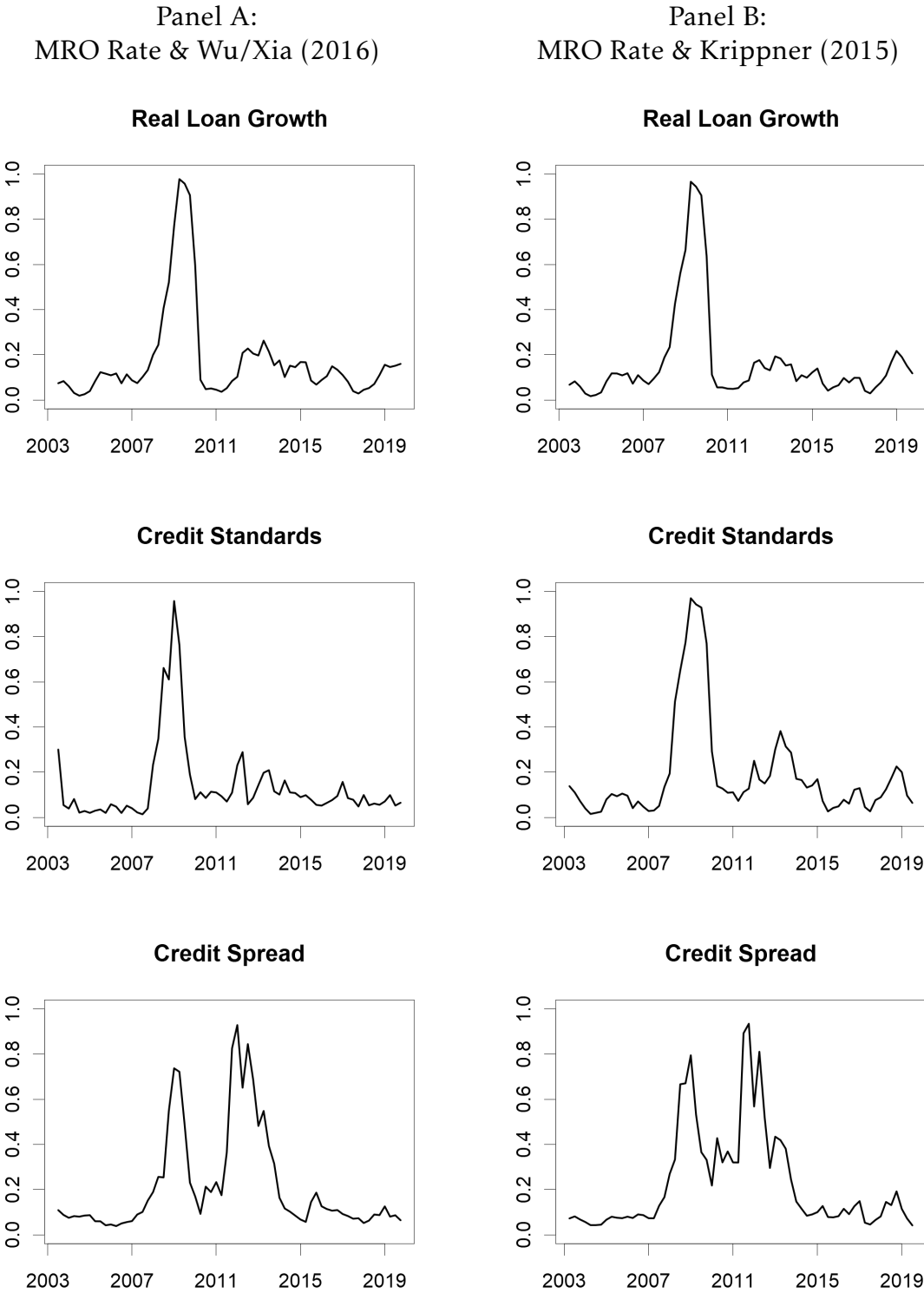
Figure B3: IRFs of Real GDP Growth for Model with Credit Spread



Notes: Solid black lines show median cumulative impulse responses of real GDP growth to a 25 bps shock in the interest rate (left panel) and a 25 bps shock in the credit spread (right panel) in the normal state. Solid red lines represent the corresponding median cumulative IRFs for the crisis state. Gray-shaded areas (red dashed lines) indicate 80% confidence bands for the normal (crisis) state. Full set of impulse responses is available on request.

