Monetary Policy During Times of Crisis

Frictions and Non-Linearities in the Transmission Mechanism

Dissertation

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Preface - Vorbemerkung

Die vorliegende Dissertation wurde zur Erlangung des akademischen Grades doctor rerum politicarum (Dr. rer. pol.) im Fachbereich IV (Wirtschafts- und Sozialwissenschaften, Mathematik, Informatikwissenschaften) der Universität Trier eingereicht. Die Arbeit wurde gemäß den Vorgaben der Promotionsordnung des Fachbereich IV vom 28. September 2004 erstellt. Kapitel 1 dient der Motivation des Themas und als thematische Einleitung. Die Kapitel 2 und 3 legen eine methodische und theoretische Fundierung. In den Kapiteln 4 bis 6 werden verschiedene inhaltliche Aspekte im Detail analysiert. Eine deutsche Zusammenfassung gemäß 5 Abs. 4 der Promotionsordnung befindet sich am Ende der Arbeit.

Aknowledgement - Danksagung

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Contents

List of Figures

List of Tables

1 Motivation - The Limitations of Monetary Policy

Monetary policy cannot do much about long-run growth, all we can try to do is to try to smooth out periods where the economy is depressed because of lack of demand.

Ben S. Bernanke, Hearing of the House Financial Services Committee, 18$^{\text{th}}$ July 2012.

For a long time it was believed that monetary policy would be able to maintain price stability and foster economic growth during all phases of the business cycle. The era of the Great Moderation, often also called the Volcker-Greenspan period, beginning in the mid 1980s was characterized by a decline in volatility of output growth and inflation among the industrialized countries. The term itself is first used by Stock and Watson (2003).

Economist have long studied what triggered the decline in volatility and pointed out several main factors. An important research strand points out structural changes in the economy, such as a decline of volatility in the goods producing sector through better inventory controls and developments in the financial sector and government spending (McConnell and Perez-Quiros, 2000; Blanchard and Simon, 2001; Stock and Watson, 2003; Kim et al., 2004; Davis and Kahn, 2008). While many believed that monetary policy was only 'lucky' in terms of their reaction towards inflation and exogenous shocks (Stock and Watson, 2003; Primiceri, 2005; Sims and Zha, 2006; Gambetti et al., 2008), others reveal a more complex picture of the story.

Rule based monetary policy (Taylor, 1993) that incorporates inflation targeting (Svensson, 1999) has been identified as a major source of inflation stabilization by increasing transparency (Clarida et al., 2000; Davis and Kahn, 2008; Benati and Surico, 2009; Coibion and Gorodnichenko, 2011). Apart from that, the mechanics of monetary policy transmission have changed. Giannone et al. (2008) compare the pre-Great Moderation era with the Great Modertation and find that the economies reaction towards monetary shocks has decreased. This finding is supported by Boivin et al. (2011). Similar to this, Herrera and Pesavento (2009) show that monetary policy during the Volcker-Greenspan period was very effective in dampening the effects of exogenous oil price shocks on the economy, while this can not be found for the period thereafter.

Yet, the subprime crisis unexpectedly hit worldwide economies and ended the era of Great Moderation. Financial deregulation and innovation has given banks opportunities for excessive risk taking, weakened financial stability (Crotty, 2009; Calomiris, 2009) and led to the build-up of credit-driven asset price bubbles (Schularick and Taylor, 2012). The Federal Reserve (FED), that was thought to be the omnipotent conductor of price stability and economic growth during the Great Moderation, failed at preventing a harsh crisis. Even more, it did intensify the bubble with low interest rates following the Dotcom crisis of the early 2000s and misjudged the impact of its interventions (Taylor, 2009; Obstfeld et al., 2009).

New results give a more detailed explanation on the question of latitude for monetary policy raised by Bernanke and suggest the existence of non-linearities in the transmission of monetary policy. Weise (1999), Garcia and Schaller (2002), Lo and Piger (2005), Mishkin (2009), Neuenkirch (2013) and Jannsen et al. (2015) find that monetary policy is more potent during times of financial distress and recessions. Its effectiveness during 'normal times' is much weaker or even insignificant. This prompts the question if these non-linearities limit central banks ability to lean against bubbles and financial imbalances (White, 2009; Walsh, 2009; Boivin et al., 2010; Mishkin, 2011).[1] As Ben S. Bernanke states in the aforementioned quote, many economists today believe that monetary policy can only 'smooth out periods where the economy is depressed' by stimulating demand.

The aim of this thesis is to analyze the scope of monetary policy. To do so, we apply different empirical models and shed light on non-linearities in the transmission mechanism and explain the macroeconomic impact of monetary policy in greater de-

[1] We will go deeper in this discussion in chapter 4 and explain the influence of the so-called financial cycle and credit-overheating on the effectiveness of monetary policy.

tail. We start in chapter 2 with introducing common time series methods, linear and non-linear, for quantitative analysis of monetary transmission. Afterwards, we take a detailed look at the traditional transmission channels in chapter 3.

In chapter 4, we will analyze the non-linear propagation of monetary policy during the so-called financial cycle. Apart from the real business cycle and the credit cycle, which are often measured by GDP and credit growth, the importance of the financial cycle is gaining further interest (Drehmann et al., 2012; Borio, 2014; Borio et al., 2016). It is based on the Credit-to-GDP gap and renders the build-up of credit-driven bubbles, which are found to be the most harmful ones for the economy through destabilizing the banking sector (Shin and Adrian, 2008; Schularick and Taylor, 2012; Brunnermeier and Schnabel, 2016). Our findings indicate that monetary policy is mostly ineffective during the phases of credit market overheating.

Chapter 5 takes a deeper look at the risk-taking channel of monetary policy in the Euro area. Banks tend to lower their lending standards and take riskier credits, associated with higher expected yields, into their portfolio in order to dampen the negative effects of decreasing interest rates on their lending margin and total profitability. This behavior is called the risk-taking channel (Gambacorta, 2009; Borio and Zhu, 2012). Our results indicate the existence of a risk-taking channel in the Euro area for the period of 2003 to 2016. Further, it highlights that expansionary monetary policy may have initially positive impact on banks' interest rate margin due to overshooting in the adjustment of their lending standards. However, banks do not seem to be able to shield their margin from lower short-term rates in the mid-run.

In chapter 6, we study the afore mentioned state-dependent transmission of monetary policy for the Euro area and develop a new empirical model, a logit mixture vector autoregressive model. Our results support previous findings and are able to account for metric regime switches from different economic sources. We thereby extend the present body of literature that focuses on binary regime switches. Chapter 7 concludes and provides policy implications.

2 Empirical Modeling of Monetary Policy Transmission

The empirical analysis of monetary policy transmission has been a key part of research for a long time. The easiest way of course would be an ordinary least squares regression treating the variable of interest as endogenous and the monetary policy instrument as well as a set of control variables as exogenous. Yet, this method is inappropriate, because the assumption of endogeneity is highly questionable in the case of monetary policy interventions. Central banks continuously react towards changes in the economy by adjusting the money base to meet liquidity demands or short-term interest rates.

One solution for this 'identification problem' is the so-called 'narrative approach' introduced by Friedman and Schwartz (1963) and Romer and Romer (1989). They analyze the Federal Open Market Committee reports and manually determine periods in which the Federal Reserve bank seems to shift towards another monetary policy stance, interpreting these shifts as exogenous. The method has been widely accepted until the end of the 1990s (e.g. Romer et al., 1990; Bernanke and Blinder, 1992; Kashyap et al., 1993; Romer and Romer, 1994; Gertler and Gilchrist, 1994; Oliner and Rudebusch, 1996). However, this method has some disadvantages as it is incrementally attached to the opinion of the researcher and not objectively replicable. Furthermore, it does not allow to distinguish between endogenous components, that are driven by the monetary policy reaction to the economic environment and exogenous decisions to regime shifts (Bernanke and Mihov, 1998a).

Another approach is application of vector autoregressive (VAR) models, first proposed by Sims (1980b,a). Although both approaches provide similar results (Leeper, 1997), VAR models allow for a deeper analysis and have prevailed as the standard method. In the following chapter, we will explain several frequently used VAR setups, starting from linear VARs with different approaches to identification up to nonlinear extensions. The notation follows the seminal book of Lütkepohl (2007). We will use the notation $A^\top$ for the transposed of A and $|A|$ as the determinant of A from here on.

2.1 Linear VAR models

The easiest model setup is a simple linear VAR model with lag order p, further on labeled as a VAR(p). It is based on the idea that every variable can be explained by past values of itself and the other variables and can be written as:

$$y_t = \nu + \sum_{i=1}^{p} A_i y_{t-i} + u_t \tag{1}$$

where $y_t = (y_{t1}, \ldots, y_{tK})$ is the $(K \times 1)$ vector of endogenous variables at period t with K being the number of endogenous variables. The A_i are the $(K \times K)$ parameter matrices up to lag order p. The $(K \times 1)$ vector of variable specific intercepts is labeled by ν and $u_t = (u_{t1}, \ldots, u_{tK})$ are the $(K \times 1)$ vectors of white noise errors, often also called innovations, implying the following properties:

$$\begin{aligned} E(u_t) &= 0 \\ E(u_t u_t^\top) &= \Sigma_u \\ E(u_t^\top u_s) &= 0 \quad , \forall t \neq s \end{aligned}$$

As Lütkepohl (2007) shows, every VAR(p) model can also be written as a VAR(1) by:

$$Y_t = \boldsymbol{\nu} + \boldsymbol{A} Y_{t-1} + U_t \tag{2}$$

using the following definitions:

$$\begin{aligned} Y_t &:= \left[y_t, y_{t-1}, \ldots, y_{t-p+1}\right]^\top \\ \boldsymbol{\nu} &:= \left[\nu, 0, \ldots, 0\right]^\top \end{aligned}$$

$$
\boldsymbol{A} := \begin{bmatrix} A_1 & A_2 & \cdots & A_{p-1} & A_p \\ I_K & 0 & \cdots & 0 & 0 \\ 0 & I_K & & 0 & 0 \\ \vdots & & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & I_K & 0 \end{bmatrix}
$$

$$
U_t := \quad \left[u_t, 0, \ldots, 0\right]^\top
$$

Writing the model as a VAR(1) results in a simple notation, when we come to the estimation and structural analysis of VAR models.

