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Abstract

In this paper, we estimate a logit mixture vector autoregressive (Logit-MVAR) model describing monetary policy transmission in the euro area over the period 1999–2015. MVARs allow us to differentiate between different states of the economy. In our model, the time-varying state weights are determined by an underlying logit model. In 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. We show that monetary policy transmission in the euro area can indeed be described as a mixture of two states. The first (second) state with an overall share of 84% (16%) can be interpreted as a "normal state" ("crisis state"). In both states, output and prices are found to decrease after monetary policy shocks. During "crisis times" the contraction is much stronger, as the peak effect is roughly one-and-a-half times as large when compared to "normal times." In contrast, the effect of monetary policy shocks is less enduring in crisis times. Both findings provide a strong indication that the transmission mechanism is indeed different for the euro area during times of economic and financial distress.

JEL Codes: C32, E52, E58.

Keywords: Economic and financial crisis, euro area, mixture VAR, monetary policy transmission, state-dependency.

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1 Introduction

There is an ongoing discussion as to whether or not the transmission mechanism of monetary policy is different during crisis times compared to normal times. For instance, the "aim at safeguarding an appropriate monetary policy transmission" is used by the European Central Bank (ECB) as justification for the Outright Monetary Transactions program (ECB, 2012).

Empirical research based on cross-country studies generally supports the notion that there are differences between normal times and crisis times. Bouis et al. (2013) and Bech et al. (2014) find that monetary policy is less effective after a financial crisis due to a partially impaired transmission mechanism. Jannsen et al. (2015) differentiate between an acute initial phase of financial crises and a subsequent recovery phase. They show that the transmission mechanism is only impaired during the recovery phase, whereas the effects on output and inflation during the acute initial phase are even stronger than during normal times. A related branch of the literature deals with the asymmetric effects of monetary policy during the "regular" business cycle. For instance, Weise (1999), Garcia and Schaller (2002), and Lo and Piger (2005) find that monetary policy is more effective during recessions than during expansions.[1]

In all of these studies, monetary policy is examined either in a linear or in a regime-switching vector autoregressive (VAR) model. We extend these approaches by using a so-called mixture VAR model. Similar to threshold VARs (Tsay, 1998), Markov-switching VARs (Hamilton, 1989, 1990), and smooth transition VARs (Weise, 1999; Camacho, 2004), mixture VARs allow us to differentiate between different states of the economy. In contrast to the three other classes of VARs, however, the regime affiliation is neither strictly binary, nor binary with a transition period. Mixture VARs (Fong et al., 2007) are comprised of a composite model with continuous state affiliations that are allowed to vary over the complete sample period and that are potentially based on multiple variables.

[1] Tenreyro and Thwaites (2016) find the opposite, as in their paper monetary policy in the United States is less powerful during recessions.

Our analysis is the first to implement the idea of Bec et al. (2008) of a concomitant logit model for the calculation of state weights in a mixture VAR model. We deviate from existing models (Dueker et al., 2011; Kalliovirta et al., 2016) by leaving the set of variables that determine these weights open to the user, rather than restricting these to the set of endogenous variables in the mixture VAR model. Employing a logit model to determine the weights also leads to a smoother transition between the different economic states and avoids the problem of jumping regime weights, as in Fong et al. (2007) and Kalliovirta et al. (2016). In addition, we provide the first implementation of a logit mixture vector autoregressive (Logit-MVAR) model in the context of monetary policy transmission. Our analysis focuses on the euro area and the period 1999–2015.

We show that monetary policy transmission in the euro area can be described as a mixture of two states. The second state with an overall share of 16% can be interpreted as a "crisis state" as its weights are particularly large after the Lehman collapse in 2008. Other, albeit smaller, peaks are found during the recession in 2002–2003, the euro area sovereign debt crisis in 2011, and the Greek sovereign debt crisis in 2015. Correspondingly, the first state with an overall share of 84% can be interpreted as representing "normal times." In both states, output and prices decrease after monetary policy shocks. During crisis times the contraction is much stronger, as the peak effect of both variables is roughly one-and-a-half times as large compared to normal times. In contrast, despite this stronger peak effect, the effect of monetary policy shocks on output and prices is less enduring during crisis times. Both findings provide a strong indication that the transmission mechanism is indeed different for the euro area during times of economic and financial distress. In line with Weise (1999), Garcia and Schaller (2002), Lo and Piger (2005), Neuenkirch (2013), and Jannsen et al. (2015), we find a stronger reaction during the acute phase of the financial crisis and during recessions.

The remainder of this paper is organized as follows. Section 2 introduces the Logit-MVAR model and the data set. Section 3 shows the empirical results. Section 4 concludes with some policy implications.

2 Econometric Methodology

The idea of non-linearities in macroeconomic variables, arising from business cycle fluctuations, has been discussed for a long time. The most common approaches to capture these regime-dependent non-linearities are the Markov-switching VAR model proposed by Hamilton (1989, 1990) and the threshold VAR model of Tsay (1998). 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 proposing a mixture VAR that assumes the co-existence of two or more states with time-varying weights. As a consequence, we are not studying a switch in regime, but the degree of dominance of one state over the other(s). Finally, we also propose a submodel to examine and understand the economic reasons for the time-varying weights.

2.1 Finite Mixture Vector Autoregressive Models

To the best of our knowledge, the only paper employing a finite mixture of VAR models in the context of monetary policy transmission is Fong et al. (2007).[2] In their paper, monetary policy transmission is described by K different components, each being linear Gaussian VAR processes with individual lag orders p_k. Their MVAR(n,K,p_1,p_2, …, p_K) model with K regimes and an n-dimensional vector of endogenous variables Y_t is given by:

$$F(y_t|\mathcal{F}_{t-1}) = \sum_{k=1}^{K} \alpha_k \Phi\left(\Omega_k^{-\frac{1}{2}}\left(Y_t - \Theta_{k0} - \Theta_{k1}Y_{t-1} - \Theta_{k2}Y_{t-2} - \ldots - \Theta_{kp_k}Y_{t-p_k}\right)\right). \quad (1)$$

[2] Lanne and Lütkepohl (2010) propose a structural VAR with non-normal residuals that are modelled as a mixture of normally distributed errors and apply their model in the context of international monetary interdependence.

$\mathcal{F}$ denotes the information set up to time $t-1$. $\Phi(.)$ is the multivariate cumulative distribution function of independent and identically distributed standard normal random variables. Θ_{k0} is the n-dimensional vector of intercepts in regime k. $\Theta_{k1},\ldots,\Theta_{kp_k}$ are the $n \times n$ coefficient matrices for the k^{th} regime, and Ω_k is the $n \times n$ variance covariance matrix for the k^{th} regime. The mixture weights $0 \leq \alpha_k \leq 1$ with $k = 1,\ldots,K$ and $\sum_{k=1}^{K} \alpha_k = 1$ can be interpreted as the time-unconditional probabilities of y_t being generated from the k^{th} VAR process. Fong et al. (2007) provide a proof of two sufficient stationarity conditions for MVAR processes.