Appendix D: Results using the Shadow Short Rate

Figure D1: Weights of Crisis State

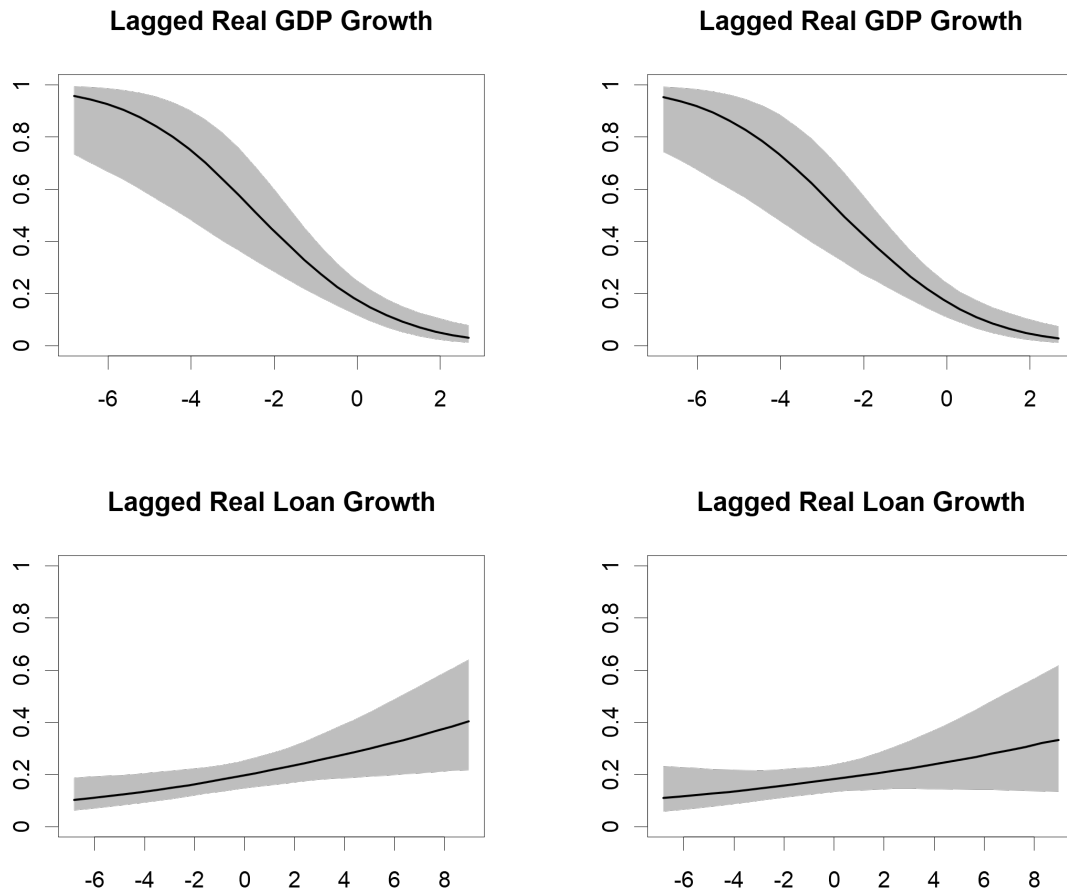


Notes: Weights of the crisis states are obtained by estimation of Eq. (2).

Figure D2: Predicted Probabilities: Model with Real Loan Growth

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

Panel B:
MRO Rate & Krippner (2015)

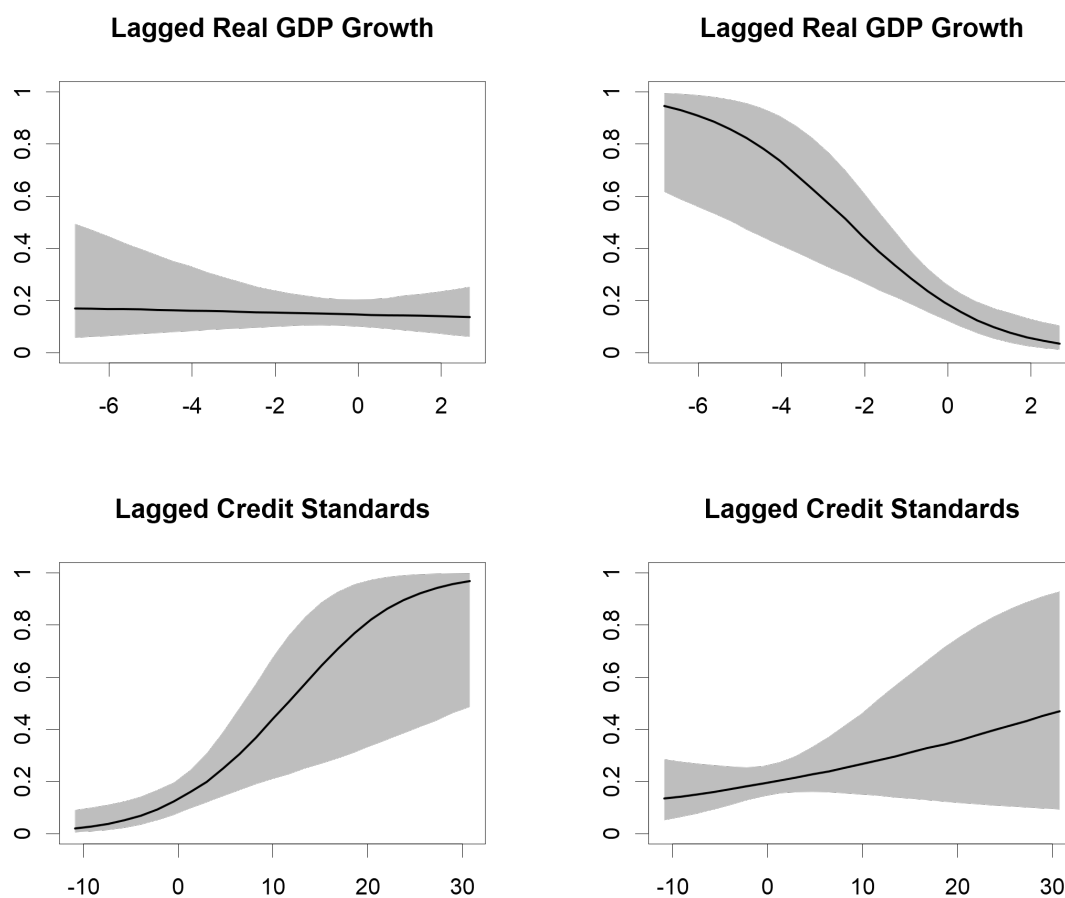


Notes: Solid lines show the predicted probabilities of the logit submodels for the crisis state and different realized values of selected explanatory variables. Gray-shaded areas indicate 80% confidence bands.