Equation (1) is often revered to as the *vector autoregressive representation* of the model. While this is useful to determine the structural innovations and can be easily estimated, there is also a so-called *moving average representation* (MA) of the model by:

$$
y_t = \mu + \sum_{i=0}^{\infty} \Phi_i u_{t-i} \tag{3}
$$

in which the model can be described by the mean vector $\mu = E(y_t)$ and past innovations. This representation is mainly used for structural interpretations, such as impulse response functions (Runkle, 1987). The MA representation can be obtained by:

$$
\begin{aligned}
y_t =& JY_t = J\boldsymbol{\mu} + \sum_{i=0}^{\infty} J\boldsymbol{A}^i J^\top J U_{t-i} \\
=& \mu + \sum_{i=0}^{\infty} \Phi_i u_{t-i}
\end{aligned} \tag{4}
$$

where $\boldsymbol{\mu} := (I_{Kp} - \boldsymbol{A})^{-1}\boldsymbol{\nu}$, $\mu := J\boldsymbol{\mu}$, $\Phi_i := J\boldsymbol{A}J^\top$ and $J := \left[I_K : 0 : \cdots : 0\right]$. Since the model is estimated in the VAR representation and the computational effort of calculating the Φ_i is rather large, the MA representation is only used sparingly, for instance, up to the given horizon of the structural analysis.

The model (1) can also be written compactly, which is more appealing for the estimation, as:

$$Y = BZ + U \tag{5}$$

where Lütkepohl (2007) takes the following definitions:

$$\begin{aligned}
Y &:= [y_1, \ldots, y_T] \\
B &:= [\nu, A_1, \ldots, A_p] \\
Z_t &:= [1, y_t, \ldots, y_{t-p+1}]^\top \\
Z &:= [Z_0, \ldots, Z_{T-1}] \\
U &:= [u_1, \ldots, u_T] \\
\boldsymbol{y} &:= vec(Y) \\
\boldsymbol{\beta} &:= vec(B) \\
\boldsymbol{b} &:= vec(B^\top) \\
\boldsymbol{u} &:= vec(U)
\end{aligned}$$

with $vec(.)$ being the column stacking operator as defined by (Lütkepohl, 2007, 661-662) and $\otimes$ denoting the Kronecker product from here on.

Estimation

The VAR(p) can then be estimated using different methods. Most commonly used are Generalized Least Squares (GLS) and maximum likelihood (ML) estimations. We will start with the GLS estimation. Since VAR models typically exhibit correlation between the components of residuals[2], applying Ordinary Least Squares (OLS) would lead to inefficient estimates. The GLS approach minimizes the sum of squared resid-

[2] Structural analysis with VAR models are in fact based on these correlations. We will come to this point with impulse response analysis.

uals, weighted by the covariance matrix and thereby accounts for these correlations.[3] The weighted sum of squared residuals for the VAR case is given by:

$$S(\boldsymbol{\beta}) = \Big[\boldsymbol{y} - (Z^\top \otimes I_K)\boldsymbol{\beta}\Big]^\top \Big(I_T \otimes \Sigma_u^{-1}\Big)\Big[\boldsymbol{y} - (Z^\top \otimes I_K)\boldsymbol{\beta}\Big] \tag{6}$$

By taking the partial derivative with respect to $\boldsymbol{\beta}$ and solving for the latter one, we get the GLS estimator:

$$\widehat{\boldsymbol{\beta}} = \Big((ZZ^\top)^{-1} Z \otimes I_K\Big)\boldsymbol{y} \tag{7}$$

Relying on the definition of $\boldsymbol{\beta}$ and rearranging equation (7) yields:

$$\widehat{B} = YZ^\top \Big(ZZ^\top\Big)^{-1} \tag{8}$$

and the respective GLS estimator for the covariance matrix:

$$\widehat{\Sigma_u} = \frac{1}{T - Kp - 1} \sum_{t=1}^{T} \widehat{u_t}\widehat{u_t}^\top \tag{9}$$

where $\widehat{u_t} = y_t - \widehat{B}Z_{t-1}$.

The ML estimator of the VAR(p) can be obtained by maximizing the log-likelihood function of the model. For that purpose, we need some further definitions:

$$\begin{aligned}
Y^0 &:= \Big((y_1 - \mu), \ldots, (y_T - \mu)\Big) \\
A &:= (A_1, \ldots, A_p) \\
Y_t^0 &:= \Big[(y_t - \mu), \ldots, (y_{t-p+1} - \mu)\Big]^\top \\
X &:= (Y_0^0, \ldots, Y_{T-1}^0)
\end{aligned}$$

[3] As Aitken (1936) has shown by applying the Gauss-Markov-theorem, in the case of correlation between the error terms, GLS yields the best linear unbiased estimator.

$$
\begin{aligned}
y^0 &:= vec(Y^0) \\
\boldsymbol{\alpha} &:= vec(A) \\
\boldsymbol{\mu}^* &= (\mu^\top, \dots, \mu^\top)^\top
\end{aligned}
$$

Since $\boldsymbol{u}$ is normally distributed with covariance matrix Σ_u, that is $\boldsymbol{u} = vec(U) \sim \mathcal{N}(0, I_T \otimes \Sigma_u)$, we can write the multivariate probability density function of $\boldsymbol{u}$ as:

$$
f_{\boldsymbol{u}}(\boldsymbol{u}) = \frac{1}{(2\pi)^{\frac{KT}{2}}} |I_T \otimes \Sigma_u|^{-\frac{1}{2}} \exp\Big[-\frac{1}{2}\boldsymbol{u}^\top (I_T \otimes \Sigma_u^{-1})\boldsymbol{u}\Big] \tag{10}
$$

Since $\boldsymbol{u} = \boldsymbol{y} - \boldsymbol{\mu}^* - \Big(X^\top \otimes I_K\Big)\boldsymbol{\alpha}$, we can use the chain rule to obtain the multivariate probability density function of $\boldsymbol{y}$:

$$
\begin{aligned}
f_{\boldsymbol{y}}(\boldsymbol{y}) =& |\frac{\partial \boldsymbol{u}}{\partial \boldsymbol{y}}| f_{\boldsymbol{y}}(\boldsymbol{y}) \\
=& \frac{1}{(2\pi)^{\frac{KT}{2}}} |I_T \otimes \Sigma_u|^{-\frac{1}{2}} \\
& \exp\Big[-\frac{1}{2}\Big(\boldsymbol{y} - \boldsymbol{\mu}^* - (X^\top \otimes I_K)\boldsymbol{\alpha}\Big)^\top \Big(I_T \otimes \Sigma_u^{-1}\Big)\Big(\boldsymbol{y} - \boldsymbol{\mu}^* - (X^\top \otimes I_K)\boldsymbol{\alpha}\Big)\Big]
\end{aligned} \tag{11}
$$

By taking the natural logarithm of equation (11), we get the log-likelihood function:

$$
\begin{aligned}
\ln l(\mu, \boldsymbol{\alpha}, \Sigma_u) =& -\frac{KT}{2}\ln 2\pi - \frac{T}{2}\ln|\Sigma_u| \\
& -\frac{1}{2}\Big[\boldsymbol{y} - \boldsymbol{\mu}^* - (X^\top \otimes I_K)\boldsymbol{\alpha}\Big]^\top (I_T \otimes \Sigma_u^{-1})\Big[\boldsymbol{y} - \boldsymbol{\mu}^* - (X^\top \otimes I_K)\boldsymbol{\alpha}\Big] \\
=& -\frac{KT}{2}\ln 2\pi - \frac{T}{2}\ln|\Sigma_u| - \frac{1}{2}tr\Big[(Y^0 - AX)^\top \Sigma_u^{-1}(Y^0 - AX)\Big]
\end{aligned} \tag{12}
$$

We then obtain the ML estimators using the first-order conditions with respect to μ, $\boldsymbol{\alpha}$ and Σ_u:

$$
\begin{aligned}
\widetilde{\mu} &= \frac{1}{T}\Big(I_K - \sum_i \widetilde{A}_i\Big)^{-1} \sum_t \Big(y_t - \sum_i \widetilde{A}_i y_{t-i}\Big) && (13)\\
\widetilde{\boldsymbol{\alpha}} &= \Big((\widetilde{X}\widetilde{X}^\top)^{-1}\widetilde{X} \otimes I_K\Big)(\boldsymbol{y} - \boldsymbol{\mu}^*) && (14)\\
\widetilde{\Sigma}_u &= \frac{1}{T}\Big(\widetilde{Y}^0 - \widetilde{A}\widetilde{X}\Big)\Big(\widetilde{Y}^0 - \widetilde{A}\widetilde{X}\Big)^\top && (15)
\end{aligned}
$$

The values $\widetilde{Y}^0$ and $\widetilde{X}$ can be obtained by replacing μ with $\widetilde{\mu}$ in their definitions.

Lag Length Selection

Another important point for the estimation of VAR models is the determination of p. An established method is the use of information criteria. All commonly approaches are based on the idea to reward for a lower sum of squared residuals, i.e. $|\Sigma_u|$, and the punishment of further lags. A higher lag order p induces more freely estimated parameters and hence reduces the degrees of freedom and the statistical accuracy of the estimators. The basic idea of this is approach is to choose the lag length that minimizes the respective criterion.

Akaike (1969, 1971) suggested to use the Final Prediction Error (FPE) resulting from a ML estimation:

$$
FPE(m) = \left[\frac{T + Km + 1}{T - Km - 1}\right]^K |\widetilde{\Sigma}_u(m)| \qquad (16)
$$

Later on, Akaike (1974) derived a similar criterion that is called Akaike's Information Criterion (AIC):

$$
AIC(m) = \ln|\widetilde{\Sigma}_u(m)| + \frac{2mK^2}{T} \qquad (17)
$$

Sometimes the AIC also includes a constant in the number of freely estimated parameters mK^2. Since adding the constant does only change the level of the AIC but not the sequence, we follow Lütkepohl (2007) and drop the constant. Another approach is the so-called Schwarz Information Criterion (SIC) (Schwarz, 1978):

$$SIC(m) = \ln|\widetilde{\Sigma}_u(m)| + \frac{\ln T}{T} mK^2 \tag{18}$$

The last commonly used is the Hannan-Quinn Criterion (HQ) introduced by Hannan and Quinn (1979) and Quinn (1980):

$$HQ(m) = \ln|\widetilde{\Sigma}_u(m)| + \frac{2\ln\ln T}{T} mK^2 \tag{19}$$

As Ivanov and Kilian (2005) show, each criterion has certain advantages, measured by the mean-squared error. The AIC is better at estimating VAR models based on monthly data, but tends to overestimate the true lag order. HQ and SIC are preferable for quarterly data, whereas the HQ performs best with sample sizes of less than 120 quarters. Often, the criteria, especially the SIC, may favor a lag length of one. However, such a low lag length is in many cases not sufficient to prevent serial correlation in the error terms.

The general point in the usage of information criteria is that they try to find a lag length that fits well to the data and is more or less parsimonious. However, this does not necessarily imply that the proposed lag length eliminates autocorrelation in the error terms. Therefore, statistical testing on the error terms of the model is advised. For example, a Box-Pierce test (Box and Ljung, 1978) on single error term series or a joint Portemonteau test (Box and Pierce, 1970) for detecting autocorrelation or a Jarque-Bera test (Jarque and Bera, 1980, 1987) on normality of the residuals are commonly used.