Kalliovirta et al. (2016) extend this MVAR model by allowing the mixture weights α_k to vary over time and thus introduce the conditional probabilities $0 \leq \alpha_{t,k} \leq 1$ with $k = 1,\ldots,K$, $\sum_{k=1}^{K} \alpha_{t,k} = 1$, and $t = 0,\ldots,T$. The resulting MVAR model is given by:

$$F(y_t|\mathcal{F}_{t-1}) = \sum_{k=1}^{K} \alpha_{t,k} \Phi\left(\Omega_k^{-\frac{1}{2}}\left(Y_t - \Theta_{k0} - \Theta_{k1} Y_{t-1} - \Theta_{k2} Y_{t-2} - \ldots - \Theta_{kp_k} Y_{t-p_k}\right)\right) \qquad (2)$$

For the parameter estimation, Fong et al. (2007) and Kalliovirta et al. (2016) propose an expectation maximization (EM) algorithm, where the missing information for computing the mixture weights is derived in the expectation step completing the likelihood. In the maximization step, this completed likelihood is then maximized. Both steps are repeated sequentially until convergence is achieved.

These weights α_k in Eq. (1) and $\alpha_{t,k}$ in Eq. (2), however, lead to very unstable estimates in our application and to a huge variability in the impulse response functions for different starting values. In addition, from an economic point of view, the transition process should be dependent on variables known or suspected to have impact on the regime weights rather than on a function of, inter alia, the residuals of the MVAR model itself. To overcome this instability problem and to base the regime weights on economic reasoning, we propose to use a submodel for the mixture weights as done in mixture models for other contexts (Thompson et al., 1998; Wedel and Kamakura, 2000; McLachlan and Peel, 2000; Grün and Leisch, 2008; Dang and McNicholas, 2015).

2.2 Logit-Mixture Vector Autoregressive Models

We 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 regime weights. The resulting Logit-MVAR is given by:

$$F(y_t|\mathcal{F}_{t-1}) = \sum_{k=1}^{K} \tau_{t,k}\Phi\left(\Omega_k^{-\frac{1}{2}}\left(Y_t - \Theta_{k0} - \Theta_{k1}Y_{t-1} - \Theta_{k2}Y_{t-2} - \ldots - \Theta_{kp_k}Y_{t-p_k}\right)\right), \tag{3}$$

where in the case of a multinomial logit submodel

$$\tau_{t,k} = \frac{e^{\zeta_t^T \gamma_k}}{\sum_{j=1}^{K} e^{\zeta_t^T \gamma_j}} \tag{4}$$

are the mixture weights that are functionally related to the covariates ζ_t of the underlying multinomial logit submodel. Let now the information set $\mathcal{F}_{t-1}$ also incorporate the exogenously given and fixed variables ζ, which also may include lagged mixture weights. In this case, the $\tau_{t,k}$ are $\mathcal{F}_{t-1}$-measurable, and thus, the conditions provided by Kalliovirta et al. (2016, 486) still hold in our extension. 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.

Analogously to Fong et al. (2007) and Kalliovirta et al. (2016), we use an EM algorithm for the parameter estimation. Starting from the aforementioned MVAR($n, K, p_1, p_2, \ldots, p_K$) process,[3] we define $Z_t = (Z_{t,1}, \ldots, Z_{t,K})^\top, \forall t = 1, \ldots, T$ as the component affiliation of Y_t:

$$Z_{t,i} = \begin{cases} 1 & \text{if } Y_t \text{ comes from the } i^{th} \text{ component}; 1 \leq i \leq K \\ 0 & \text{otherwise.} \end{cases} \tag{5}$$

[3]Note that it is possible to specify different lag lengths for each mixture component. This could be particularly helpful in the context of a mixed frequency setting (see also Schorfheide and Song 2015).

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

$$l_t = \sum_{k=1}^{K} Z_{t,k} \log(\alpha_k) - \frac{1}{2}\sum_{k=1}^{K} Z_{t,k} \log|\Omega_k| - \frac{1}{2}\sum_{k=1}^{K} Z_{t,k}(e_{kt}^{\top}\Omega_k^{-1}e_{kt}) \tag{6}$$

where

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

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

$$l = \sum_{t=p+1}^{T} l_t = \sum_{t=p+1}^{T}\left(\sum_{k=1}^{K} Z_{t,k}\log(\alpha_k) - \frac{1}{2}\sum_{k=1}^{K} Z_{t,k}\log|\Omega_k| - \frac{1}{2}\sum_{k=1}^{K} Z_{t,k}(e_{kt}^{\top}\Omega_k^{-1}e_{kt})\right) \tag{7}$$

Expectation Step

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

$$\alpha_{t,k} = \frac{\alpha_k |\Omega_k|^{\frac{1}{2}} \mathrm{e}^{-\frac{1}{2}e_{kt}^{\top}\Omega_k^{-1}e_{kt}}}{\sum_{k=1}^{K}\alpha_k|\Omega_k|^{\frac{1}{2}}\mathrm{e}^{-\frac{1}{2}e_{kt}^{\top}\Omega_k^{-1}e_{kt}}}, \quad \forall k = 1, \ldots, K, \tag{8}$$

as in Kalliovirta et al. (2016). These weights $\alpha_{t,k}$, as already stated, lead to very unstable parameter estimates and variable impulse response functions for different starting values. In addition, we prefer describing the transition process with an econometric model to obtain further insights into the factors explaining the time-varying regime weights.

Therefore, we employ the mixture weights obtained in Eq. (8) as dependent variables in the 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:

$$\widehat{\tau}_{t,k} = \frac{e^{\zeta_t^T \gamma_k}}{\sum_{j=1}^{K} e^{\zeta_t^T \gamma_j}} \tag{9}$$

In the empirical application below, we restrict the description of the economy to a mixture of two states and, accordingly, estimate a binary logit model as the submodel, which simplifies Eq. (9) as follows:

$$\widehat{\tau}_{t,k} = \frac{1}{1 + e^{-(\sum_{j=0}^{n} \beta_j x_{t,j})}} \tag{10}$$

β denotes the coefficients of the logit model and n is the number of exogenous variables x_j with $x_0 = 1$.

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. (7) with respect to each variable. This yields the following estimates:

$$\widehat{\alpha}_k = \frac{1}{T-p} \sum_{t=p+1}^{T} \widehat{\tau}_{t,k} \tag{11}$$

$$\widehat{\widetilde{\Theta}}_k^{\top} = \left(\sum_{t=p+1}^{T} \widehat{\tau}_{t,k} X_{kt} X_{kt}^{\top} \right)^{-1} \left(\sum_{t=p+1}^{T} \widehat{\tau}_{t,k} X_{kt} Y_t^{\top} \right) \tag{12}$$

$$\widehat{\Omega}_k = \frac{\sum_{t=p+1}^{T} \widehat{\tau}_{t,k} \widehat{e}_{kt} \widehat{e}_{kt}^{\top}}{\sum_{t=p+1}^{T} \widehat{\tau}_{t,k}} \tag{13}$$

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

2.3 Data and Lag Length Selection

Our data set covers the period January 1999–December 2015. We estimate a four-variable Logit-MVAR model for the euro area with (i) the industrial production index (IP, in logs), (ii) the harmonized index of consumer prices inflation rate, and (iii) the VSTOXX volatility index (end of month data) as endogenous variables. The fourth variable is a composite indicator for the monetary policy stance. Until October 2008, we use the ECB's main refinancing rate (MRR).[4] After that date, we replace the MRR 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 normal times and crisis times in a single variable. All variables are linearly de-trended. Figure A1 in the Appendix shows all four variables over the sample period. Augmented Dickey-Fuller tests reject the null hypothesis of non-stationarity at the 1% level for all variables.

The selection of lag structures is based on a battery of specifications with different lag lengths for all four variables 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.[5] 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 four 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.

[4]Note that replacing the MRR with the EONIA leaves the results virtually unchanged.

[5]Figure A2 in the Appendix shows the regime-independent residuals alongside tests for autocorrelation, which do not reject the null hypothesis of no autocorrelation at the 10% level.

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.

2.4 Calculation of Impulse Response Functions

The focus of our paper is to introduce a Logit-MVAR model in the context of monetary policy transmission. Therefore, we follow Sims (1980a,b) and employ a rather simple recursive identification scheme using a Cholesky decomposition. The ordering of the baseline model follows the standard in the literature as IP is ordered first, followed by the inflation rate, the interest rate, and the VSTOXX. This identification scheme implies that monetary policy shocks affect output and prices only with a time lag, whereas monetary policy shocks can affect stock market volatility instantaneously. As part of our robustness tests, we allow for a contemporaneous reaction of monetary policy to stock market volatility shocks and order the interest after the VSTOXX while leaving the remaining order unchanged.

The calculation of impulse response functions is based on the bootstrap idea of Runkle (1987) with an adjustment to the multinomial context of the mixture model literature and done using the following six steps. First, we use the original sample and calculate the estimates $\widehat{\tau}_{t,k}$, $\widehat{\widetilde{\Theta}_k}$, and $\widehat{\Omega}_k$ using Eqs. (11)– (13). Second, we use the original regime-dependent error terms $e_{k1}, \ldots, e_{kt}$ 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 500 bootstrap samples using the centered errors $\mathbf{e}^*_{t,n}$. Fifth, we calculate the orthogonalized impulse responses for each of the 500 bootstrap samples with a horizon of 48 periods and the above mentioned identification scheme. Finally, we obtain the impulse response functions by calculating the mean over the 500 bootstrapped samples for each horizon. The corresponding confidence bands are calculated using the 2.5%, 16%, 84%, and 97.5% quantile of the distribution over the 500 bootstrapped samples for each horizon.

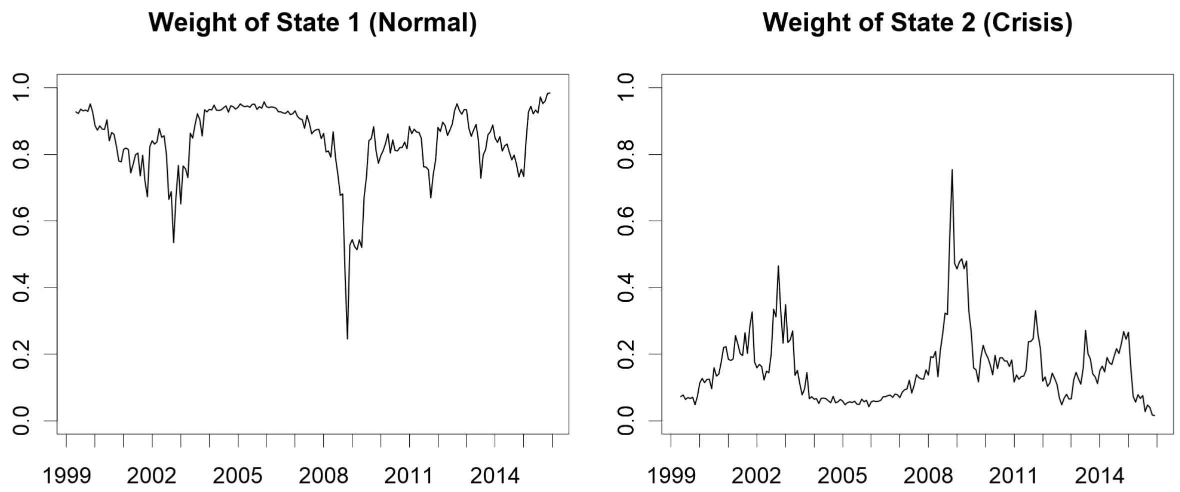
It is worth highlighting that for the calculation of the impulse responses we do not have to assume that the economy remains in a single state as is done in many Markov-switching VAR applications. The overall impulse response function is a continuously varying mixture of the impulse responses for both states, with the weights being determined by the underlying logit model.

3 Empirical Results

3.1 State Weights

In a first step, we present the weights of the different states obtained with the help of the logit submodel. Figure 1 shows a plot of the weights over time.

Figure 1: Weights of Both States



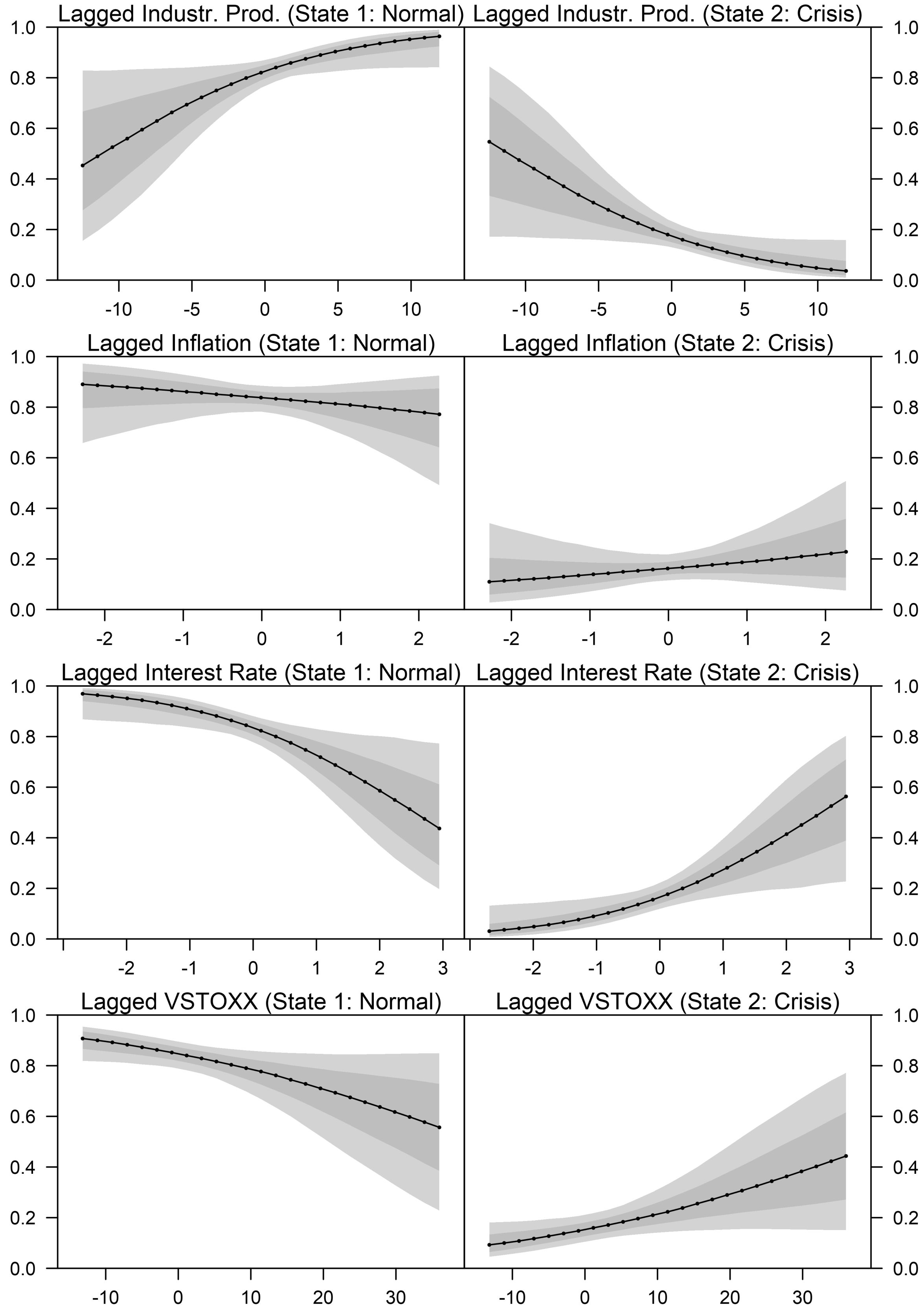
Notes: Weights of both states over time are obtained by estimation of Eq. (9).

State 2, in the right panel with an overall share of 15.8%, can be interpreted as a "crisis state" as its weights are particularly large after the Lehman collapse in 2008 with a share of 75.4%. Other, albeit smaller, peaks are found during the recession in 2002–2003, the euro area sovereign debt crisis in 2011, and the Greek sovereign debt crisis in 2015. Correspondingly, State 1, in the left panel with an overall share of 84.2%, can be interpreted as representing "normal times." Consequently, the impulse responses for Models 1 and 2 will provide a quantification of monetary policy transmission during "normal times" and "crisis times," respectively.

Figure 2 shows the predicted probabilities of the logit submodel based on the procedure by Hanmer and Kalkan (2013) for both states, and different realized values of lagged industrial production, lagged inflation, the lagged interest rate indicator, and the lagged VSTOXX. Higher values of industrial production, lower inflation rates, lower interest rates, and lower stock market volatility increase (decrease) the probability of being in State 1 (State 2). Three out of the four variables appear to play an important role in determining the regime weights, indicating that the focus on a single variable (e.g., as in smooth transition VARs) might oversimplify the state-determining process.

For small values of industrial production the probability of being in State 1 is 45.9%, whereas for large values the probability increases up to 96.4%. Similarly, the likelihood of being in the normal state decreases from 97.1% for small values of the interest rate (90.8% for the VSTOXX) to 43.8% (55.8%) when considering particularly large values. The predicted probabilities of inflation are—compared to the other three variables— rather flat around the overall average share of 84% for normal times (88.6% for low levels of inflation and 77.7% for high levels of inflation). When calculating the bivariate correlation of the crisis state weights (see the right panel of Figure 1) with all four variables of the submodel, it turns out that the one with the VSTOXX is the most pronounced ($\rho = 0.74$), followed by the interest rate ($\rho = 0.34$), industrial production ($\rho = -0.19$), and inflation ($\rho = 0.12$).

Figure 2: Predicted Probabilities of Logit Submodel



Notes: Figure shows the predicted probabilities of the logit submodel for both states and different realized values of industrial production, inflation, the interest rate indicator, and the VSTOXX. Dark gray-shaded areas indicate 68% confidence bands and light gray-shaded areas indicate 95% confidence bands.

3.2 Impulse Response Functions

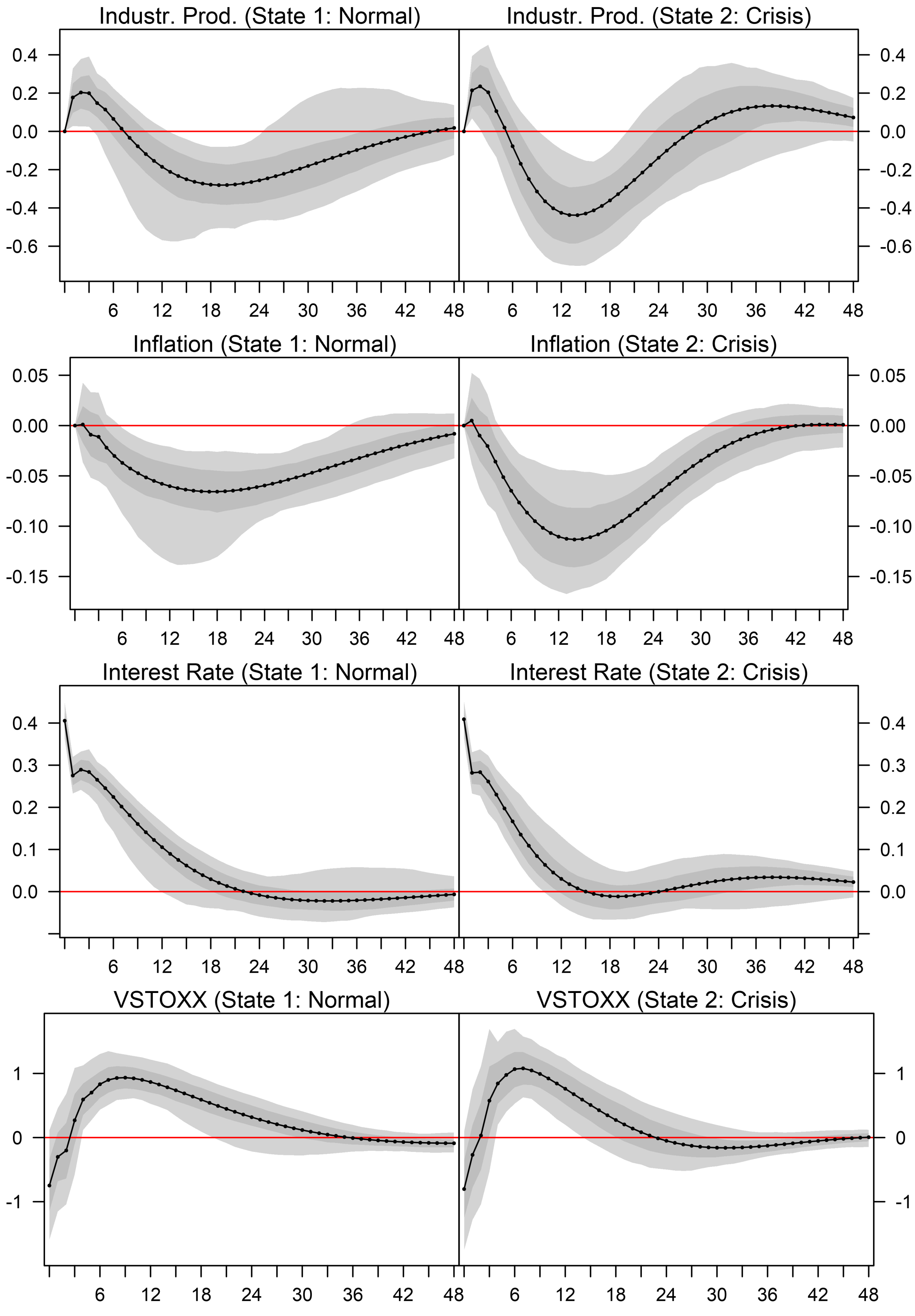
In a second step, we derive the impulse response after a one standard deviation shock in the error terms of the interest rate equation, which corresponds to roughly 40 basis points (bps) and is the same in both states. The results of the baseline ordering are shown in Figure 3. The following discussion of the significance of the impulse responses is based on the conservative 95% confidence bands. The discussion of differences in the responses across the states, however, will be based on the 68% confidence bands as statistical testing fails to differentiate across normal times and crisis times when using the 95% confidence bands.

There are three striking findings. First, all impulse responses are significant for prolonged time periods when considering the 95% confidence bands. This is typically not the case in linear VARs where researchers often resort to the 68% confidence bands (see also the reaction of IP in Figure 4 below).

Second, the contractionary effects are stronger in the crisis state as a monetary policy shock leads to a maximum reduction in IP by 43.8 bps 14 months after the shock and to a peak decrease in inflation by 11.3 bps 14 months after the shock. During normal times, the reduction in output and prices is less than two thirds of the aforementioned sizes (28.1 bps after 19 months for IP and 6.6 bps after 17 months for inflation).[6] Similarly, the VSTOXX increases more strongly in the crisis state (107.9 bps after seven months) than in the normal state (93.5 bps after nine months).

[6]Note that the response of IP is significantly positive on impact in both states, a finding in line with previous literature for the euro area using a linear VAR (e.g., Neuenkirch, 2013). If at all, we would expect such an increase over the very short-run for inflation (i.e., the "prize puzzle"). As part of our robustness test (not shown but available on request), we transformed the indicator for industrial production in several ways. However, the result of a short-run increase after a contractionary monetary policy shock is robust to these modifications. A possible solution could be to employ sign restrictions to identify a contractionary monetary policy shock, that is, to restrict the responses of IP and inflation to be negative for a certain horizon after an increase in the interest rate. Since the focus of our paper is to introduce a Logit-MVAR model in the context of monetary policy transmission for the first time, this is something we leave for future research.

Figure 3: Reaction to Contractionary Monetary Policy Shock: Baseline Ordering



Notes: Impulse responses for both states are obtained by the bootstrap procedure described in Section 2.4 and the following ordering: (i) IP, (ii) inflation, (iii) interest rate, and (iv) VSTOXX. Dark gray-shaded areas indicate 68% confidence bands and light gray-shaded areas indicate 95% confidence bands.

Third, however, the effect of monetary policy shocks is less enduring during crisis times compared to normal times. The effects become insignificant in the crisis state after 20 months (IP), 30 months (inflation), and 14 months (VSTOXX), respectively, whereas in the normal state the influence becomes insignificant four to five months later (after 24/34/19 months for IP/inflation/the VSOTXX). The outside lag, in turn, does not differ by much for the three variables over the two states.

Combining the aforementioned two findings, statistical testing indicates a significantly stronger negative reaction for IP in the crisis state 5–17 months after the shock, whereas the picture reverses after roughly two years (after 25–47 months), when the negative response is stronger in the normal state. A similar picture emerges for inflation where the response in the crisis (normal) state is stronger 5–22 (32–47) months after the shock. In case of the VSTOXX, a significantly stronger positive reaction for the crisis (normal) state is found after 5–6 (15–37) months. One possible explanation of the fact that the reaction is less enduring during crisis times might be that the monetary policy shocks themselves are—despite their equal size in both states—less persistent in the crisis state. Indeed, statistical testing reveals that these are larger during normal times 7–20 months after the shock.

As part of our robustness tests, we allow for a contemporaneous reaction of monetary policy to stock market volatility shocks and order the interest rate after the VSTOXX while leaving the remaining order unchanged. The underlying idea is that the ECB reacts instantaneously to changes in stock market volatility, which also might serve as proxy for uncertainty or financial stress. A more technical reason in favor of this alternative ordering is that we rely on the shadow rate for the period after the Lehman bankruptcy. Movements in volatility might affect the term premia, which, in turn, are relevant for our indicator of the monetary policy stance as the term structure of interest rates is transformed into a single variable measuring all conventional and unconventional monetary policy measures.

Figure A3 in the Appendix shows the impulse responses after a contractionary monetary policy shock for this alternative ordering. We do not find much of a difference in the reactions of IP, inflation, and the interest rate itself to monetary policy shocks as compared to the results for the baseline ordering. The peak responses for the VSTOXX are also roughly the same for both orderings. The only difference is that its reaction is restricted to being zero on impact in the alternative ordering, whereas we observe an insignificant negative reaction on impact in the baseline ordering. To summarize, we are confident that the results are robust with respect to the two different recursive orderings employed in this paper.

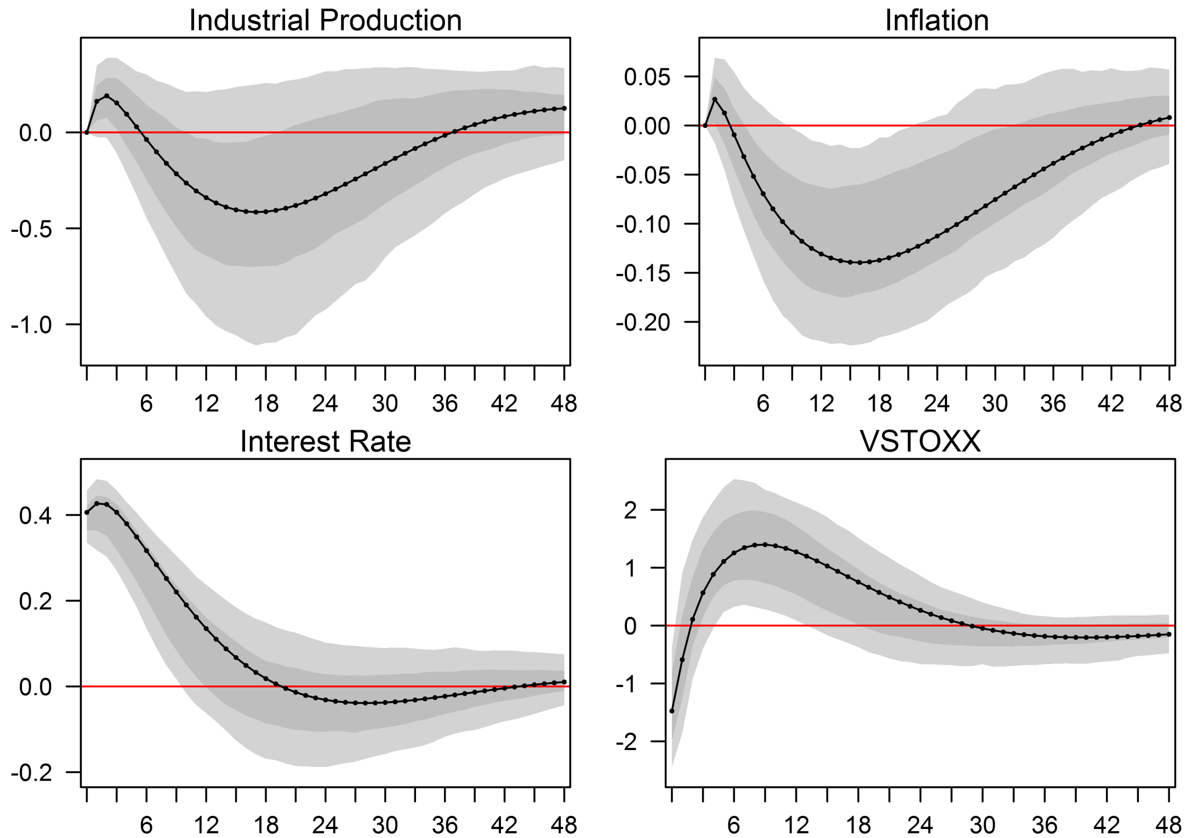
3.3 Comparison to Linear VAR

One crucial advantage of the Logit-MVAR model is the gain in efficiency compared to a standard linear VAR model. Figure 4 shows the impulse responses of a contractionary shock of 40 bps (i.e., the same size as for the Logit-MVAR) for a linear VAR model obtained using the baseline identification strategy described in Section 2.4.

The maximum contractionary effect found for IP in the linear VAR (−41.5 bps) is in between those of the crisis state and the normal state of the Logit-MVAR. In the case of inflation (−14.0 bps) and the VSTOXX (139.9 bps), the peak effects are even larger than in the crisis state of the Logit-MVAR. However, the significance of the impulse responses is much more pronounced in the Logit-MVAR. Indeed, the reaction of IP is never significant when considering the 95% confidence bands. Furthermore, the reaction of inflation (the VSTOXX) becomes insignificant after 21 (12) months as compared to 30 and 34 (14 and 19) months in the two states of the Logit-MVAR.

Comparing the residual sum of squares (RSS) to the Logit-MVAR indicates a worse fit for the linear VAR in all four equations. The decrease in fit ranges from 9.9% for the inflation equation to 31.4% for the IP equation. Moreover, at least the 68% confidence bands of the Logit-MVAR are symmetric around the mean responses. In contrast, this is not the case for a linear VAR where the mean is clearly below or above the median, presumably due to outliers (or due to forcing two different states in a single one). In short, monetary policy transmission in the euro area can be described more efficiently with the help of a Logit-MVAR model than with a conventional linear VAR model.

Figure 4: Impulse Reponses for Linear VAR



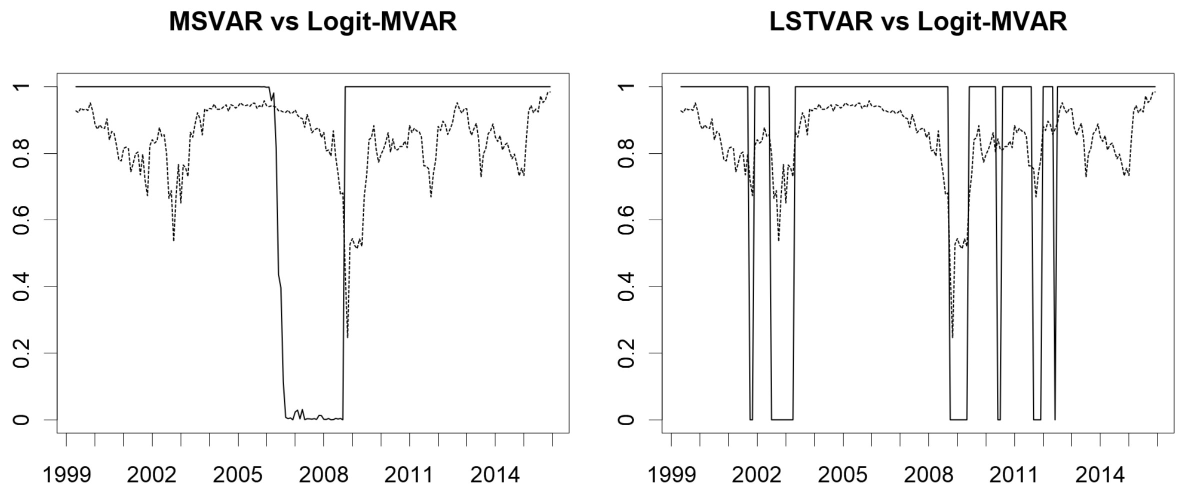
Notes: The figure shows impulse responses to a shock in the interest rate indicator with the same size as in the Logit-MVAR. Dark gray-shaded areas indicate 68% confidence bands and light gray-shaded areas indicate 95% confidence bands that are created by bootstrapping and 500 replications.

3.4 Comparison to Non-Linear VARs

Next, we compare the performance of our Logit-MVAR 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.

The left panel of Figure 5 shows an almost perfect binary distinction of regimes for the MSVAR. Interestingly, the first non-zero value for the non-dominant state is observed in March 2006, whereas the last one can be found in September 2008, that is, the month of the Lehman collapse. Hence, the non-dominant regime cannot be considered as a crisis regime. In line with this finding, the correlation of the non-dominant regime is strongest with IP (ρ=0.78), followed by the interest rate (ρ=0.72), and inflation (ρ=0.36). Here, the VSTOXX ranks last (ρ=−0.19). Consequently, the non-dominant regime can be considered as capturing the build-up to the financial crisis.

Figure 5: Regime Probabilities of Non-Linear VAR Models



Notes: The solid line in the left (right) panel shows the probabilities to be in the dominant state for the MSVAR (LSTVAR) model. The dashed lines shows the state weights for "normal" times for the Logit-MVAR model, which are taken from the left panel in Figure 1.

In line with our previous results for the Logit-MVAR, we use the VSTOXX as the transition variable for the LSTVAR model. The right panel of Figure 5 favors a "sharp" threshold VAR model, as there is no observation with a regime probability other than 0 or 1.[7] The non-dominant state of the LSTVAR can be interpreted as a "crisis state" as it takes the value 1 during the recession in 2002–2003, after the Lehman collapse in 2008, and during the euro area sovereign debt crisis in 2011. Indeed, the correlation with the crisis state in the Logit-MVAR is quite pronounced ($\rho = 0.74$), showing that both models capture similar crisis episodes.

Figure 5 indicates one major advantage of the Logit-MVAR model. In this model, the state affiliations are allowed to continuously vary over the complete sample period. Therefore, the Logit-MVAR model allows for different "degrees" of crises, which in turn are captured by different weights of the two states in the impulse response functions. In the other two types of non-linear models, we see an almost perfect bi-

[7]Note that the estimated smoothness parameter ($\gamma = 92.0$) is larger than in the original paper of Weise (1999). However, restricting the smoothness parameter to a very small value of, say, $\gamma = 1$ does not change the pattern of the binary regime distinction with the data set at hand.

nary distinction of the regimes, a finding that only allows for two extreme cases and no states in between.

Similar to the case of the Logit-MVAR, we find no evidence for autocorrelation in the residuals of the MSVAR or the LSTVAR at the 10% significance level. Comparing the RSS of the MSVAR (LSTVAR) to the Logit-MVAR indicates a slightly (clearly) better fit in all four equations. For the MSVAR, the increase in fit ranges from 2.1% for the interest rate equation to 7.4% for the VSTOXX equation. In the case of the LSTVAR, the improvement ranges from 9.4% for the inflation equation to 31.2% for the VSTOXX equation.

As a final step, we calculated impulse responses for both regimes in both non-linear VAR models.[8] For both the MSVAR and the LSTVAR, the impulse responses for the dominant regime are well-behaved. However, those for the non-dominant regime are not stable at all as these start exploding after roughly 18 months in the case of the MSVAR, and after roughly nine months in the case of the LSTVAR, respectively. Hence, the Logit-MVAR provides a stable identification of two states in the monetary policy transmission mechanism for the euro area. Given the better fit of the MSVAR and LSTVAR, it might be the case that these models suffer from overfitting, at least for the data set at hand. Furthermore, the identification of continuously varying state weights might be helpful in obtaining stable impulse responses as we do not have to assume that the economy remains in a single state when calculating these.

4 Conclusions

In this paper, we estimate a logit mixture vector autoregressive model describing monetary policy transmission in the euro area over the period 1999–2015. This model allows us to differentiate between different states of the economy with the time-varying state weights being determined by an underlying logit model. In contrast to other classes of non-linear VARs, the regime affiliation is neither strictly binary, nor binary with a transition period. Mixture VARs are comprised of a composite model with con-

[8] The impulse responses are not shown but available on request.

tinuous state affiliations that are allowed to vary over the complete sample period and that are potentially based on multiple variables.

We show that monetary policy transmission in the euro area indeed can be described as a mixture of two states. The second state with an overall share of 16% can be interpreted as a "crisis state" as its weights are particularly large after the Lehman collapse in 2008. Other, albeit smaller, peaks are found during the recession in 2002–2003, the euro area sovereign debt crisis in 2011, and the Greek sovereign debt crisis in 2015. Correspondingly, the first state with an overall share of 84% can be interpreted as representing "normal times."

In both states, output and prices decrease after monetary policy shocks. During crisis times, the contraction is much stronger, as the peak effect of both variables is roughly one-and-a-half times as large when compared to normal times. In contrast, despite this stronger peak effect, the effect of monetary policy shocks on output and prices is less enduring during crisis times. Both results provide a strong indication that the transmission mechanism for the euro area is indeed different during times of economic and financial distress and are well in line with previous findings in the literature.

One implication of our results is that monetary policy can be a powerful tool for economic stimulus during crisis times in the euro area. However, the expansionary effects are found to be rather short-lived indicating that more persistent interest rate cuts (or other expansionary non-conventional policy measures) are required to move the economy out of a recession.

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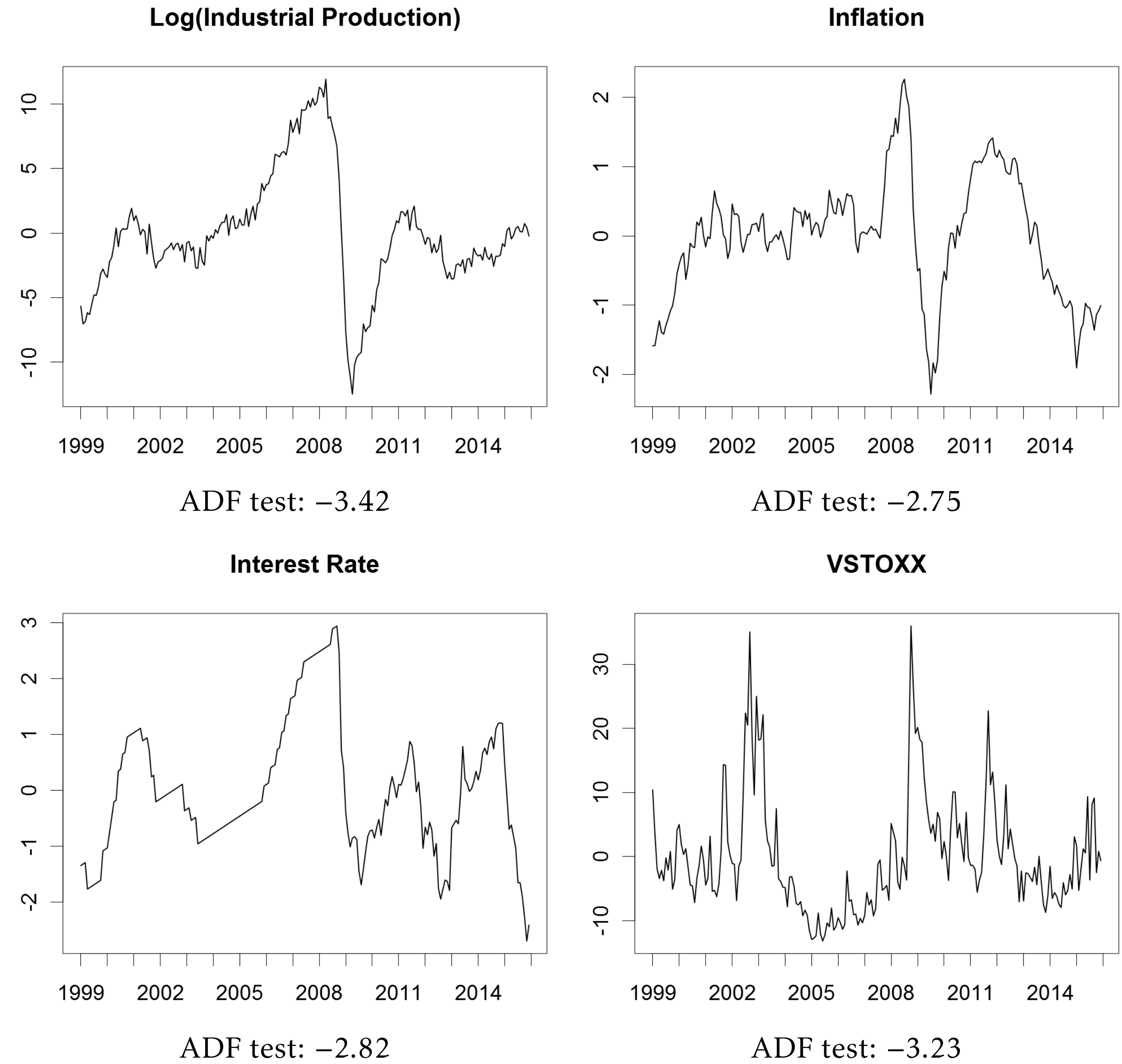
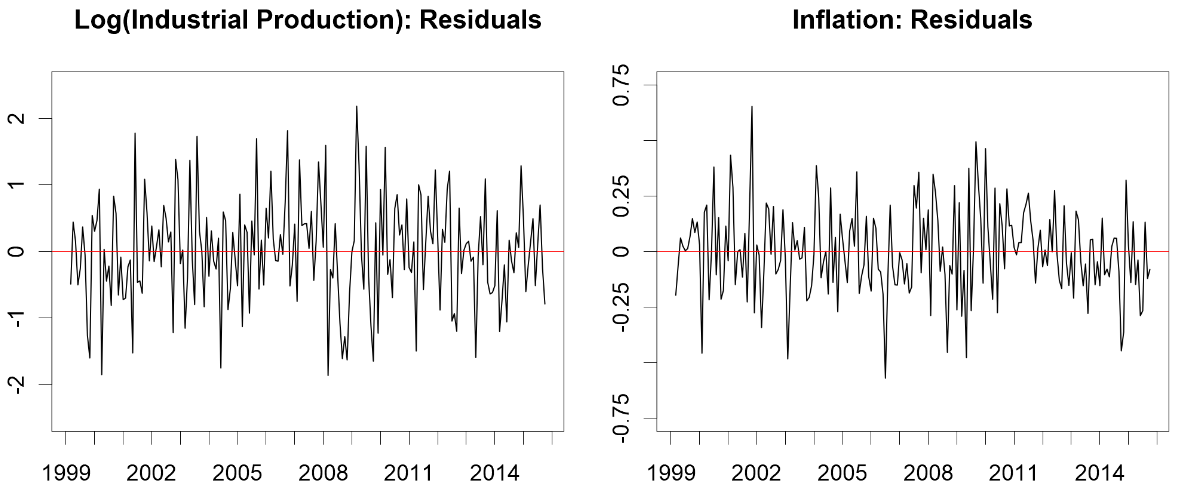
Appendix

Figure A1: Macroeconomic Variables for the Euro Area 1999–2015

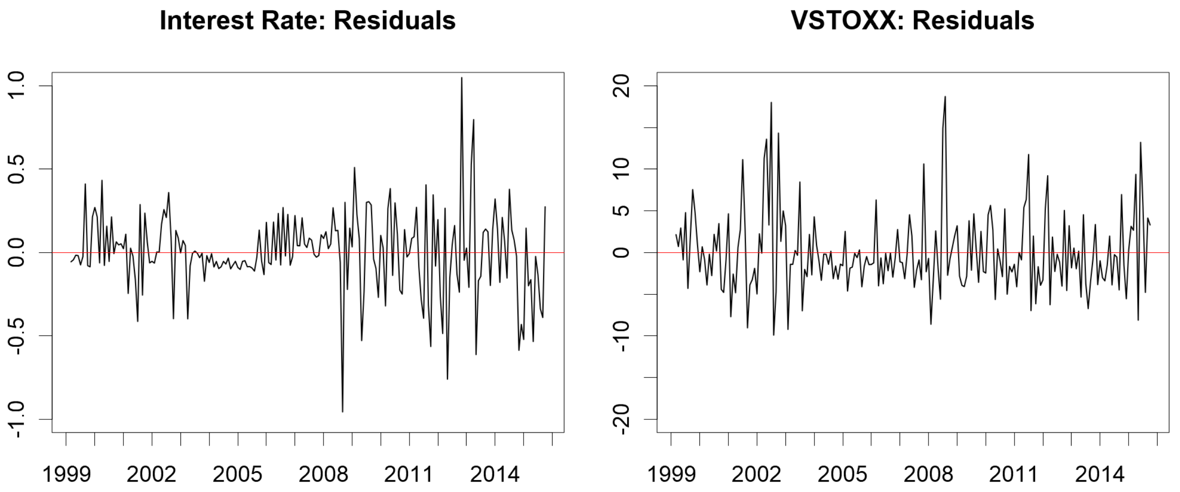


Notes: All series are linearly de-trended. All Augmented Dickey-Fuller (ADF) tests reject the null hypothesis of non-stationarity at the 1% significance level. *Source:* ECB (IP, inflation, and MRR), Wu and Xia (2016) (shadow interest rate), and STOXX Limited (VSTOXX).

Figure A2: Residuals of Logit-MVAR(4,4) Model



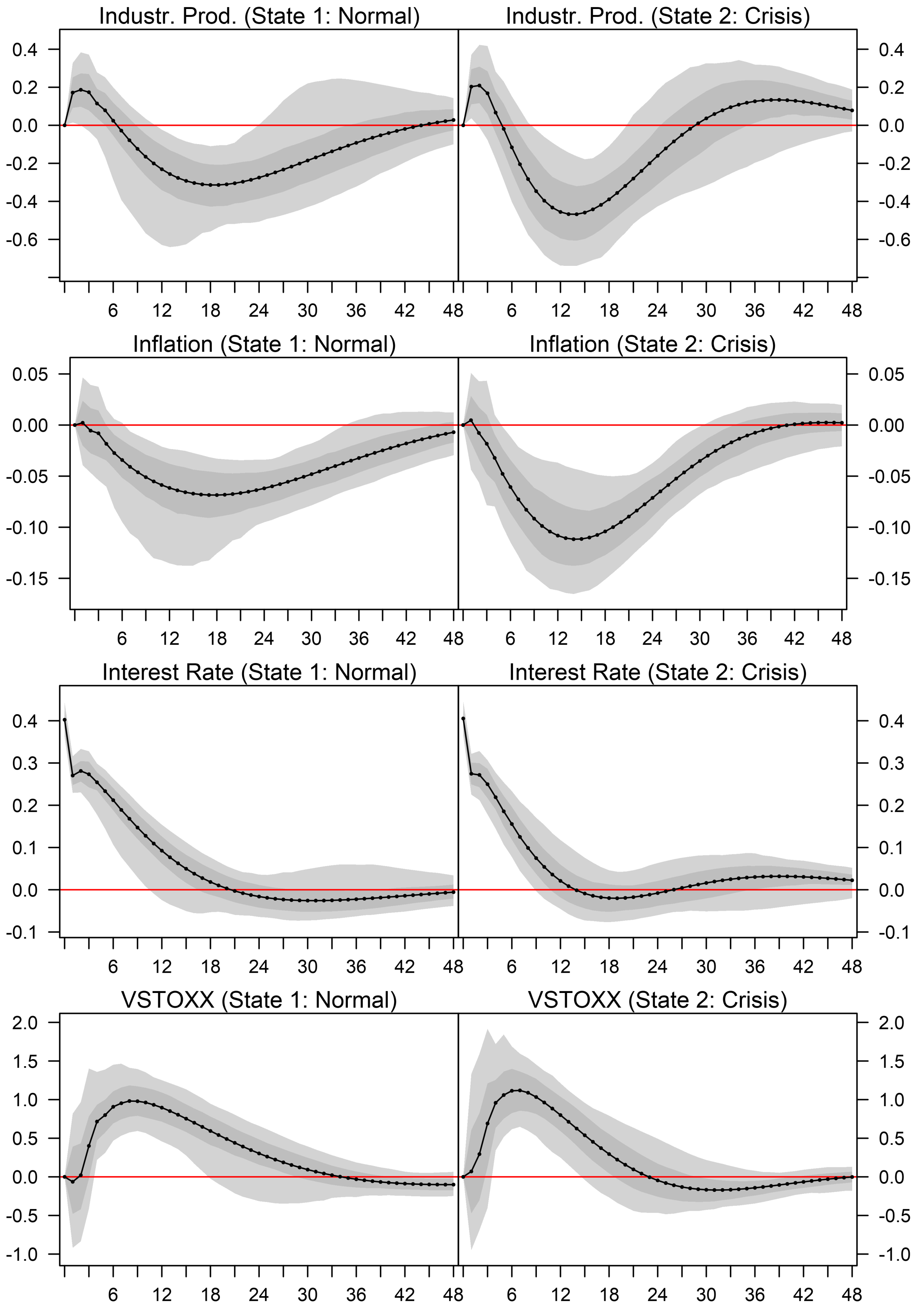
Box-Ljung test: 0.42 Box-Ljung test: 2.70



Box-Ljung test: 4.85 Box-Ljung test: 2.26

Notes: All Box-Ljung tests for autocorrelation with six lags do not reject the null hypothesis of no autocorrelation at the 10% significance level.

Figure A3: Reaction to Contractionary Monetary Policy Shock: Alternative Ordering



Notes: Impulse responses for both states are obtained by the bootstrap procedure described in Section 2.4 and the following ordering: (i) IP, (ii) inflation, (iii) VSTOXX, and (iv) interest rate. Dark gray-shaded areas indicate 68% confidence bands and light gray-shaded areas indicate 95% confidence bands.