Figure D3: Predicted Probabilities: Model with Credit Standards

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

Panel B:
MRO Rate & Krippner (2015)

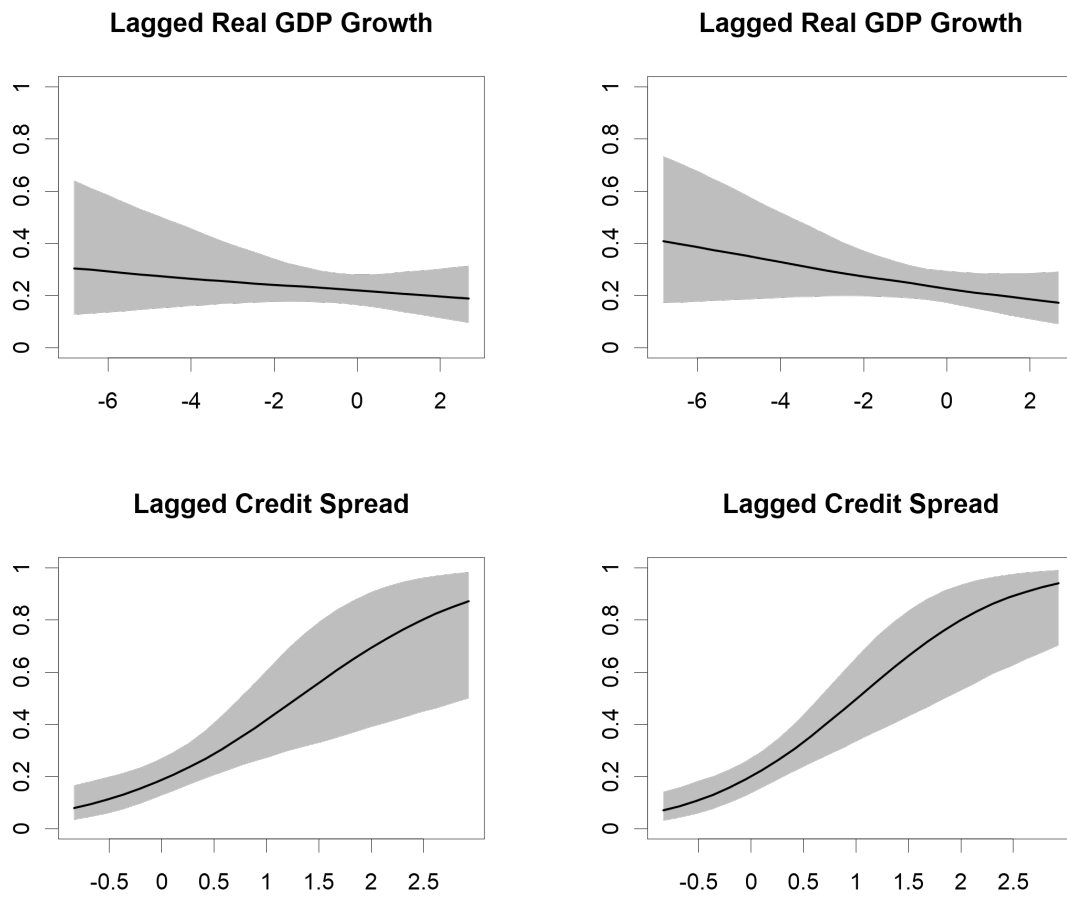


Notes: Solid lines show the predicted probabilities of the logit submodels for the crisis state and different realized values of selected explanatory variables. Gray-shaded areas indicate 80% confidence bands.

Figure D4: Predicted Probabilities: Model with Credit Spread

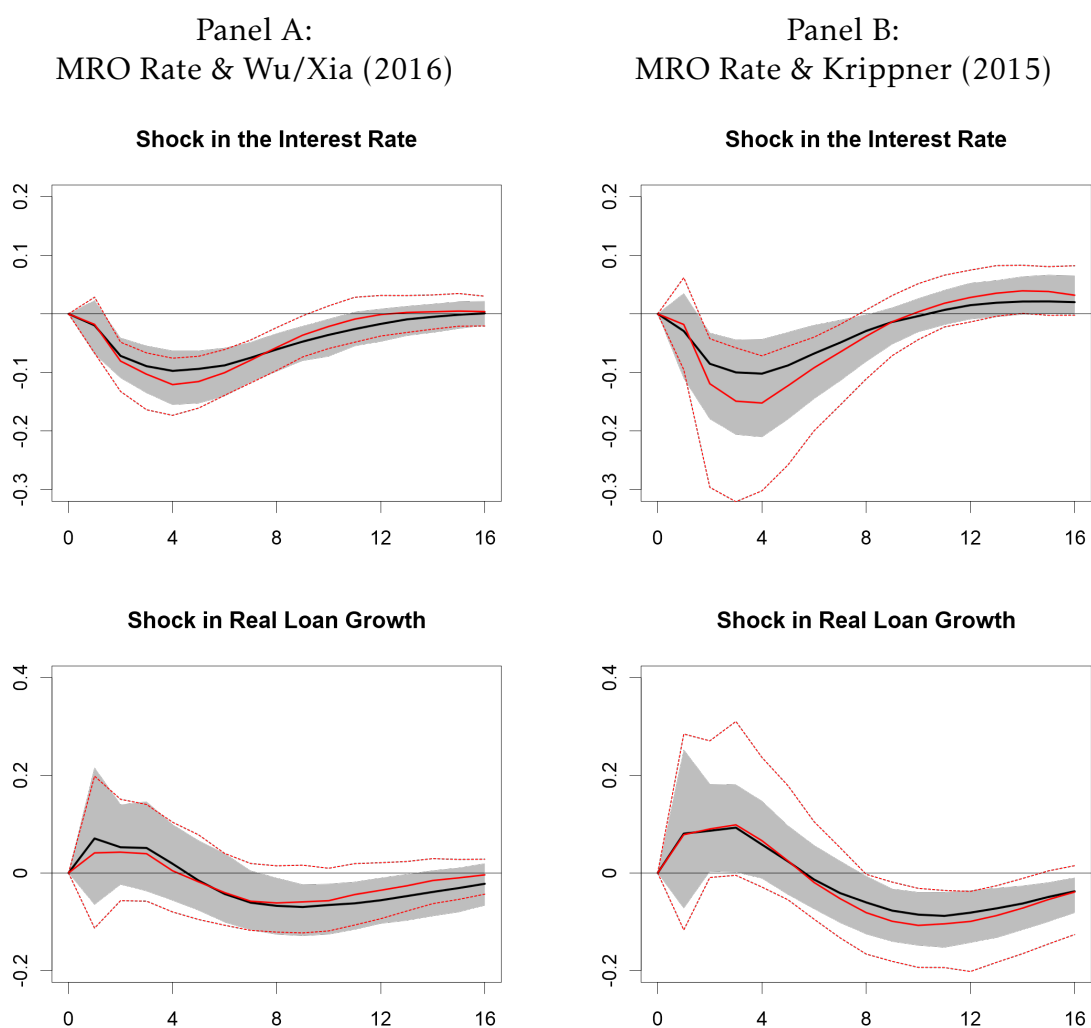
Panel A:
MRO Rate & Wu/Xia (2016)

Panel B:
MRO Rate & Krippner (2015)



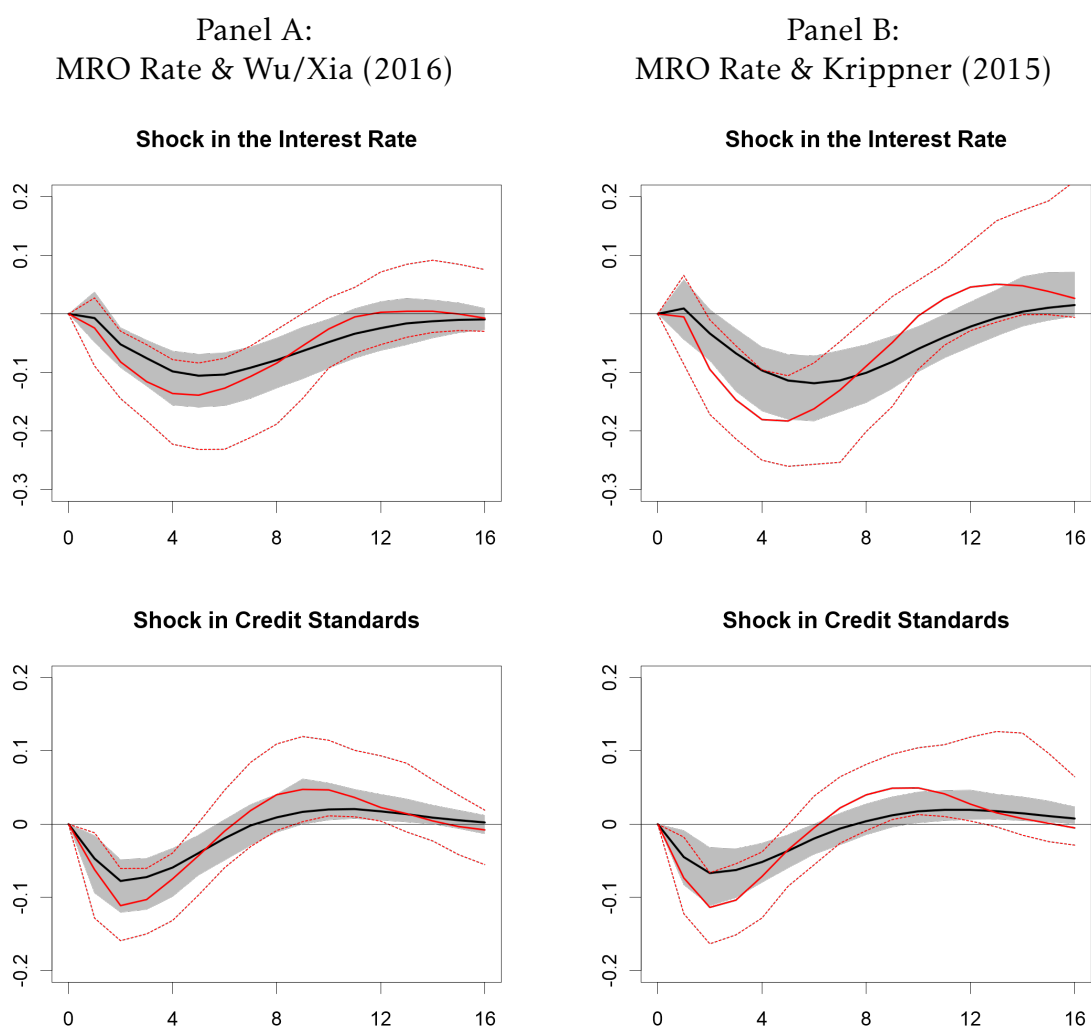
Notes: Solid lines show the predicted probabilities of the logit submodels for the crisis state and different realized values of selected explanatory variables. Gray-shaded areas indicate 80% confidence bands.

Figure D5: IRFs of Real GDP Growth for Model with Real Loan Growth



Notes: Solid black lines show median 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 median IRFs for the crisis state. Gray-shaded areas (red dashed lines) indicate 80% confidence bands for the normal (crisis) state. Full set of impulse responses is available on request.

Figure D6: IRFs of Real GDP Growth for Model with Credit Standards

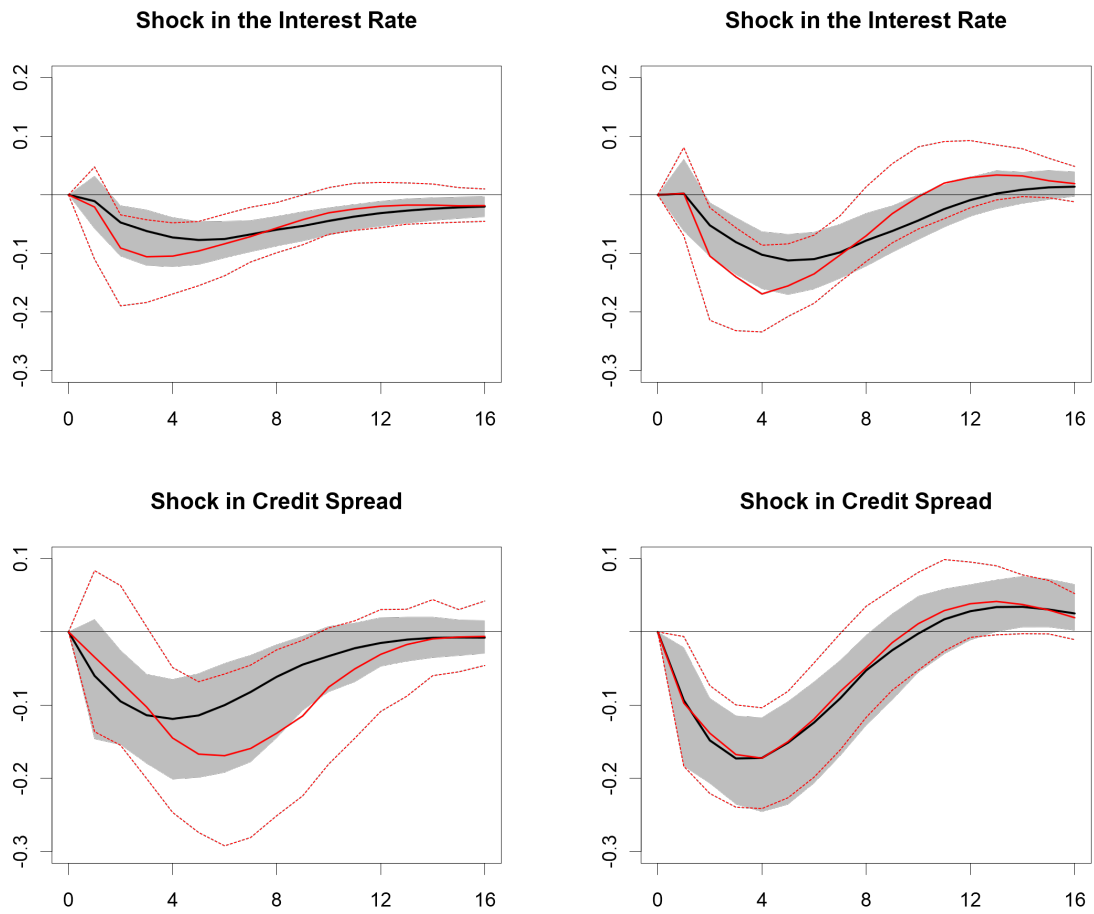


Notes: Solid black lines show median impulse responses of real GDP growth to a 25 bps shock in the interest rate (upper panel) and one-pp shock in credit standards (lower panel) in the normal state. Solid red lines represent the corresponding median IRFs for the crisis state. Gray-shaded areas (red dashed lines) indicate 80% confidence bands for the normal (crisis) state. Full set of impulse responses is available on request.

Figure D7: IRFs of Real GDP Growth for Model with Credit Spread

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

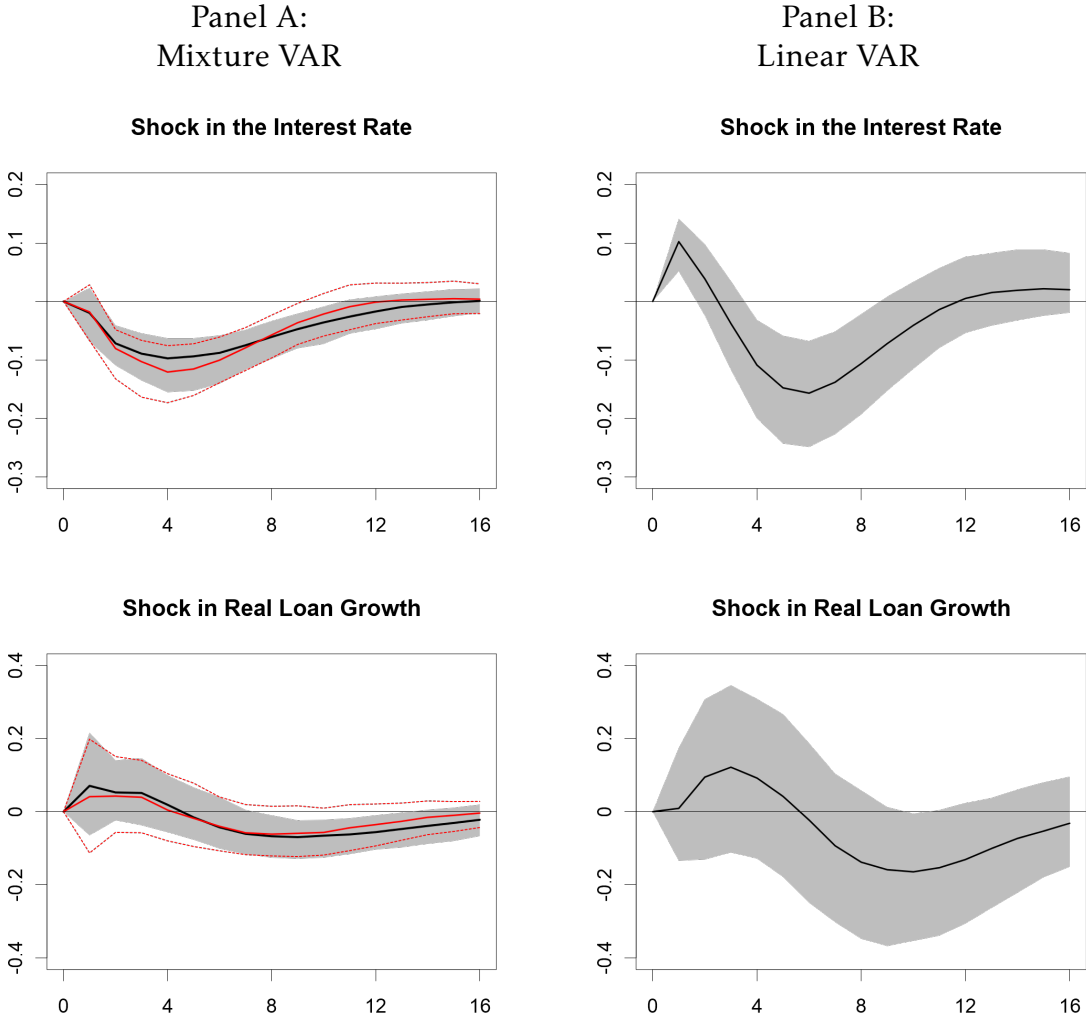
Panel B:
MRO Rate & Krippner (2015)



Notes: Solid black lines show median 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 median IRFs for the crisis state. Gray-shaded areas (red dashed lines) indicate 80% confidence bands for the normal (crisis) state. Full set of impulse responses is available on request.

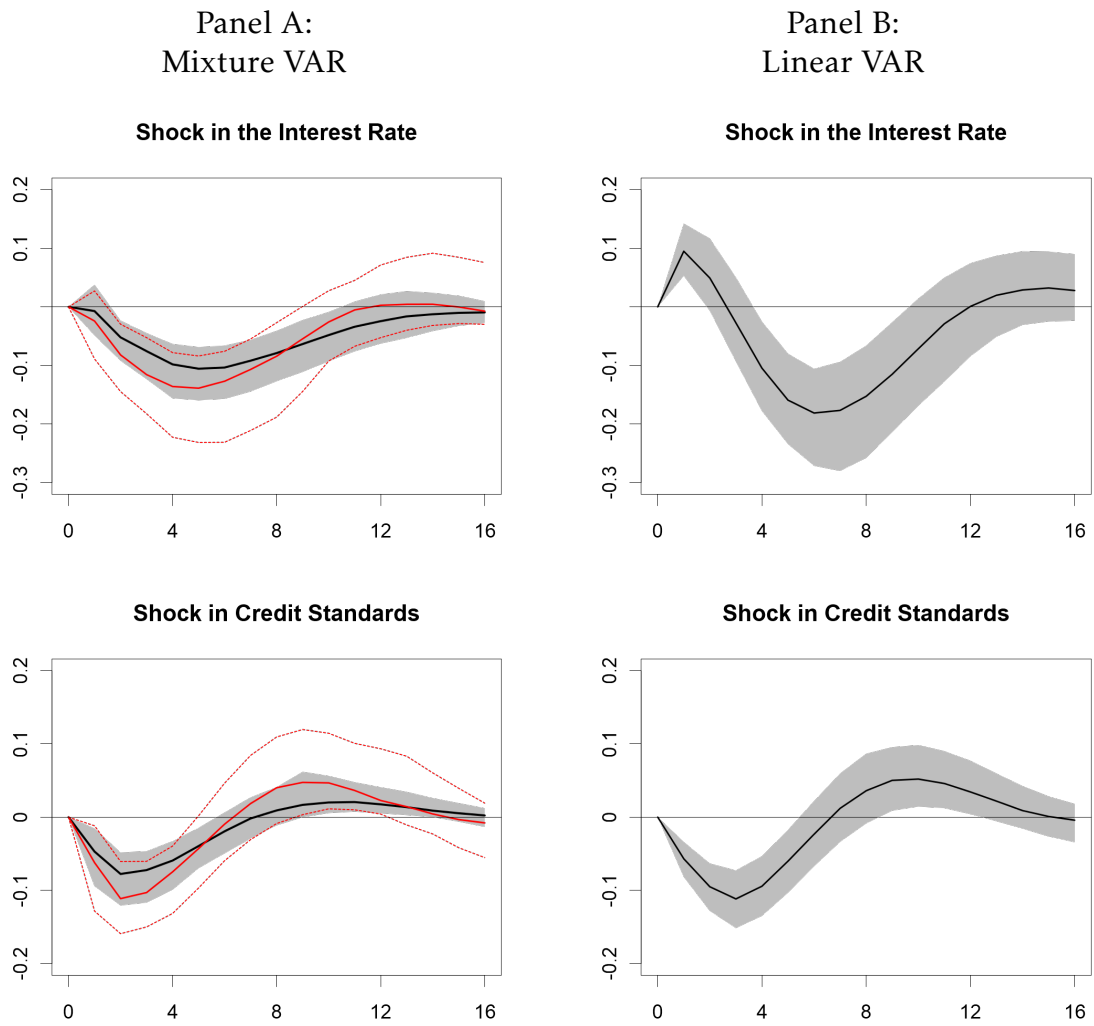
Appendix E: Results for Other Types of VAR Models

Figure E1: IRFs of Real GDP Growth for Model with Real Loan Growth



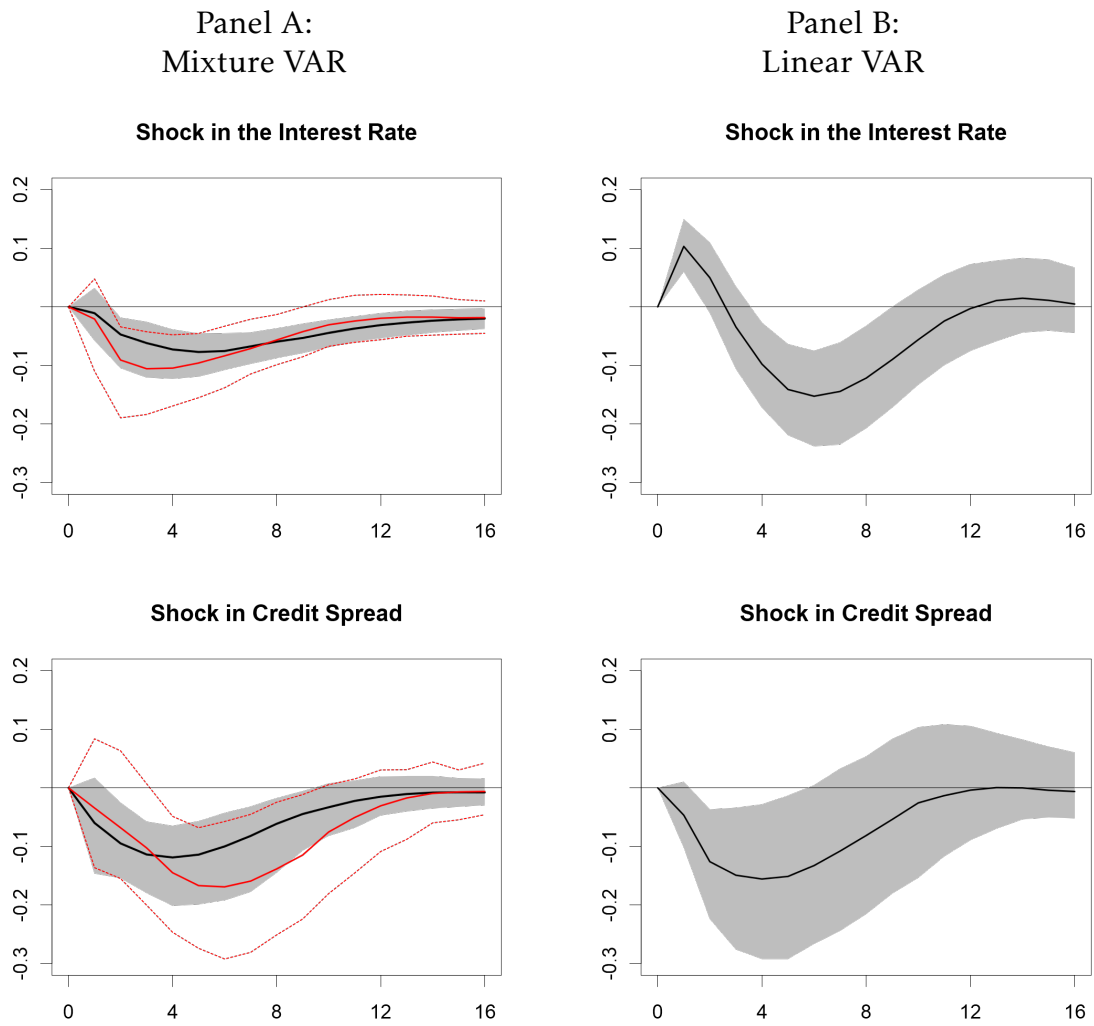
Notes: Solid black lines show median impulse responses of real GDP growth to a 25 bps shock in the interest rate and a one-pp shock in real loan growth in the normal state of the mixture VAR model (left panel) and for the one-state linear VAR model (right panel). Solid red lines represent the corresponding median IRFs for the crisis state in the mixture VAR model. Gray-shaded areas (red dashed lines) indicate 80% confidence bands. Full set of impulse responses is available on request.

Figure E2: IRFs of Real GDP Growth for Model with Credit Standards



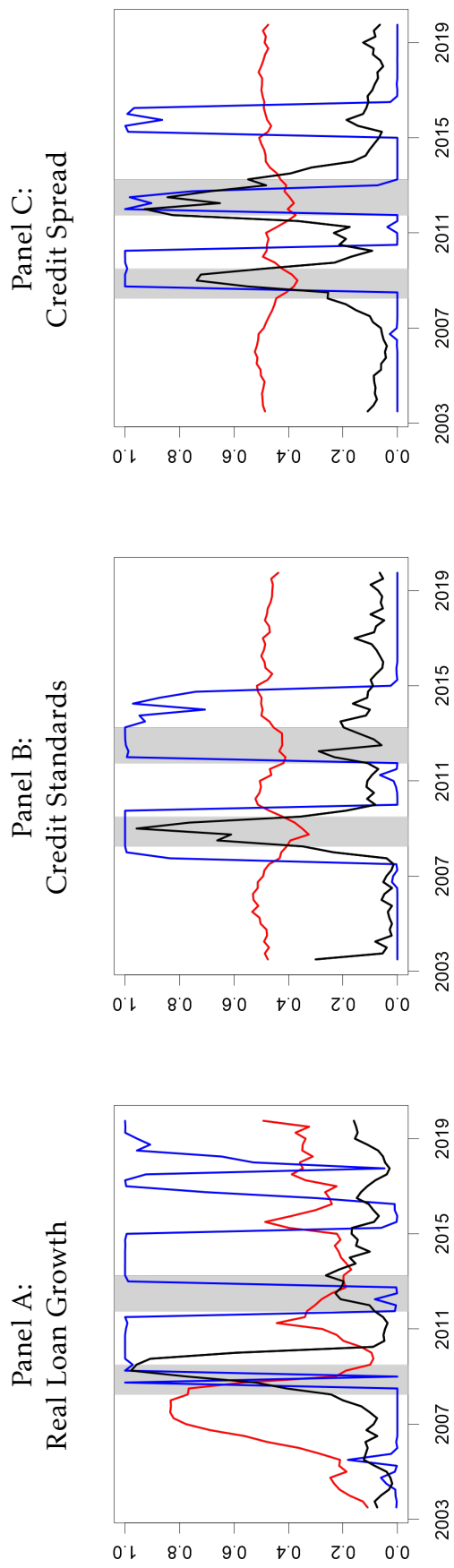
Notes: Solid black lines show median impulse responses of real GDP growth to a 25 bps shock in the interest rate and a one-pp shock in credit standards in the normal state of the mixture VAR model (left panel) and for the one-state linear VAR model (right panel). Solid red lines represent the corresponding median IRFs for the crisis state in the mixture VAR model. Gray-shaded areas (red dashed lines) indicate 80% confidence bands. Full set of impulse responses is available on request.

Figure E3: IRFs of Real GDP Growth for Model with Credit Spread



Notes: Solid black lines show median impulse responses of real GDP growth to a 25 bps shock in the interest and a 25 bps shock in the credit spread in the normal state of the mixture VAR model (left panel) and for the one-state linear VAR model (right panel). Solid red lines represent the corresponding median IRFs for the crisis state in the mixture VAR model. Gray-shaded areas (red dashed lines) indicate 80% confidence bands. Full set of impulse responses is available on request.

Figure E4: Weights of Crisis State for Different Multi-State VAR Models



Notes: Black lines show the crisis weights of the logit mixture VAR model (see also Section 3.1) and blue (red) lines show the weights of the non-dominant state in the Markov-switching (Logistic Smooth Transition) VAR model. Gray-shaded areas indicate recessions according to the definition by the Euro Area Business Cycle Network.