Impulse Response Analysis

An interesting point to analyze the monetary policy transmission channel is the response of the system to a shock of a single variable, for instance, the proxy of the monetary policy stance. These so-called *impulse response functions* are calculated from the MA-representation of the VAR in equation (3).

The reaction $\phi_{jk,i}$ of the j'th variable to a unit shock in variable k that occured i periods ago is nothing else as the jk'th element of the matrix Φ_i from equation (3). That is, the reaction of the whole system is given by the k'th column of Φ_i. However, the response can only be economically interpreted when the error terms are independent, that is Σ_u has to be orthogonal. A simple way to orthogonalize Σ_u is by assuming a recursive identification scheme. This can be achieved using the Choleski decomposition $\Sigma_u = PP^\top$:

$$y_t = \mu + \sum_{i=0}^{\infty} \Theta_i \omega_{t-i} \tag{20}$$

where the ω_t are serially uncorrelated error terms with unit variance, i.e. $\Sigma_\omega = I_K$. $\Theta_i := \Phi_i P$ and $\omega_t := P^{-1} u_t$ with P being a lower triangular matrix. The response of the system to a unit shock of variable j in period i after the shock is then obtained by the j'th column of Θ_i, where $\Theta_0 = P$. The orthogonalized impulse responses allow for an economic interpretation, resolved of the influence of shocks from other variables within the system. For our purpose, this will mostly be the influence of an exogenous monetary policy shock to the system, that is key macro variables like the price level and economic or credit activity measures.

Runkle (1987) proposes the calculation of confidence bands, which is nowadays frequently used to determine the statistical significance of impulse response functions. Confidence bands are based on the empirical distribution of the estimated impulse responses. The most frequently used approach for this purpose is bootstrap resampling as proposed by Efron (1979, 1981). The basic idea of bootstrapping is that the estimated residuals of the VAR model can be understood as a representative sample of the true disturbances of the underlying processes. Therefore, we can create artificial realizations of the data generating processes by randomly sampling from the estimated error terms $\widehat{U}$. One then generates a large number of those artificial data sets and estimates the VAR model along with the impulse response functions for each set. From the resulting distribution, one can easily calculate empirical confidence bands (Runkle, 1987).

2.1.1 Structural Models

Although Sims (1980a) presents his recursive identification approach as atheoretical, there are several vulnerable points. Main contributors to this criticism are, among others, Bernanke (1986) and Cooley and Leroy (1985), who point out that the recursive ordering theme does have impact on the results of structural analysis. Further, economic theory typically exhibits simultaneous systems (Keating, 1990) whereas the recursive approach often assumes no contemporaneous reaction on monetary policy shocks. Hence, estimates based on recursive models may yield wrong and non-robust results. Economic theory should therefore be reflected in structural identification approaches (Stock and Watson, 2001).

The resulting class of models is called structural vector autoregression (SVAR). They can be distinguished into the subclasses: $\mathcal{A}$-models, $\mathcal{B}$-models and $\mathcal{AB}$-models. The $\mathcal{A}$-model attaches directly to the relations between the endogenous variables. This is achieved by multiplying equation (1) with matrix $\mathcal{A}$ and leads to the following structural form:

$$\mathcal{A}y_t = \sum_{i=1}^{p} \mathcal{A}_i^* y_{t-i} + \varepsilon_i \tag{21}$$

where $\mathcal{A}_i^* := \mathcal{A}A_i\,(i = 1,\cdots,p)$ and $\varepsilon_i := \mathcal{A}u_i \sim (0, \Sigma_\varepsilon = \mathcal{A}\Sigma_u\mathcal{A}^\top)$. Since we only have $\frac{K(K-1)}{2}$ equations for the estimation and K^2 parameters in $\mathcal{A}$, we need $\frac{K(K+1)}{2}$ restrictions. The first and most convenient is to normalize the diagonal elements of $\mathcal{A}$ to be one. This leads to standard deviation shocks in the ε_i and accounts for the first K restrictions (Gottschalk, 2001). Therefore, only $\frac{K(K-1)}{2}$ further restrictions have to come up from theory. If we assume a recursive ordering for illustration, we get:

$$\mathcal{A} = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ a_{21} & 1 & & 0 \\ \vdots & & \ddots & \vdots \\ a_{K1} & a_{K2} & \cdots & 1 \end{bmatrix} \tag{22}$$

Such a model is just-identified. Of course one can make more than the $\frac{K(K-1)}{2}$ restrictions and obtain an over-identified SVAR model. However, this is uncommon (Lütkepohl, 2007) and should be based on strong theoretical foundation.

Since structural analysis only use the unexpected shocks to variables, one can also directly identify the structural innovations ε_t from the reduced form error terms u_t of equation (1) by assuming a linear relationship in the form of $u_t = \mathcal{B}\varepsilon_t$. Hence, for the covariance matrices we get $\Sigma_u = \mathcal{B}\Sigma_\varepsilon\mathcal{B}^\top$. Normalizing the structural residuals, that is assuming $\epsilon_t \sim (0, I_K)$, leads to $\Sigma_U = \mathcal{B}\mathcal{B}^\top$.

Again, we need $\frac{K(K-1)}{2}$ restrictions besides the normalization assumption. Equation (1) together with the relation $u_t = \mathcal{B}\varepsilon_t$ is called a $\mathcal{B}$-model. The recursive ordering implied by the Choleski decomposition can be seen as a special case of this class.

The last class are $\mathcal{AB}$-models that allow for restrictions on both matrices. The model can be written as:

$$\mathcal{A}y_t = \sum_{i=1}^{p} \mathcal{A}_i^* y_{t-i} + \mathcal{B}\varepsilon_t \tag{23}$$

where we need a minimum number of $K^2 + \frac{K(K-1)}{2}$ restrictions for both matrices combined to have a just-identified model. $\mathcal{A}-$ and $\mathcal{B}$-models can also be seen as special cases of $\mathcal{AB}$-models, where we set $\mathcal{B} = I_K$ or $\mathcal{A} = I_K$ respectively (Pfaff, 2008).

All structural models can be estimated by ML estimation with the log-likelihood function:

$$\ln l(\mathcal{A},\mathcal{B}) = -\frac{KT}{2}\ln(2\pi) + \frac{T}{2}\ln|\mathcal{A}^2| - \frac{T}{2}\ln|\mathcal{B}^2| - \frac{T}{2}tr\Big(\mathcal{A}^\top \mathcal{B}^{-1\top}\mathcal{B}^{-1}\mathcal{A}\widetilde{\Sigma}_u\Big) \tag{24}$$

where $\widetilde{\Sigma}_u = T^{-1}\Big(Y - \widehat{A}X\Big)\Big(Y - \widehat{A}X\Big)$ is an estimate of the reduced form covariance matrix. Minimizing the log-likelihood function has to be done using numerical methods, for instance, the scoring algorithm given by Amisano and Giannini (1997), since a closed form solution does often not exist (Lütkepohl, 2007).

Although SVAR models allow for a richer set of applications to economic theory, they are still far away from being invariant to the identification restrictions. As Sarte (1997) or Cooley and Dwyer (1998) show, the resulting impulse responses can strongly react to minor changes in the corresponding $\mathcal{A}$ or $\mathcal{B}$ matrix and lead to non-robust results.

2.1.2 Sign Restricted VARs

A major disadvantage of all SVAR models, be they recursive or not, is that the econometrician has to set contemporaneous zero restrictions - a very strict assumption - and the whole system of K innovations has to be identified. Following the idea of Bernanke and Mihov (1998b,a) and Christiano et al. (1999), who use a block recursive identification scheme for $K-1$ innovations and concentrate on the innovation of interest, Uhlig (2005) proposes a bayesian approach to identification with sign-restrictions rather than zero restrictions. He focuses on identifying only a single impulse vector of interest, for instance the monetary policy impulse vector. The starting point is again the AR representation of the VAR model from equation (1):

$$y_t = \sum_{i=1}^{p} B_i y_{t-i} + u_t$$

For simplicity, we drop the constant and label the coefficient matrices as B_i to avoid confusion. An impulse vector is herein defined as a vector $a \in \mathbb{R}^K$, if and only if there is some matrix A, so that $AA^\top = \Sigma_u$ and so that a is a column of A. If we let $\widetilde{A}\widetilde{A}^\top = \Sigma_u$ be a Choleski decomposition of Σ_u, a is an impulse vector if and only if there is an K-dimensional vector α of unit length so that:

$$a = \widetilde{A}\alpha \tag{25}$$

Impulse responses can be calculated as follows. We define $r_i(k) \in \mathbb{R}^K$ to be the vector response of the system at horizon k to the i'th shock in a Choleski decomposition of Σ_u, that is $r_i(k)$ is the i'th column of the orthogonalized response Θ_k. Since we only identify a single impulse vector, the impulse response $r_a(k)$ for a is given by:

$$r_a(k) = \sum_{i=1}^{K} \alpha_i r_i(k) \tag{26}$$

Since these impulse vectors are not unique, the impulse vector of interest is then identified by setting several inequality restrictions on $r_a(k)$ to hold for a predefined horizon K_r. For example, a restrictive monetary policy shock should be reflected by an increase in the policy rate, and decrease in money supply and the price level. The set of all possible impulse vectors conditional on the coefficient matrices $B = [B_1^\top, \ldots, B_p^\top]$, the error covariance matrix Σ_u and the horizon for inequality restrictions K_r, is labeled as $\mathscr{A}(B, \Sigma_u, K_r)$. The set will in general be very large, but decreases strongly with the amount of restrictions and horizon K_r, ultimately leading to an empty set, if the restrictions or horizon do not fit the data and are too unrealistic.[4] For simplicity we stick to the pure sign-restriction approach. Uhlig (2005) also proposes a penalty approach

[4]Examples could be a too high horizon or restrictions that contradict one another, like an increase in the federal funds rate and prices at the same time.

in which violations of the restrictions are treated by low weights through minimizing an objective function.

To explain the estimation, we first have to draw a simple picture of Bayesian estimation techniques. The basic idea of Bayesian statistics is to update an estimation with new information using Bayes theorem:

$$p(\theta|X,\alpha) \propto p(X|\theta)p(\theta|\alpha) \tag{27}$$

where $p(\theta|\alpha)$ is the prior density of the vector of parameters θ conditional on the hyperparameter α of the assumed distribution. $p(X|\theta)$ is the sampling distribution of the data conditional on the parameter vector θ.[5] $p(\theta|X,\alpha)$ is the posterior distribution of the parameter vector or matrix to be estimated. Bayesian vector autoregression (BVAR) models thus have several advantages over commonly used estimation methods. First, the method pays respect to the uncertainty in the specification process of empirical analysis, that is the model parameters are explicitly understood as random variables with uncertain distribution characteristics (Sims, 1982; Litterman, 1984). Secondly, BVAR models are estimated using Monte Carlo Markov Chain (MCMC) techniques and by repeated sampling from the posterior distribution, they perform far better for finite samples. Finally, the combination of both can capture the actual distribution of the parameters (Litterman, 1986). Hence, their forecasting accuracy is clearly superior to conventional methods based on GLS or ML estimations. However, BVAR models are only 'in spirit' of purely Bayesian methods, since they typically rely on prior distributions that are standardized and easy to calculate (Doan et al., 1984).

There are numerous prior distributions established in the literature, the most prominent being the Minnesota prior (Litterman, 1986), Jeffrey's prior (Tiao and Zellner, 1964; Geisser, 1965), the Normal-Wishart prior (Attias, 1999), the Normal-Diffuse prior (Zellner, 1971) and the Extended Natural Conjugate prior (Ando and Kaufman,

[5] This is often labeled by $L(\theta|X)$ as the likelihood of the parameter vector or matrix θ conditional on the observed data X.

1964; Richard and Steel, 1988).[6] For his approach, Uhlig (2005) uses a Normal-Wishart prior. A Normal-Wishart distribution is parameterized by a mean coefficient matrix $\overline{B}(Kp \times K)$, a positive definite covariance matrix $S(K \times K)$, a positive definite matrix $N(Kp \times Kp)$ and a degrees-of-freedom real number $v \geq 0$, that is Σ_u^{-1} follows a K-dimensional Normal-Wishart distribution $\mathscr{W}_K(S^{-1}/v, v)$ with $E[S^{-1}] = \Sigma_u^{-1}$ and conditional on Σ_u, $vec(B)$ follows a Normal distribution $\mathscr{N}(vec(\overline{B}), \Sigma_u \otimes N^{-1})$ (Uhlig, 2005).

Using the compact notation of the VAR model from equation (5) for the case of a model without constants, the ML estimators are given by:

$$
\begin{aligned}
\widehat{B} &= \left(X^\top X\right)^{-1} X^\top Y \\
\widehat{\Sigma}_u &= \frac{1}{T}\left(Y - X\widehat{B}\right)^\top \left(Y - X\widehat{B}\right)
\end{aligned}
$$

Uhlig (1994) states, that if the prior distribution is described by $\overline{B}_0$, N_0, S_0 and v_0, the posterior follows a Normal-Wishart distribution parameterized by $\overline{B}_T$, N_T, S_T and v_T with (Leamer, 1978; Uhlig, 1994):

$$
\begin{aligned}
v_T &= T + v_0 \\
N_T &= N_0 + X^\top X \\
\overline{B}_T &= N_T^{-1}\left(N_0 \overline{B}_0 + X^\top X \widehat{B}\right) \\
S_T &= \frac{v_0}{v_T} S_0 + \frac{T}{v_T}\widehat{\Sigma}_u + \frac{1}{v_T}\left(\widehat{B} - \overline{B}_0\right)^\top N_0 N_T^{-1} X^\top X \left(\widehat{B} - \overline{B_0}\right)
\end{aligned}
$$

For simplicity, Uhlig (2005, 1994) chooses the above mentioned Normal-Wishart prior, which is a flat prior, that is $N_0 = 0$ and $v_0 = 0$.[7] Following this, $\overline{B}_0$ and S_0 can be chosen

[6] A broad overview of estimation techniques and the influence of the chosen prior is given by Kadiyala and Karlsson (1997).

[7] Usually a flat prior would impose $v_0 = -p$, but as Uhlig (1994) writes, it is more logically to set $v_0 = 0$.

arbitrarily, since they simply canceling out and simple calculus yields that $\overline{B}_T = \widehat{B}$, $S_T = \widehat{\Sigma}_u$, $\upsilon_T = T$ and $N_T = X^\top X$.

A major advantage of the Normal-Wishart distribution as prior and posterior is that one can directly draw from the posterior distribution (Kadiyala and Karlsson, 1997), which makes it very appealing to create inference for the impulse responses using a MCMC algorithm. The steps of creating the set of impulse responses that meet the sign restrictions is as follows (Danne, 2015):

1. We run an unrestricted VAR in order to get the ML estimators $\widehat{B}$ and $\widehat{\Sigma}_u$.
2. We create orthogonal innovations from the model by applying a Choleski decomposition of $\widehat{\Sigma}_u$.
3. We calculate the corresponding impulse responses as discussed in section (2.1).
4. We randomly draw an orthogonal impulse vector α
5. We multiply the impulse response from step 3. with α to obtain a normalized impulse response r_a.
6. If the impulse response vector matches our sign restrictions, we keep it. If not, we flip signs and check again. If in both cases the vector does not meet the restrictions, we reject the run.
7. Repeat steps 2 to 6 to get enough, say 1000, accepted draws to obtain reliable results.

In step 4. we first take n_1 draws of $\overline{\Sigma}_u$ and $\overline{B}$ from the posterior. $\overline{B}$ can directly be drawn from the above mentioned Normal distribution. $\overline{\Sigma}_u$ can be calculated by $\overline{\Sigma}_u = \left(R * R^\top\right)^{-1}$, where the matrix $R(K \times T)$ can be obtained by column-wise independent draws from a Normal distribution $\mathcal{N}(0, S_T^{-1}/T)$. For each of these posterior draws, we calculate n_2 draws for $\overline{\alpha}$ by drawing $\widetilde{\alpha}$ from an K-dimensional standard Normal distribution and normalize by $\overline{\alpha} = \frac{\widetilde{\alpha}}{\|\widetilde{\alpha}\|}$ (Uhlig, 2005; Danne, 2015). Credible intervals, the Bayesian equivalent to confidence bands, are then calculated by the respective quantiles of all accepted draws, for instance the 16% as quantile lower and the 84% as upper bound in order to get a 68% credible set.[8]

However, this approach has some shortcomings. Shocks cannot be clearly identified since, for example, a shock to monetary policy can be assumed to have the same effects as a shock to money demand.[9] Furthermore, the direction of restrictions as well as the horizon on which they are assumed to hold are questionable. Paustian (2007) proposes to ground restrictions and the corresponding horizon on results of comparable DSGE models.

Nevertheless, this approach has been applied a lot in the recent VAR literature. Dedola and Neri (2007) identify the impact of technology shocks in the US, Rafiq and Mallick (2008) analyze the effects of monetary policy on output in the EMU, Vargas-Silva (2008a) examines the impact of monetary policy on the US housing market and Mountford and Uhlig (2009) apply a BVAR to fiscal policy shocks. Peersman and Straub (2009), Kilian and Murphy (2012) and Inoue and Kilian (2013) develop methods to combine fully or partially identified structural models with sign restrictions.

2.1.3 FAVAR Models

Another major disadvantage of standard VAR models is their susceptibility in regard to the set of variables. The afore mentioned curse of dimensionality causes econometricians to apply only small sets of variables, typically three to eight. First of all, it is questionable that these variables span the complete space of information used by the monetary authorities and hence, estimations might be biased. Furthermore, many concepts, such as economic activity or inflation, are hard to measure by only one available

[8]Another, yet similar, method for sign restricted VAR estimation is given by Rubio-Ramirez et al. (2010).

[9]If we assume a simple LM model in the form of $\frac{M^s}{P} = L(Y,i)$, a positive shock to money supply M^s has similar effects on the economy as a negative shock on money demand $L(Y,i)$. Hence, identification with sign restricted VAR models can be inconclusive.

time series.[10] Besides that, standard VAR approaches only allow to calculate impulse response functions for the set of endogenous variables.

To overcome these problems, Bernanke et al. (2005) propose the so-called Factor-Augmented Vector Autoregressive (FAVAR) approach. The basic idea is to expand the standard VAR model with the information content of comprehensive factors F_t[11], leading to the following transition equation:

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + u_t \tag{28}$$

where Y_t is, the $(K \times 1)$ vector of observable variables, F_t is the $(M \times 1)$ vector of latent factors, $\Phi(L)$ is a conformable $(K + M \times K + M)$ lag polynomial of order p and u_t are the $(K + M \times 1)$ non-structural error terms with mean zero and covariance matrix Σ_u.

If all coefficients in $\Phi(L)$ that relate Y_t to F_{t-1} are zero, the FAVAR model reduces to a standard VAR model in Y_t. Hence, the FAVAR model nests standard VAR models, which is very appealing for comparison between both.

Since the latent factors F_t are unobservable, we have to estimate them from an 'informational' set of variables X_t $(N \times 1)$, where N is assumed to be much greater than $K+M$. The time series X_t are assumed to be related to the latent factors F_t and the observed variables Y_t through the following observation equation:

$$X_t = \Lambda^f F_t + \Lambda^y Y_t + e_t \tag{29}$$

[10]For example, economic activity can be measured by real GDP, industrial production, output gaps or many other concepts. The same holds for inflation, which can be calculated, relying on the GDP deflator, consumer price indexes or core inflation, that is excluding energy and food prices.

[11]That is, a large set of N variables is represented by a linear combination of M latent, unobservable factors with M being much smaller than N, thus comprising the information content to better render the general economic environment than with conventional VAR models.

where Λ^f is an $(N \times M)$ matrix of factor loadings, Λ^y is an $(N \times K)$ matrix and e_t are $(N \times 1)$ vectors of error terms with mean zero. The covariance of the e_ts depends on the estimation method.

For the estimation of the model, Bernanke et al. (2005) propose two different approaches: the first is a two-step principal components approach using GLS or ML estimation, the second is a single-step Bayesian approach using likelihood-based Gibbs sampling (Geman and Geman, 1984; Gelman and Rubin, 1992; Carter and Kohn, 1994; Kim and Charles, 1999). We will only explain the two-step approach in detail, since it better captures the basic idea in a simple manner.[12]

The two-step approach provides a non-parametric way of estimating the common space $C(F_t, Y_t)$ of the factors of X_t with principal component analysis (Pearson, 1901; Hotelling, 1933, 1936). In the first step, one estimates $M + K$ principal components, labeled as $\widehat{C}(F_t, Y_t)$, from the set of informational time series X_t using standard techniques. To obtain the estimated factors $\widehat{F_t}$ from these components, one has to determine the part of $\widehat{C}(F_t, Y_t)$ that is not spanned by Y_t, i.e. the we have to remove the dependence of $\widehat{C}(F_t, Y_t)$ from the observable variables Y_t. An easy method for this is given by Bernanke et al. (2005) by splitting X_t into a subset of slow-moving variables, e.g. wages, price and economic activity measures etc, that are by theory not contemporaneous affected by Y_t. Principal components from this subset yield an estimate $\widehat{C^*}(F_t)$. We then make a regression of the form $\widehat{C}(F_t, Y_t) = b_{C^*}\widehat{C^*}(F_t) + b_Y Y_t + e_t$, where $\widehat{C}(F_t, Y_t)$ are the principal components based the complete set X_t. The estimate for the latent factors F_t is then obtained by $\widehat{F_t} = \widehat{C}(F_t, Y_t) - \widehat{b}_Y Y_t$. In the second step, a VAR in $(\widehat{F_t}, Y_t)$ is estimated and identified using a recursive scheme as explained above.

Since the model is econometrically unidentified and we do not want to impose restrictions on equation (28), we have to set restrictions on equation (29). For the two-step approach, this can be accomplished by normalizing the principal components by assuming that $\frac{C^\top C}{T} = I$, where $C^\top = \left[C(F_1, Y_1), \ldots, C(F_T, Y_T)\right]$, which implies that $\widehat{C} = \sqrt{T}\widehat{Z}$

[12] The detailed derivation of the Bayesian approach using Gibbs sampling is given in Appendix A of Bernanke et al. (2004).

with $\widehat{Z}$ being the respective M largest eigenvalues of $XX^{\top}$ ordered in descending order (Bernanke et al., 2005).

Impulse response functions for the variables in Y_t can be obtained by the standard technique from chapter 2.1. The calculation of impulse responses for variables included in X_t can be obtained through the relation given in equation (29) by:

$$X_t^{IRF} = \left[\widehat{\Lambda^f}\ \widehat{\Lambda^y}\right] \begin{bmatrix} \widehat{F}_t \\ Y_t \end{bmatrix} = \left[\widehat{\Lambda^f}\ \widehat{\Lambda^y}\right] \widehat{\delta}(L)\, \varepsilon_t \tag{30}$$

where $\widehat{\delta}(L) = \left[\widehat{\Theta}(L)\right]^{-1}$ is a lag polynomial up to horizon h with $\widehat{\lambda}(L) = \widehat{\lambda}_0 - \widehat{\lambda}_1 L - \ldots - \widehat{\lambda}_h L^h$ and $\widehat{\Theta}_i$ are the respective parameter matrices from the MA representation of the model (Soares, 2011).

Through its appealing advantages and computational simplicity, FAVAR models have been widely adopted in their basic setup (examples among others are given by Vargas-Silva, 2008b; Jimborean and Méesonnier, 2010; Gupta and Kabundi, 2010; Lombardi et al., 2012; Dave et al., 2013; Vasishtha and Maier, 2013; Belke and Rees, 2014; Fernald et al., 2014; Wu and Xia, 2016). Uhlig and Ahmadi (2012) combine the Bayesian sign-restriction approach with a FAVAR model in order to combine the advantages of additional an additional information set with a less restrictive identification scheme. Ellis et al. (2014), Eickmeier et al. (2015) and Abbate et al. (2016) apply the idea of time-varying parameters on the FAVAR context.[13]

2.2 Non-linear VAR models

So far we have discussed the most prominent linear VAR models. Yet, it is clear that in reality, the transmission is impaired by non-linearities arising from different sources. DeLong et al. (1988), Cover (1992), Morgan (1993), Thoma (1994), Kandil (1995) and Karras (1996) find evidence for the existence of asymmetric effects concerning the sign

[13] A good overview of the time-varying VAR literature is given by Primiceri (2005).

of policy shocks. (1999), Garcia and Schaller (2002) and Lo and Piger (2005) find that monetary policy is more effective during recessions and Ravn and Sola (1996) identify asymmetries in the size of monetary shocks.

To account for such influences, many non-linear VAR models have been proposed throughout the last two decades. We will hereby focus on threshold models. Other classes, such as time-varying VARs or Markov-switching VARs are not addressed. The class of mixture model VARs are explained in chapter 6.

2.2.1 Threshold VARs

The first class of non-linear VAR models are threshold vector autoregression (TVAR) models. It is founded on the observation of many researchers (the first among others being Blinder, 1987; Bernanke and Gertler, 1989; McCallum, 1991; Azariadis and Smith, 1998) that the transmission channel works differently throughout the different stages of the business and credit cycle. A first approach in this direction has been made by Tong (1978), Tong and Lim (1980) and Tsay (1989) for the univariate case. Tsay (1998) and Hansen (1996, 1999) derive the multivariate case and Balke (2000) provides the first application. The model itself is straight forward to understand and builds on the idea that a linear VAR model shifts between two (or potentially more) regimes according to the behavior of a transition variable that has to be included in the set of endogenous variables. A structural TVAR model can thus be written as:

$$Y_t = A_1 Y_t + B_1(L) Y_{t-1} + \Big(A_2 Y_t + B_2(L) Y_{t-1}\Big) I\Big(c_{t-d} > \gamma\Big) + U_t \tag{31}$$

where $B_1(L)$ and $B_2(L)$ are the regime dependent lag polynomial matrices and U_t are structural innovations as explained in chapter 2.1. $I(c_{t_d} > \gamma)$ is an indicator function that takes the value 1, when the condition $c_{t-d} > \gamma$ is met and 0 else, where c_{t-d} is the transition variable and γ the threshold value. The threshold effect is assumed to cause a regime shift with a lag of $d \geq 1$ periods.[14] Since γ is a priori unknown, a grid search over all realized values of the transition variable is performed, that is the model is estimated for all values using GLS and the optimal threshold value γ^* is chosen by minimizing the sum of squared residuals.

Testing for linearity is done by applying a Wald or likelihood ratio test and compare a linear VAR with a TVAR model. Inference is then created via the proposed bootstrap method of Hansen (1996). Following Andrews (1993) and Andrews and Ploberger (1994), sup-Wald (supremum), avg-Wald (average) and exp-Wald (exponential) statistics are calculated.

Impulse response analysis are based on the generalized impulse response functions (GIRF) proposed by Gallant et al. (1993) and Koop et al. (1996). The basic idea is that the GIRF is depending on the historical information set Ω_{t-1}, the sign of the shock and its size. The GIRF for horizon k is then calculated by:

$$GIRF_k = E\Big[Y_{t+k}|\Omega_{t-1}, u_t^*\Big] - E\Big[Y_{t+k}|\Omega_{t-1}\Big] \tag{32}$$

where u_t is a particular realization of an exogenous shock, e.g. one sets $u_t^* = [0,\ldots,1]^\top$ to get the impact of a standard deviation shock of variable K on the system. Since the shocks are $U_t \sim N(0, \Sigma_U)$, the corresponding shocks will be zero in average, that is simulating 500 bootstrap draws from the model, results in the average conditional expectation of the impulse response to the predefined shock u_t^*.

Smooth transition vector autoregressive (STVAR) models are based on the same basic idea as TVARs. The only difference is that they model a logistic transition process between the regimes. Weise (1999) proposes a model of the form:

$$Y_t = A_0 + A(L)Y_{t-1} + \Big(\theta_0\theta(L)Y_{t-1}\Big)F(z_t) + u_t \tag{33}$$

[14] A lag of 0 would assume a direct effect of the transition variable onto Y_t, which would contradict the idea of the VAR model identification. Hence, this case is excluded.

where $A(L)$ and $\theta(L)$ are lag polynomials, u_t are error terms, z_t is the transition variable and $F(z_t) = 1/\big(1 + \exp(-\gamma(z_t - c)/\sigma_z)\big)$. The threshold value for z_t to change between regimes is labeled by c, σ_z denotes the standard deviation of the transition variable and γ is a smoothing parameter for the model. If $\gamma \mapsto \infty$ the model reduces to a TVAR. Estimation of the model is done using full-information maximum likelihood methods (Chow, 1973; Belsley, 1980).[15]

Applications of TVAR models are often related to credit conditions (Afonso et al., 2011; Zheng, 2013). Avdjiev and Zeng (2014) extend this idea to a three regime TVAR model. Baum and Koester (2011) apply a TVAR model to show the differences in fiscal policy innovations during the business cycle, while Shen and Chiang (1999) investigate for non-linearities between low and high inflationary regimes and Huang et al. (2005) study the impact of oil price shocks during different regimes of oil dependency. Applications of STVAR models are, among others, given by Camacho (2004), Chelley-Steeley (2005) and Rahman and Serletis (2010). Gefang and Strachan (2009) propose a mixture of Bayesian sign-restrictions and a STVAR model.

[15] The presented model is, for simplicity, the standard approach to a logistic STVAR model. A broader overview of different STVAR models is given by Teräsvirta (1994) and van Dijk et al. (2002).

3 Traditional Channels of Monetary Policy Transmission

In the following chapter, we will investigate the channels of monetary policy transmission and exemplify them with simple empirical evidence.[16] Monetary policy affects real economic activity and inflation in various ways. Since it is hard to capture all possible channels and new developments in research, we focus on the traditional channels as summarized by Mishkin (1995), Taylor (1995), Bernanke and Gertler (1995) or, more recently, by Boivin et al. (2011) and distinguish them into four main effects: (1) the interest rate channel, (2) exchange rate effects, (3) consumption-based channels and (4) credit channels.

3.1 Interest Rate Channel

The direct interest rate channel is possibly the most conventional transmission mechanism and reflects the understanding of the basic IS-LM model from a Keynesian perspective. It can be traced back to Keynes (1936) or Hicks (1937) and is part of nearly every New Keynesian model. It incorporates the impact of the policy rate on the costs of capital and operates mainly through changes in the real interest rate, which can be calculated using the Fisher equation (Fisher, 1930):

$$r = \frac{1+i}{1+\pi_e} - 1 \tag{34}$$

where r is the real interest rate, i the nominal interest rate and π_e the expected rate of inflation. Fisher (1930) assumes the real interest rate to be constant over time, implying that inflation expectations perfectly adapt to changing interest rates.[17] Fama (1975) supports this with a joint test on market efficiency and constancy of real re-

[16] We used monthly US Data from Jan 1992 to Dec 2008 and applied Uhlig's (2005) Bayesian rejection approach to calculate impulse response functions. The respective restrictions are given in table 3. A detailed variable explanation is given in table 1 and 2 in Appendix A. For simplicity, we will refer to changes in log level as percent changes from hereon.

[17] This assumption is also know as the Fisher hypothesis or the Fisher effect and can be extended to various areas of application.

turns in the US bond market. However, Nelson and Schwert (1977), Carlson (1977), Garbade and Wachtel (1978) and Levi and Makin (1979) falsify this finding and verify time-variation in the relationship between inflation and interest rates. Rose (1988) and Mishkin (1992) explain these contradicting findings by stating that the relationship is indeed constant for the period before 1979 and VanderHoff (1984) points out that this is due to a varying effect of expected inflation on interest rates. Finally, Hafer and Hein (1982), Makin (1983) and Pennacchi (1991), among others, find that real interest rates are only affected by unanticipated monetary interventions.

The influence of monetary policy, through inflation expectations, on the real interest rate nowadays implemented in every New Keynesian model (Boivin et al., 2011). One way is to assume sticky wages and prices, modeled by a Calvo rule (Calvo, 1983), where firms have a certain probability to adjust their prices, or by a Taylor approach (Taylor, 1980) in which every period a certain proportion of firms can reset their prices. This leads to a delayed reaction of inflation. Expectations are commonly modeled in the New Keynesian Phillips Curve context as forward looking (Roberts, 1995; Gali and Gertler, 1999). However, this approach fails to explain the importance of lagged inflation on its future development (Rudd and Whelan, 2005), the leading role of output gap on inflation (Fuhrer and Moore, 1995) and the economic costs associated with periods of disinflation (Gordon et al., 1982; Ball, 1995).

Based on the model of Fischer (1977), Mankiw and Reis (2002) propose the implementation of sticky information, that is firms can adjust their prices every period, but only a fraction of them updates their information. The corresponding remainder of firms bases its expectations on outdated developments.

A similar approach to model the lagged reaction of prices is 'rational inattention' and has been put forth by Sims (2003, 2006). It is based on the definition of Shannon (1956, 1958) of noisy information channels and the idea that economic agents can be understood as finite-capacity information channels. Hence, receiving information is associated with costs per unit and it can be rational not to process all available information as under the rational expectation hypothesis.[18]

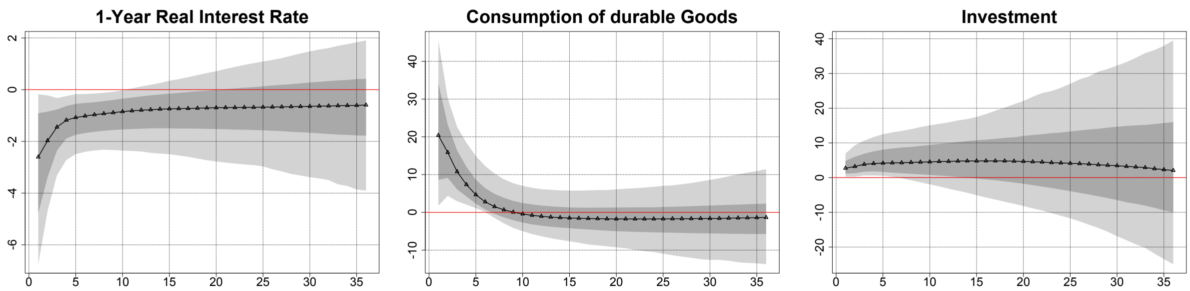
The general statement in all mentioned approaches is that inflation expectations adapt with a lag. Since central banks are assumed to have direct control over short-term interest rates, this leaves room for monetary policy to affect real interest rates until expectations have adapted.

The real interest rate is more important for long-term investment decisions, since it represents the inflation adjusted costs of borrowing. Hence, a lower real interest rate makes consumption of durable goods or business investment more attractive, giving a positive stimulus to economic activity (Mundell, 1963; Dupor, 2001). From this, we can derive the following reaction chain:

$$M \uparrow \Rightarrow i \downarrow \Rightarrow r \downarrow \Rightarrow I \,\&\, C_{db} \uparrow \Rightarrow Y \uparrow$$

By increasing the money supply M under a given money demand, the nominal interest rate and subsequent the real interest rate will drop. Increasing investment I and consumption of durable goods C_{db} then lead to a rise in output Y.

Figure 1: Selective Responses of the Interest Rate Channel



* Light gray shaded areas reflect the 95% confidence level, dark gray shaded areas the 68% confidence level. All responses are given in percent.

This mechanism is illustrated in figure 1 with some selective impulse responses following to an expansionary monetary shock. Similar to Strongin (1995) and Christiano et al. (1999), we can see a significant decline in the real interest rate. A one percent cut

[18] A deeper and more formal insight to this topic is given in (Sims, 2010).

in nominal interest leads to an overshooting of 3 percent of the real interest rate. This stimulates consumption of durable goods and business investment. Angeloni et al. (2003) investigate the interest rate channel and compare the US to the EA. They find that for the US, consumption is the main driver of output changes, while for the EA, investment is the driving force. Our findings indicate that in the US consumption is very sensitive towards monetary policy with a maximum impact of 20 % contemporaneous change, while investment is less reactive and increases for about 5%.

3.2 Exchange Rate Channel

Since nowadays international trade is even more important than ever and all industrialized countries promote more or less flexible exchange rate regimes, the effects of monetary policy interventions on net exports play an important role its transmission to the real economy. The first, among others, to highlight the importance of this channel were Taylor (1995), Obstfeld and Rogoff (1995) and Mishkin (1995).

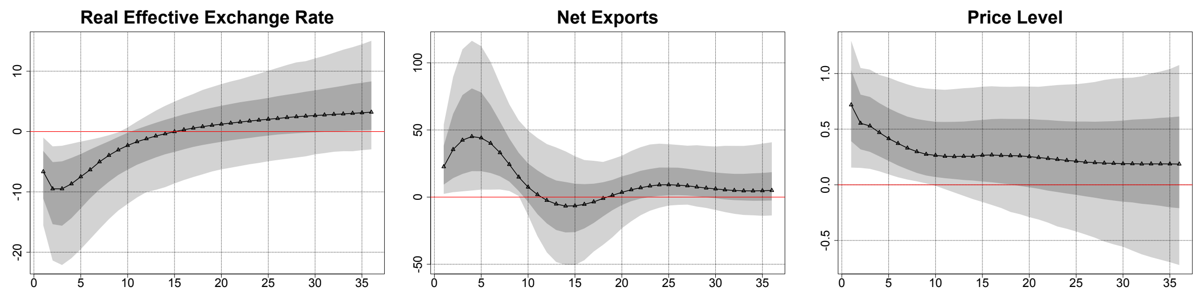
As mentioned before, changes in the nominal interest rate are positively related to changes in the real interest rate. The theory of interest rate parity (Stein, 1962; Glahe, 1967) explicates, that for example a decrease in the US real interest rate will make US bonds less profitable. This will reduce the value of the dollar relative to other currencies (E) due to investors restructuring their portfolios away from US bonds and hence lower dollar demand and foreign currency supply. The dollar depreciation in turn lowers the real exchange rate and makes US products cheaper for foreign consumers and imports more expensive for US consumers, giving the US a cost advantage and leading to an increase in net exports (Cumby and Obstfeld, 1981; Taylor, 2001). In the long-run, prices and wages will adjust and level off this comparative advantage (Taylor, 1995):

$$M \uparrow \Rightarrow i \downarrow \Rightarrow r \downarrow \Rightarrow E \downarrow \Rightarrow NX \uparrow \Rightarrow Y \uparrow$$

Another important point to note is that nominal and real exchange rates are known to exhibit overshooting behavior. This is due to the rigid prices in goods markets relative to asset markets in combination with freely flexible nominal exchange rates. In order to achieve a new short-run equilibrium in asset markets, averting arbitrage, foreign exchange markets overreact and gradually reprice towards the new long-run equilibrium as prices in the goods market slowly adjust (Dornbusch, 1976; Buiter and Miller, 1982).

Empirical evidence for this channel is stated by Dornbusch (1976), Taylor (1995), Smets and Wouters (2002) or Bruno and Shin (2015). Leitemo et al. (2002) show that central banks benefit from the exchange rate channel to get a better control over future inflation. Aleem and Lahiani (2014) investigate non-linearities in the exchange-rate pass through in Mexico and find that the response of inflation is insignificant during times of low inflation and strongly significant, if for high inflation periods.

Figure 2: Selective Responses of the Exchange Rate Channel



* Light gray shaded areas reflect the 95% confidence level, dark gray shaded areas the 68% confidence level. All responses are given in percent.

For our own purposes, we illustrate the exchange rate channel in figure 2 with the responses of real effective exchange rate[19] and net exports. The effects of an negative one percent shock of the federal funds rate on both variables has only short- to mid-run effects. We clearly see the above explained overshooting in the real effective exchange rate, decreasing for about 10% for two to three months. Net exports strongly decrease for ten months. The price level adjusts more slowly.

[19]The real effective exchange rate data is published by the Bank of International Settlements and based on the proposed methodology of Turner and Van ’t dack (1993).

3.3 Asset Price Channels

One of the key ideas of monetarism is, that monetary policy interventions affect the real economy indirectly through asset price fluctuations (Friedman, 1956; Mishkin, 1995). Relative asset prices are assumed to be a key driver of business investment and consumption decisions. Of course the universe of relative prices is huge and changing throughout the business cycle. In order to keep track of the most important facets, we focus on three dominating price channels.

Equity Price Channel

Tobin (1969) provides a framework in which he explains the incentive for firms to further invest into production facilities, introducing q as the firm's market value in ration of its replacement costs:

$$q = \frac{\text{market value of firm}}{\text{replacement costs of capital}} \tag{35}$$

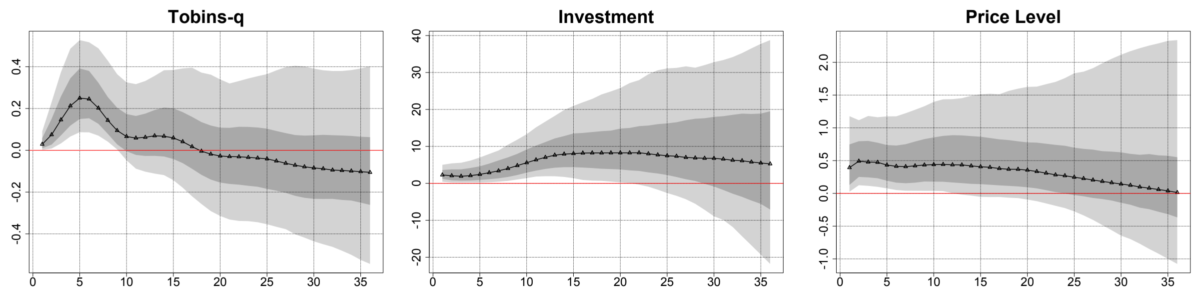
Tobins-q is an easy variable for analyzing whether the investment environment is appealing or not. If q is is greater than one, further investment is reasonable since firms can easily emit new shares for a relatively higher price than what they need for scaling up their business.

Monetary policy shocks affect stock prices and the price of other company shares (P_S). Hence, following to decline in short-term interest rates, q will rise, making investments more interesting and leading to an increase in production:

$$M \uparrow \Rightarrow i \downarrow \Rightarrow P_S \uparrow \Rightarrow q \uparrow \Rightarrow I \uparrow \Rightarrow Y \uparrow$$

Of course q is a very simple measure and a major problem arises from the fact, that we can only observe the average value of current equity rather than the marginal value of newly issued shares. A further look into this discussion is given by Hayashi (1982) and von Furstenberg et al. (1977). General critique on the Tobins-q measure arises from the fact, that stock prices are very volatile and often deviate from fundamentals, hence making *q* an imprecise measure (Gilchrist and Leahy, 2002; Bond and Cummins, 2001). Bernanke and Gertler (1989) use an accelerator approach and argue that balance sheet positions are affected by the state of the business cycle and further influence investment demand. Ehrmann and Fratzscher (2004) find non-linearities in the equity price channel. Firms with weak balance sheets and low cash-flows are more affected by expansionary monetary policy shocks, since they are more constrained from financial markets, that is, they have less access to and worse credit conditions.

Figure 3: Selective Responses of the Equity Price Channel



* Light gray shaded areas reflect the 95% confidence level, dark gray shaded areas the 68% confidence level. The responses of Investment and Price Level are given in percent, the response of Tobins-q in units of the index.

Figure 3 illustrates the effects of monetary policy through asset price fluctuations. As we can see, Tobins-q strongly rises following a one percent decrease of the federal funds rate. Investment rises for about 8% at maximum and the price level adjusts gradually.

Consumption-based Channels

The so called *wealth effect* is a basic idea of economics and is based on the life cycle hypothesis of saving and consumption (Brumberg and Modigliani, 1954; Ando and Modigliani, 1963).[20] Consumers are assumed to maximize their Credit-to-GDP Gap temporal utility subject to their intertemporal budget constraint, determined by life-

[20] A more recent summary of this idea is given by Browning and Crossley (2001).

time resources. Monetary easing increases household wealth mainly through increasing stock market prices (financial wealth) and housing prices (non-financial wealth).[21] Through their intertemporal expected utility maximization, this will lead households to consume more in the present and aggregate output will rise:

$$M \uparrow \Rightarrow i \downarrow \Rightarrow \text{Financial Wealth} \,\&\, \text{Non-Financial Wealth} \uparrow \Rightarrow C \uparrow \Rightarrow Y \uparrow$$

The idea of the life cycle hypothesis is closely linked to Friedman's (1957) permanent income hypothesis. Friedman splits income and consumption into a permanent and a transitory part and assumes a functional long-run link between both permanent fractions and allows for further influencing variables.

Another point through which monetary policy indirectly affects relative prices is the time preference in the typical Euler equation (Ramsey, 1928; Tintner, 1937; Parker, 2008). Lower short-term interest rates make it less attractive to save for future consumption. Hence, consumers will restructure towards consumption today.

Though, empirical evidence suggests the relationship exhibits non-linearities and thus is more complex. Based on Friedman's hypothesis, Zellner et al. (1965) show that liquidity[22] is a key driver of short-term consumption decisions. Wiseman (1975) finds that unexpected jumps in stock prices lead to increased short-term consumption. If these windfalls are rather small, they are unmitigatedly used for consumption, while large windfalls change the saving behavior of consumers due to increasing expected returns on stocks. This finding is supported by Steindel and Ludvigson (1999). Pissarides (1978) is the first to point out that the cointegration relationship between liquidity and consumption is influenced by different factors, such the individual discount rate and transaction costs. Hence, tests for cointegration tend to reject the relationship on an aggregate level (Rudd and Whelan, 2006). Also, Mankiw and Zeldes (1991) find

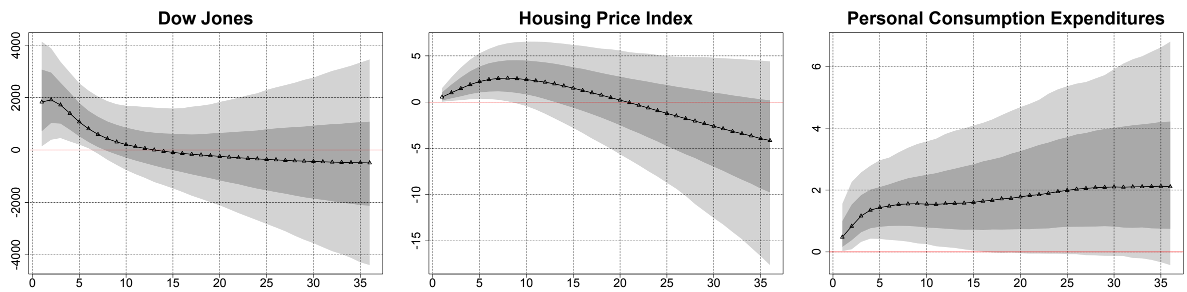
[21] Increases in housing and plot prices are often referred to as the *housing price channel*. Since both effects are based on the life cycle hypothesis, we subsume both as consumption based.

[22] Since listed shares are easy to liquidate without huge losses, they can also be counted as liquidity and shocks on stock prices can be assumed to change households liquidity holding in a broader sense.

that the reaction differs between consumers who are stockholders and those who are not. The consumption of stockholders is more volatile and reacts stronger to stock price fluctuations since they are directly affected by gains and losses. Nonstockholders are only indirectly influenced through changes in consumer sentiment.[23]

Case et al. (2005) estimate a relatively bigger effect for increases in housing prices compared to stock prices, while Dvornak and Kohler (2007) relativize this finding. Similarly, they find a stronger effect for stock prices increases. However, they argue that the average share of housing wealth on total wealth is twice as big as for stocks, leading to a comparable effect for both. Non-linearities in wealth effects arise from different angles. Campbell and Cocco (2007) show that the impact is highest for old homeowners and insignificant for young renters. This finding is clarified by Disney et al. (2010) who find out that the age of consumers has no effect, but the property status. Homeowners benefit from increases in housing prices, while renters hardly face any difference. Lastly, Slacalek (2009) and MacDonald et al. (2011) point out that lower borrowing constraints amplify wealth effects and MacDonald et al. (2011) further estimate that expansionary shocks have greater impact than contractionary ones.

Figure 4: Selective Responses of Consumption-Based Channels



* Light gray shaded areas reflect the 95% confidence level, dark gray shaded areas the 68% confidence level. The responses of the Housing Price Index and Personal Consumption Expenditures are given in percent, the response of the Dow Jones in units of the index.

Our own small scale examination of wealth effects supports these findings on an aggregate level. Yet, the impact on consumption is far below the common value of 3% used

[23] A good summary of this topic is given, aside from his general finding that stock prices have a robust influence on consumption, in Poterba (2000).

in the literature (Poterba, 2000). We use the Dow Jones Index as a measure for financial wealth, since we assume households to invest in known and rather conservative industrial and service companies. Stock prices show a more pronounced direct effect, while the reaction for housing prices is longer-lasting, similar to the overall effect on aggregate consumption.

3.4 Credit Channels

In contrast to the aforementioned channels that handle demand side effects on either lending or consumption, the credit channel deals with supply side effects in bank lending. Its based on the failure of the Modigliani-Miller theorem for banks (Modigliani and Miller, 1958, 1963).[24]

Bernanke and Blinder (1988) were one of the first to point out that there might be frictions inside the credit market and highlight the special role of banks in the transmission of monetary policy.[25] Nowadays, we divide the credit channel into three main aspects: the bank lending channel, the bank capital channel and the balance sheet channel.

The *bank lending channel* is based on several assumptions. First, banks are given a special role to overcome information problems in the process of financial intermediation. Many borrowers cannot perfectly substitute bank credit with other sources of financing (Bernanke and Gertler, 1995; Huang, 2003). The second assumption is that central banks directly affect banks' deposits and liquidity. Banks cannot make up for this shortfall without frictions and thus adjust their lending activities (Bernanke and Blinder, 1992; Kashyap and Stein, 1995; Boivin et al., 2011). Typically, smaller banks have less ability to finance their lending activities through uncovered deposits or other

[24]In short, the theorem states that the capital structure of a firm has no effects on its costs of capital. The original idea was derived in 1958 assuming a tax-free world and expanded by taxes in the 1963 paper.

[25]Bernanke and Gertler (1995) also introduce the concept of an 'external finance premium', the difference between the costs of internal versus external funding. This difference can be proxied by interest rate spreads between higher yield bonds and supposedly risk-free assets as argued by Bernanke and Gertler (1995) or later by Gertler and Lown (1999) and De Graeve (2008).

sources (such as corporate bonds) and contractionary monetary policy leads to a liquidity drain, forcing a slowdown in credit growth (e.g. Stein, 1998; Kashyap and Stein, 2000). Kakes and Sturm (2002) point out that big banks, even if they hold less liquidity, are better able to raise funds. The recent increase in securitization has of course increased banks general access to liquidity and weakened the bank lending channel (Altunbas et al., 2009). This effect appears to be procyclical, since securitization activity typically co-moves with the business cycle, thus worsening banks access to liquidity during downturns. An unanticipated dry up of this source of liquidity, following a financial crisis as observed after the sub-prime burst, has strong negative effects on bank lending (Gambacorta and Marques-Ibanez, 2011). Possible counteractions are fast and large scale liquidity injections of central banks (Diamond and Rajan, 2011).

The so called *bank capital channel* explains the impact of monetary policy on banks' balance sheets[26] and its transition onto their lending behavior. A rise in short-term interest rates is associated with a fall in asset prices. Banks may face losses, as seen in the recent financial crisis, and their equity base erodes. To maintain their capital quota, banks will either have to raise new equity, which is extraordinary problematic during financial crisis, or cut down their risk-weighted assets (RWA).[27] Hence, banks are likely to decrease loan supply. Another point in bank capital is that it can works as a boundary for banks' lending. Lowly capitalized banks can easily face a situation in which they would have enough liquidity for further lending, yet they reach their minimum capital ratio (Kishan and Opiela, 2006). Relatedly, banks might want to hold a buffer above their minimum capital ratio (Van den Heuvel, 2002), since a violation of certain quotas is associated with strict penalties.[28] The asymmetrically stronger effect on banks with low equity ratios is a very frequent finding in literature (Kishan and Opiela, 2000; Van den Heuvel, 2002; Kishan and Opiela, 2006; Jiménez et al.,

[26]In contrast to the bank lending channel that focuses on the asset side of the balance sheet, the bank capital channel deals with effects on the liability side.

[27]According to Basel III there are three types of risk: (i) credit risk, (ii) market risk and (iii) operational risk. Credit risk plays the predominant role of these three parts (Avramova and Le Leslé, 2012) and hence cuts in lending activity are the easiest way to decrease the sum of RWAs.

[28]For instance, only a slight violation of the Basel III capital conservation buffer leads to a profit retention of 40% (Basel Committee on Banking Supervision, 2011) and gives a negative market signal associated with a fall in the respective banks stock prices.

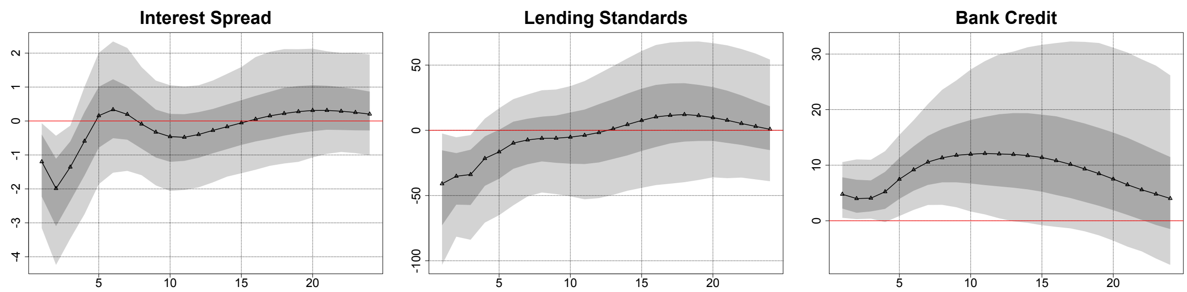
2012). Altunbas et al. (2002) also find that this effect is even more pronounced in small EMU countries due to a worse access to financial markets. More recently, Disyatat (2011) argue that liquidity and equity are no longer predominant restrictions. The general health status of banks, proxied by the individual external risk premium, better explains credit movements on the micro level.

Further, expansionary monetary policy interventions negatively affect banks profitability. This effect is mainly driven by flattening the yield curve and compressing banks' interest margin (Hancock, 1985; Borio et al., 2015). Banks react by taking on more risk in their credit portfolio and lowering lending standards, that is increasing the expected rate of return, the so-called risk-taking channel, that can be seen as a subchannel of the bank capital channel (Boivin et al., 2011). We will come to this in greater detail at chapter 5, when we analyze the risk-taking channel of monetary policy in the Euro Area.

The last facet of the credit channel is the *balance sheet channel*. It originates from asymmetric information (Stiglitz and Weiss, 1992) and adverse-selection (Akerlof, 1970) inside the credit market. Borrowers typically have better information about their financial situation and collateral can only partially solve this problem. Expansionary shocks increase the value of collateral and borrowers net worth, thus help to overcome this frictions and amplify the effects of monetary policy. Models that incorporate this mechanism are often referred to as accelerator models (e.g. Bernanke and Gertler, 1989; Stein, 1995; Bernanke et al., 1996, 1999; Aoki et al., 2002, 2004; Iacoviello, 2005; Almeida et al., 2006; Christensen and Dib, 2008). Research has proven that small firms and consumers are bank credit dependent (Gertler and Gilchrist, 1993, 1994; Reifschneider et al., 1997; Kakes and Sturm, 2002) and have less ability to finance investments through internal sources (Oliner and Rudebusch, 1996). This is consistent with the 'flight to quality'[29] and 'flight home'[30] literature. Peek and Rosengren (1997) even find evidence for an international transmission of monetary policy shocks through international lending and balance sheet effects. Mortgage markets, as an example of credit dependent durable goods consumption, respond stronger to monetary policy shifts in countries where mortgage credits are more bank based (Iacoviello and Minetti, 2008) and in countries with higher loan-to-value ratios (Almeida et al., 2006).

Contrary to the existing evidence of a credit channel, there is still controversy. Romer and Romer (1989) argue that the banks ability to raise funds significantly increased after the Regulation Q[31] and doubt the influence of bank credit on inflation and output. Mauskopf et al. (1990) points out that the degree of credit rationing by banks dramatically decreased after the deregulation in the 1980's. Ramey (1993) finds no significant impact of bank lending on industrial production. More recently, Ashcraft (2006) recognizes financial constraints to play an important role in the transmission of monetary shocks to the credit system. Yet, he argues that bank credit is not a unique source of funding and finds that the biggest proportion of loan supply fluctuations is driven by output growth.

Figure 5: Selective Responses of the Credit Channel



* Light gray shaded areas reflect the 95% confidence level, dark gray shaded areas the 68% confidence level. The responses of the Interest Spread and Bank Credit are given in percent, the response of Lending Standards in units of the index.

[29]The 'flight to quality' literature shows that banks switch towards high quality borrowers after a monetary tightening or other external shocks that increase the degree of information asymmetry (Lang and Nakamura, 1995; Bernanke et al., 1996; Dell'Ariccia and Marquez, 2004; Beber et al., 2009; Acharya and Naqvi, 2012).

[30]The 'flight home' effect means that banks have a clear home bias for new credits during times of economic disruptions (Rajan, 1992; Giannetti and Laeven, 2012a,b; De Haas and Van Horen, 2013).

[31]For a deeper summary of Regulation Q, we advise the interested reader to Gilbert (1986).

Our own evidence is reported in figure 5 and shows selected impulse responses to a negative shock in the policy rate of 1%. As we can see, the interest spread reacts quickly and exhibits overshooting behavior. This finding is in line with the literature (among others: Stock and Watson, 1989; Friedman and Kuttner, 1992; Kashyap et al., 1993). Lending standards strongly decrease in the short-run, indicating a supply shock from banks' side. The impact on bank credit takes about three years to fully come into effect with a peak of about 12% increase in bank lending.

3.5 Appendix A

Table A1: Dataset used for Estimations in Chapter 3.4

Variable Name	Frequency	Unit	FRED Code
Industrial Production Index	Quarterly	Log (Index 2012=100, SA)	INDPRO
Consumer Price Index less Food and Energy	Quarterly	Log (Index 1984 = 100, SA)	CPILFESL
Bank Credit of All Commercial Banks	Quarterly	Log (Bil. of USD, SA)	TOTBKCR
Net Percentage of Domestic Banks Tightening Standards for Commercial and Industrial Loans to Small Firms	Quarterly	Percent (NSA)	DRTSCIS
Baa Corporate Bond Yield Spread to 10-Year Treasury Constant Maturity	Quarterly	Percent (NSA)	BAA10Y
Federal Funds Rate	Quarterly	Percent (NSA)	FEDFUNDS

Remark: Lending standard data refer to net percentages from the Senior Loan Officer Opinion Survey on Bank Lending Practices (The Federal Reserve Board, 2016). Quarterly values of all other variables are calculated by their average.

Table A2: Dataset used for Estimations in Chapter 3.1-3.3

Variable Name	Frequency	Unit	FRED Code
Industrial Production Index	Monthly	Log (Index 2012=100, SA)	INDPRO
Consumer Price Index less Food and Energy	Monthly	Log (Index 1984 = 100, SA)	CPILFESL
Federal Funds Rate	Monthly	Percent (NSA)	FEDFUNDS
Commercial and Industrial Loans	Monthly	Log (Bil. of USD, SA)	BUSLOANS
Real personal consumption expenditures: Durable goods	Monthly	Log (chain-type quantity index 2009=100, SA)	DDURRA3M086SBEA
1-Year Real Interest Rate	Monthly	Percent (NSA)	*REALINTEREST*
Baa Corporate Bond Yield Spread to 10-Year Treasury Constant Maturity	Monthly	Percent (NSA)	BAA10Y
Tobins-q	Monthly (Interpolated)	Mil. of (USD/1000)/(Bil. of USD)	(NCBEILQ027S/1000)/ TNWMVBSNNCB
Real Personal Consumption Expenditures	Monthly	Log (Bil. of Chained 2009 USD, SAAR)	PCEC96
Dow Jones Industrial Average	Monthly	Index (NSA)	*Yahoo Finance Code (INDEXDJX)*
S&P/Case-Shiller U.S. National Home Price Index	Monthly	Log (Index 2000=100, SA)	CSUSHPISA
Net Exports of Goods and Services	Monthly (Interpolated)	Log (Bil. of USD, SAAR)	NETEXP
Real Effective Exchange Rates Based on Manufacturing CPI	Monthly	Log (Index 2010=1, SA)	CCRETT01USM661N

Remark: Tobin-q and Net Exports have been linearly interpolated. Monthly values of the Dow Jones Index have been calculated, using end of period values (Yahoo Finance, 2016). The 1-Year Real Interest Rate is calculated by the Federal Reserve Bank of Cleveland using its own inflation expectation data (Federal Reserve Bank of Cleveland, 2016).

Table A3: Sign Restrictions for Estimations in Chapter 3.1-3.4

1. Interest Rate Channel					
INDPRO	$CPILFESL_g$	BUSLOANS	$DDURRA3M086SBEA_g$	REALINTEREST	FEDFUNDS
+	+	+	+	-	-
2. Exchange Rate Channel					
INDPRO	CPILFESL	NETEXP	CCRETT01USM661N	FEDFUNDS	
+	+	+	-	-	
3. Equity Price Channel					
INDPRO	$CPILFESL_g$	BUSLOANS	(NCBEILQ027S/1000) /TNWMVBSNNCB	BAA10Y	FEDFUNDS
+	+	+	+	-	-
4. Consumption-Based Channels					
INDPRO	$CPILFESL_g$	PCEC96	$CSUSHPISA_g$	INDEXDJX	FEDFUNDS
+	+	+	+	+	-
5. Credit Channel					
INDPRO	CPILFESL	TOTBKCR	DRTSCIS	BAA10Y	FEDFUNDS
none	none	+	-	-	-

Remark: '+' reveres to the assumption of a positive response, '-' reveres to a negative response, 'none' means that no assumption about the response has been made. Subscript g indicates that the yearly growth rate is used. Models 1-4 are assumed to hold the sign restrictions for nine months. Model 5 is assumed to hold the sign restrictions for three quarters.

4 Non-linear Propagation of Shocks during the Financial Cycle

Chapter Abstract

Using quarterly US Data reaching from 1954 to 2007, we apply a Threshold Vector Autoregression (TVAR) model to examine the impact of monetary, real and credit shocks throughout different stages of the financial cycle. In contrast to the existing literature, we apply the Credit-to-GDP gap as our transition variable and allow for three regimes. By doing so, we are able to capture the relationship of the credit market and the real economy rather than focusing exclusively on one sector. Statistical tests strongly support the existence of three regimes in the financial cycle. Generalized impulse analysis reveal that the effects of monetary policy shocks are severely weakened during the up- and downswing of the financial cycle. In addition, credit shocks turn out to be more harmful during the upswing. Our findings help to explain why leaning against the subprime bubble of 2007 was ineffective.

4.1 Introduction

One of the key questions for central banks is if and how they should respond to asset prices, the so-called lean versus clean debate. It resolves around the benefits and disadvantages of monetary interventions towards asset price bubbles and is based on different understandings of central banks abilities and scope to influence the economy during different phases.

The prevailing opinion, the clean-up approach, is represented by Greenspan (2002) as well as Bernanke and Gertler (2001), Bernanke (2009), Mishkin (2001, 2007) and Yellen (2009). They argue to stay neutral towards asset prices in order to maintain the primary goal of price stability over the medium term. Interventions are only desirable if financial crisis occur as central banks stimulate lending and stabilize the economy. Justifications are mainly based on three pillars.

First of all it is believed that central banks are not able to detect deviations from trends, that may lead to bubbles, ahead of the financial market. And even if they could, the monetary policy authorities will face delays. The collection and processing of information, decision-making processes on monetary policy interventions and their implementation devour possible information advantages. In addition, changes of policy rates are commonly found to take up approximately two years to fully display their impact (Bernanke and Gertler, 1995). Secondly, monetary policy is considered a very blunt tool. It is impossible to affect only a single sector that is concerned by a bubble. However many sectors are heavily dependent on banks lending activity. But certainly not every sector is affected by worrying deviations of prices that could indicate the build-up of a bubble. