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Working Paper

State-dependent transmission of monetary policy in the euro area

Research Papers in Economics, No. 15/16

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Suggested Citation: Burgard, Jan Pablo; Neuenkirch, Matthias; Nöckel, Matthias (2016) : State-dependent transmission of monetary policy in the euro area, Research Papers in Economics, No. 15/16, Universität Trier, Fachbereich IV – Volkswirtschaftslehre, Trier

This Version is available at:
https://hdl.handle.net/10419/156260

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State-Dependent Transmission of Monetary Policy in the Euro Area

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State-Dependent Transmission of Monetary Policy in the Euro Area*

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December 21, 2016

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 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 (short) transition period. 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 80% (20%) 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 more than twice 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.

*Thanks to Tobias Kranz and Peter Tillmann for their helpful comments on earlier versions of the paper. The usual disclaimer applies.

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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 following 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 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 (short) 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.

[1] Tenreyro and Thwaites (2016) find the opposite. In their paper, US monetary policy is less effective 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 during 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 20% can be interpreted as a "crisis state," as its weights are particularly large during the recession in 2002–2003, after the Lehman collapse in 2008, during the euro area sovereign debt crisis in 2011, and during the Greek sovereign debt crisis in 2015. Correspondingly, the first state with an overall share of 80% 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 more than twice 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 a 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, could be a more realistic description of the data. Smooth transition VAR models (Weise 1999; Camacho 2004) attempt to fill this gap. Nevertheless, outside of the short transition period, the economy remains rigidly in one state in this class of models.

2.1 Mixture Vector Autoregressive Models

In contrast to these models, MVAR models proposed by Fong et al (2007) allow for a composite model with the weights of the states continuously varying over the complete sample period. The model consists of K components, each following a linear Gaussian VAR process with an individual lag order p_k. The estimation is performed using an expectation-maximization algorithm. An MVAR(n,K,p_1,p_2,...,p_K) model with K regimes and an n-dimensional vector of endogenous variables Y_t is defined as:

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

$\mathcal{F}$ denotes the information set up to time $t-1$. $\Phi(.)$ is the multivariate cumulative distribution function of the Gaussian distribution with mean zero and variance-covariance matrix equal to the n-dimensional identity matrix I_n. The probability for the k^{th} component to occur is labeled by α_k. 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. In order to get a unique characterization of the model, we have to constrain $\alpha_1 \geq \alpha_2 \geq \ldots \geq \alpha_K \geq 0$ and $\sum_{k=1}^{K} \alpha_k = 1$

(Titterington et al 1985; McLachlan and Basford 1988). Fong et al (2007) provide a proof of two sufficient stationarity conditions for MVAR processes.

2.2 Estimation

Starting from the aforementioned MVAR(n,K,p_1,p_2,...,p_K) process, we define $Z_t = (Z_{t,1},\ldots,Z_{t,K})^\top, \forall t = 1,\ldots,T$ as the component affiliation of Y_t:

$$Z_{t,i} = \begin{cases} 1 & \text{if } Y_t \text{ comes from the } i^{th} \text{ component; } 1 \leq i \leq K \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

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

$$l_t = \sum_{k=1}^{K} Z_{t,k} \log(\alpha_k) - \frac{1}{2}\sum_{k=1}^{K} Z_{t,k} \log|\Omega_k| - \frac{1}{2}\sum_{k=1}^{K} Z_{t,k}(e_{kt}^\top \Omega_k^{-1} e_{kt}) \tag{3}$$

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:

$$l = \sum_{t=p+1}^{T} l_t = \sum_{t=p+1}^{T} \left(\sum_{k=1}^{K} Z_{t,k} \log(\alpha_k) - \frac{1}{2}\sum_{k=1}^{K} Z_{t,k} \log|\Omega_k| - \frac{1}{2}\sum_{k=1}^{K} Z_{t,k}(e_{kt}^\top \Omega_k^{-1} e_{kt}) \right) \tag{4}$$

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 $\tau_{t,k} \equiv E(Z_{t,k}|\widetilde{\Theta}, Y_1,\ldots,Y_T)$ to be the conditional expectation of the k^{th} compo-

nent of Z_t, we obtain the mixture weights:

$$\widetilde{\tau}_{t,k} = \frac{\alpha_k |\Omega_k|^{\frac{1}{2}} \mathrm{e}^{-\frac{1}{2} e_{kt}^\top \Omega_k^{-1} e_{kt}}}{\sum_{k=1}^{K} \alpha_k |\Omega_k|^{\frac{1}{2}} \mathrm{e}^{-\frac{1}{2} e_{kt}^\top \Omega_k^{-1} e_{kt}}}, \quad \forall k = 1, \ldots, K \tag{5}$$

These weights $\tau_{t,k}$, however, lead to very unstable estimates and 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 regime changes 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 changes on economic theory, we propose to use a submodel for the mixture weights as done in mixture models for other contexts (Dang and McNicholas 2015; Grün 2008; McLachlan and Peel 2000; Thompson et al 1998; Wedel and Kamakura 2000).

Similar to Thompson et al (1998) and Wong and Li (2001), we use a multinomial logit model for the transition process. The mixture weights obtained in Eq. (5) are employed as dependent variables and the explanatory variables are denoted by the vector ζ. The γ_j's are the estimated parameters of the multinomial logit model, where we set $\gamma_1 \equiv 0$ for identification reasons. The predicted mixture weights are then the predictions of the submodel given ζ, that is:

$$\widetilde{\tau}_{t,k} = \frac{\mathrm{e}^{\zeta_t^T \gamma_k}}{\sum_{j=1}^{K} \mathrm{e}^{\zeta_t^T \gamma_j}} \tag{6}$$

In the empirical application below, we restrict the description of the economy to a mixture of two states allowing us to estimate a binary logit model as submodel that simplifies Eq. (6) as follows:

$$\widetilde{\tau}_{t,k} = \frac{1}{1 + \mathrm{e}^{-(\sum_{j=0}^{n} \beta_j x_{t,j})}} \tag{7}$$

β denotes the coefficients of the logit model and n is the number of exogenous variables x_j with $x_0 = 1$. In each iteration step, we replace the values for $\widetilde{\tau}_{t,k}$ from Eq. (5) with

the expected value of the logit model in Eq. (7):

$$\widehat{\tau}_{t,k} = E\left[\frac{1}{1+\mathrm{e}^{-(\sum_{j=0}^{g}\beta_j x_{t,j})}} \mid X_{kt}, \beta_j\right] \quad \forall k = 1,\ldots,K, \forall j = 1,\ldots,n \tag{8}$$

One major advantage of our approach compared to threshold VARs and smooth transition VARs is that we do not require a weakly stationary transition variable. Hence, we do not lose information in the levels of non-stationary time series.[2]

Maximization Step

Given the expected values for Z, we can obtain estimates for the α_k's, the parameter matrixes $\widetilde{\Theta}_k$, and the variance-covariance matrices Ω_k by maximizing the log-likelihood function l in Eq. (4) with respect to each variable. This yields the following estimates:

$$\widehat{\alpha}_k = \frac{1}{T-p}\sum_{t=p+1}^{T}\widehat{\tau}_{t,k} \tag{9}$$

$$\widehat{\widetilde{\Theta}}_k^{\top} = \left(\sum_{t=p+1}^{T}\widehat{\tau}_{t,k}X_{kt}X_{kt}^{\top}\right)^{-1}\left(\sum_{t=p+1}^{T}\widehat{\tau}_{t,k}X_{kt}Y_t^{\top}\right) \tag{10}$$

$$\widehat{\Omega}_k = \frac{\sum_{t=p+1}^{T}\widehat{\tau}_{t,k}\widehat{e}_{kt}\widehat{e}_{kt}^{\top}}{\sum_{t=p+1}^{T}\widehat{\tau}_{t,k}} \tag{11}$$

Both iteration steps are repeated until we achieve convergence using a tolerance parameter of 10^{-6}.

2.3 Data

Our dataset covers the period January 1999–December 2015. We estimate a five-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, (iii) the monetary aggregate M3 (in logs), and (iv) the VSTOXX volatility index as endogenous variables. The fifth variable is a composite indicator for the monetary policy stance.

[2]Note that an augmented Dickey-Fuller test indeed fails to reject that the key variable in the underlying logit model (i.e., the VSTOXX) is non-stationary (see Section 3.1).

From January 1999 through October 2008, we use the ECB's main refinancing rate (MRR).[3] After October 2008, 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 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.

We add the monetary aggregate M3 and the VSTOXX to a standard monetary policy transmission model with output, prices, and interest rates for two reasons. First, the ECB places an emphasis on monetary analysis in its two pillar strategy. Second, financial market turbulences clearly play a role for monetary policy makers and, in particular, for unconventional monetary policy (see also Gambacorta et al 2014).

Our concomitant model that determines the state weights includes four of these five variables: (i) industrial production in logs, (ii) the inflation rate, (iii) the composite interest rate indicator, and (iv) the VSTOXX volatility index.[4] Figure A1 in the Appendix shows all five variables over the sample period.

2.4 Lag Length Selection

We use the Bayesian information criterion (BIC), the Hannan-Quinn information criterion (HQ), and the Akaike information criterion (AIC) to select an appropriate lag length for each mixture component k. Following Fong et al (2007), we use the weighted sum of component densities as the multivariate application of the weighted sum of the conditional log likelihood:

$$\log \mathcal{L} = \sum_{t=1}^{T} \log \sum_{k=1}^{K} \alpha_k \left\{ |\Omega_k|^{-\frac{1}{2}} \, \mathrm{e}^{-\frac{1}{2} e_{kt}^{\top} \Omega_k^{-1} e_{kt}} \right\} \tag{12}$$

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

[4] We do not include the monetary aggregate M3 into the submodel as this leads to non-stationary impulse responses. Interestingly, the inclusion of M3 into the main model is a key requirement for obtaining stationary impulse responses.

The information criteria are then defined as:

$$BIC = -2\log\mathcal{L} + \log(T - p_{\max})\left\{\left(n^2\sum_{k=1}^{K}p_k\right) + K\left[\frac{n(n+1)}{2} + n + 1\right] - 1\right\} \quad (13)$$

$$AIC = -2\log\mathcal{L} + 2\left\{\left(n^2\sum_{k=1}^{K}p_k\right) + K\left[\frac{n(n+1)}{2} + n + 1\right] - 1\right\} \quad (14)$$

$$HQ = -2\log\mathcal{L} + 2\log\Big[\log(T - p_{\max})\Big]\left\{\left(n^2\sum_{k=1}^{K}p_k\right) + K\left[\frac{n(n+1)}{2} + n + 1\right] - 1\right\} \quad (15)$$

Table 1 shows the information criteria for different lag combinations.[5] All three information criteria favor a lag length of two for both states. Consequently, we estimate a Logit-MVAR model with five endogenous variables (IP, inflation, M3, interest rate, and VSTOXX), two states, two lags per state, and four variables in the submodel determining the state weights (IP, inflation, interest rate, and VSTOXX).

Table 1: Lag Length Selection

Lags	AIC	BIC	HQ
2,2	171.82	638.28	360.55
3,2	240.60	788.94	462.48
4,2	279.04	909.01	533.98
3,3	282.86	913.79	538.16
4,3	324.45	1036.88	612.76
4,4	377.51	1172.41	699.20

2.5 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 (1980) and employ a rather simple recursive identification scheme using a Cholesky decomposition. The ordering follows the standard in the literature as IP is ordered first, followed by the inflation rate, M3, the interest rate, and the VSTOXX. This identification scheme implies that monetary policy shocks affect output, prices, and the monetary aggregate only with a time lag, whereas monetary policy shocks can affect stock market volatility instantaneously.

[5]Note that we do not allow for combinations with one lag in a particular state as in such a parsimonious specification the impulse responses fail to sufficiently capture the dynamics in the model.

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. We complete the calculation 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. (9)–(11). 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 $\mathbf{e}^*_{t,n} = \mathbf{e}_{t,n} - \sum_{t=1}^{T} \mathbf{e}_{t,n}$ 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 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.

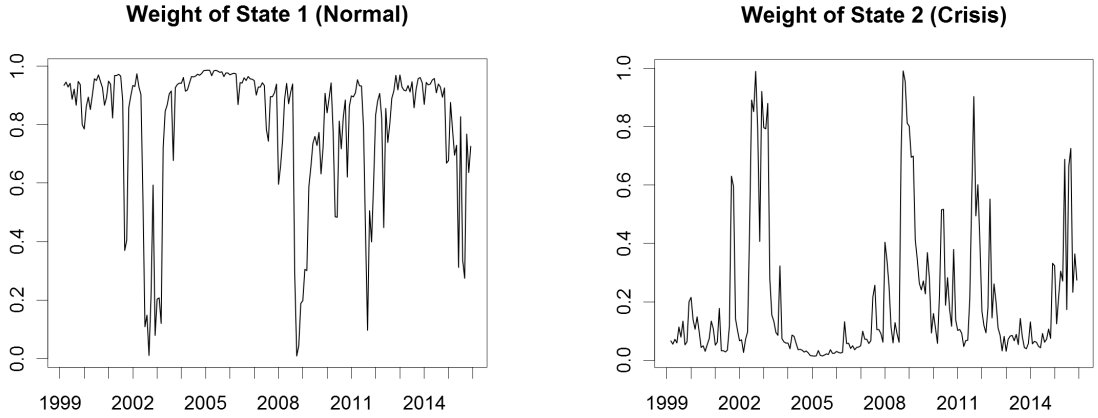
3 Empirical Results

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. State 2 in the right panel with an overall share of 20.1% can be interpreted as a "crisis state" as its weights are particularly large during the recession in 2002–2003, after the Lehman collapse in 2008, during the euro area sovereign debt crisis in 2011, and during the Greek sovereign debt crisis in 2015. Correspondingly, state 1 in the left panel with an overall

share of 79.9% 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 1: Weights of Both States



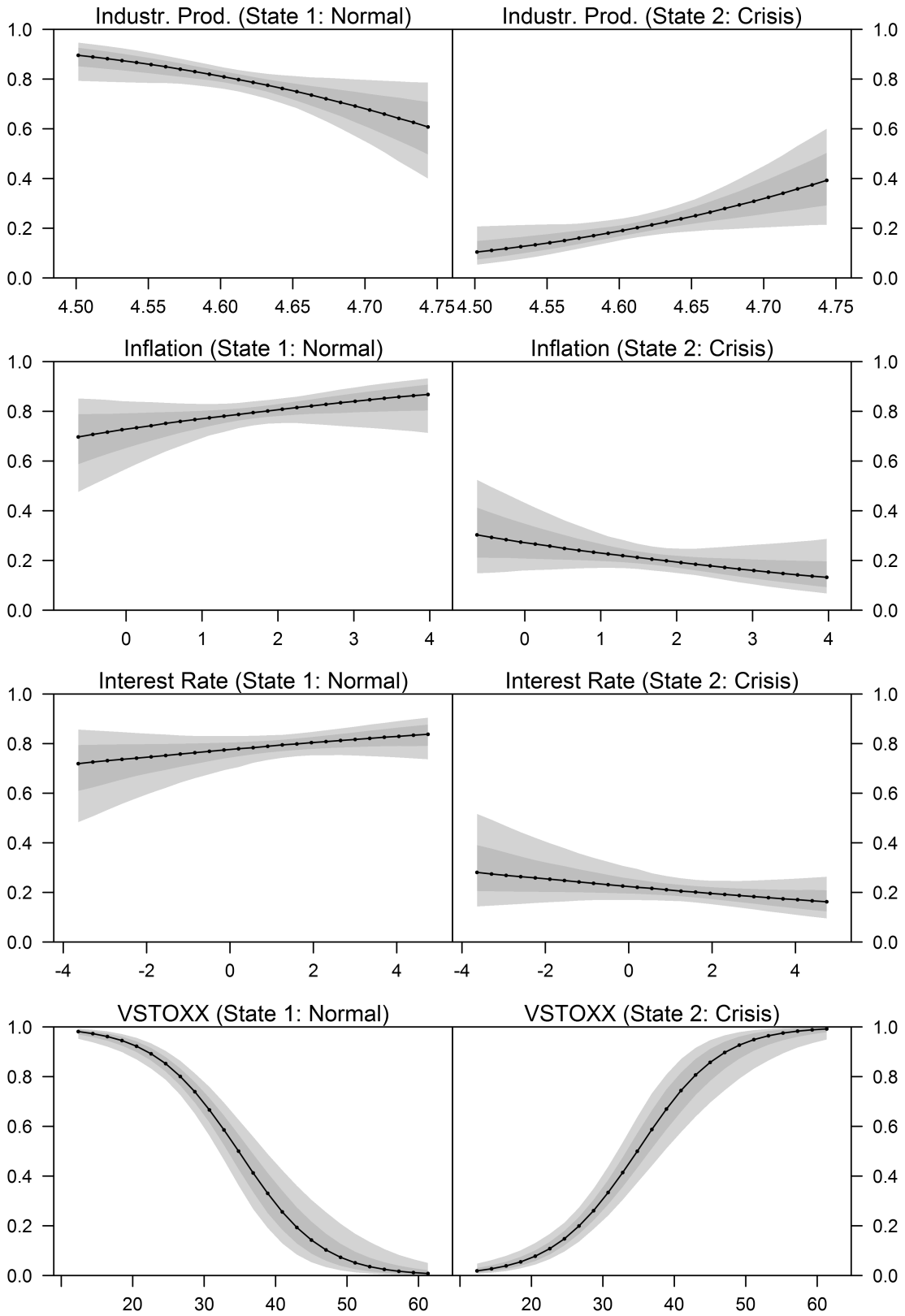
Notes: Weights of both states over time are obtained by estimation of Eq. (6).

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 industrial production, inflation, the interest rate indicator, and the VSTOXX. The most striking result is that the VSTOXX clearly separates the regimes. For small values of the volatility index the probability of being in state 1 is almost 100% (left panel), whereas for large values the probability of being in state 2 is almost 100% (right panel).

The predicted probabilities of the other three variables are rather flat around the overall shares of 80% (normal times) and 20% (crisis times) found in Figure 1. Higher levels of inflation and the interest rate are associated with a larger probability of being in normal times. In contrast, larger figures for industrial production lead to a higher probability of being in crisis times. The latter counterintuitive result might be explained by collinearity as there is substantial correlation between industrial production and inflation in our sample ($\rho = 0.48$).[6]

[6]Note that based on these results we also considered reducing the submodel to a single variable, that is, the VSTOXX. However, the state weights in Figure 1 and the impulse responses in Figure 3 are less distinct in such a parsimonious setting. Therefore, we stick to the setup with the four-variable logit submodel.

Figure 2: Predicted Probabilities of Logit Model

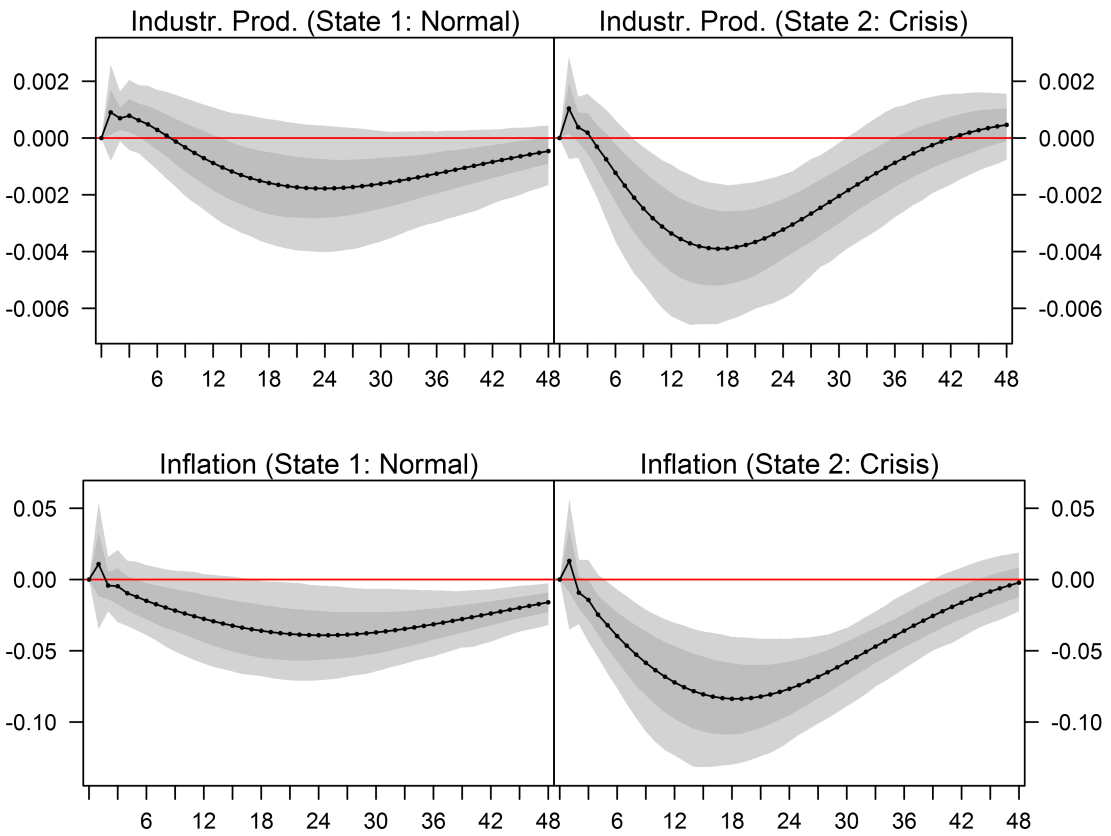


Notes: Figure shows the predicted probabilities of the logit submodel for both states and different realized values of industrial production, inflation, the interest rate indicator, and the VSTOXX. Dark grey-shaded areas indicate 68% confidence bands and light grey-shaded areas indicate 95% confidence 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 40.37 basis points.[7] The results for output and prices are presented in Figure 3.

Figure 3: Reaction of Output and Inflation to Shocks in the Interest Rate



Notes: Impulse responses for both states are obtained by the bootstrap procedure described in Section 2.5. Dark grey-shaded areas indicate 68% confidence bands and light grey-shaded areas indicate 95% confidence bands.

There are three striking findings. First, the impulse responses are much more significant in the crisis state. Even at the conservative 5% level the responses for output and inflation are significant 9–30 and 5–38 months after the monetary policy shock, respectively. In contrast, in the normal state the responses for output are never significant at the 5% level and the responses for inflation become significant for the first time 16 months after the interest rate shock. Second, the contractionary effects are stronger

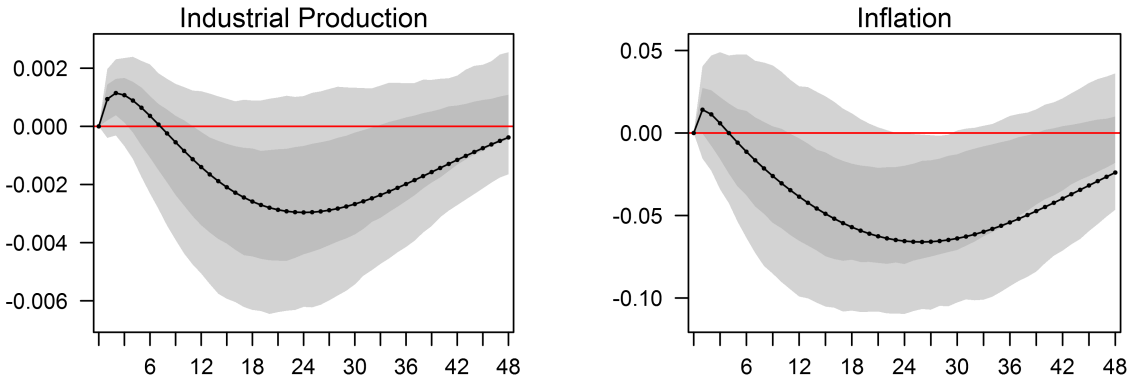
[7] Note that the shock size is the same in both states.

in the crisis state, as a monetary policy shock leads to a reduction in industrial production by 0.38% 18 months after the shock and to a decrease in inflation by 0.08 percentage points (pp) 19 months after the shock. During normal times, the reduction in both output and prices is less than half of the aforementioned sizes (0.17% after 23 months for IP and 0.04 pp after 24 months for inflation). Third, however, the effect of monetary policy shocks is less enduring during crisis times compared to normal times. When considering the 68% confidence bands the effects become insignificant in the crisis state after 35 months (IP) and after 43 months (inflation), respectively, whereas in the normal state the influence on IP becomes insignificant after 47 months and the impact on inflation is significant even beyond 48 months.[8]

3.3 Discussion

One crucial advantage of the Logit-MVAR model is the gain in efficiency, for instance, compared to a standard linear VAR model. Figure 4 shows the corresponding impulse responses for a standard linear VAR model obtained using the identification strategy described in Section 2.5.

Figure 4: Impulse Reponses for Linear VAR



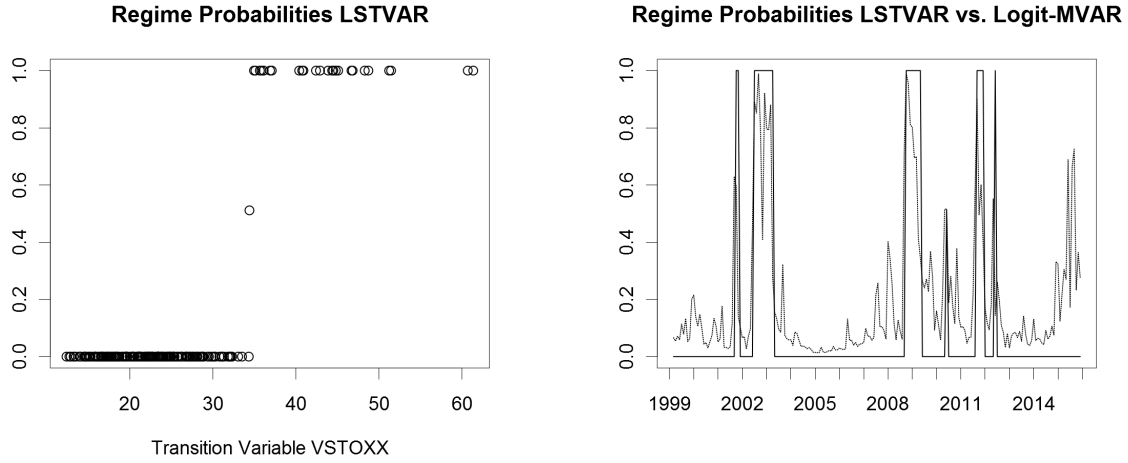
Notes: The figure shows selected impulse responses to a one standard deviation shock in the interest rate indicator for a linear VAR. Dark grey-shaded areas indicate 68% confidence bands and light grey-shaded areas indicate 95% confidence bands that are created by bootstrapping and 500 replications.

[8]Note that the impulse response function for inflation in normal times eventually becomes insignificant and approaches zero when considering horizons longer than 48 months.

Whereas the maximum contractionary effects found for the linear VAR are in between those of the crisis state and the normal state of the Logit-MVAR, the latter's impulse responses are much more significant. Moreover, the 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 the median, presumably due to outliers (or due to forcing two different states in a single model). 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 VAR model.

As a final step, we compare the performance of our Logit-MVAR model to that of a standard logistic smooth transition VAR (LSTVAR) model with the same set of variables. In line with our previous results (see Figure 2), we use the VSTOXX as transition variable for the LSTVAR model. In this model, the estimated smoothness parameter ($\gamma = 174.8$) is even larger than the parameter found in the original paper of Weise (1999). The left panel of Figure 5 shows the regime probabilities for different realized values of the VSTOXX. The threshold value of the VSTOXX is 34.4 (i.e., the 87% quantile of this variable) and the plot almost favors a "sharp" threshold VAR model as there is only a single observation with a regime probability other than 0 or 1.

Figure 5: Regime Probabilities of LSTVAR Model



Notes: The left panel shows the regime probabilities of the LSTVAR model for different realized values of the VSTOXX. The right panel shows the regime probabilities of the LSTVAR model over time (solid line) compared to the weights of the crisis state in the Logit-MVAR model (dotted line), the latter of which are taken from the right panel in Figure 1.

The right panel of Figure 5 shows the regime probabilities of the LSTVAR model over time (solid line) compared to the weights of the crisis state in the Logit-MVAR model (dotted line), the latter of which are taken from the right panel in Figure 1. The correlation between both series is quite high ($\rho = 0.74$) showing that both models capture similar crisis episodes. However, the plot 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 (see Figures 1 and 3). In the LSTVAR model, we see an almost perfect 0/1 distinction of the regimes, a finding that only allows for two extreme cases and no states in between.

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 state weights being determined by an underlying logit model. In contrast to other classes of nonlinear VARs, the regime affiliation is neither strictly binary nor binary with a (short) transition period. Mixture VARs allow for a composite model with the weights of the states continuously varying over the complete sample period.

We show that monetary policy transmission in the euro area can indeed be described as a mixture of two states. The second state with an overall share of 20% can be interpreted as a "crisis state" as its weights are particularly large during the recession in 2002–2003, after the Lehman collapse in 2008, during the euro area sovereign debt crisis in 2011, and during the Greek sovereign debt crisis in 2015. Correspondingly, the first state with an overall share of 80% 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

more than twice 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 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 strong interest rate cuts (or other expansionary non-conventional policy measures) are required to move the economy out of a recession.

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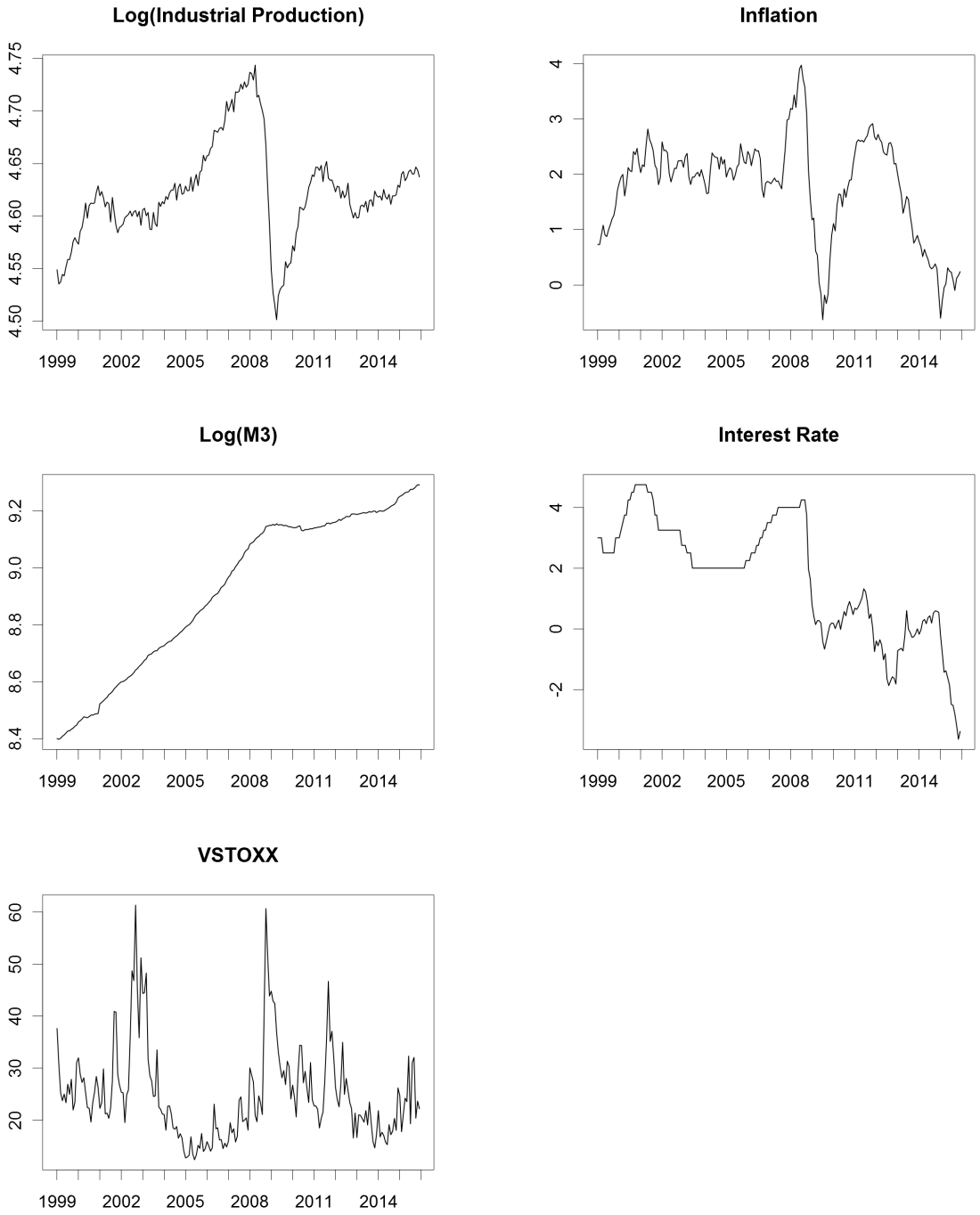
Appendix

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



Source: ECB (IP, inflation, M3, and MRR), Wu and Xia (2016) (shadow interest rate), and STOXX Limited (VSTOXX).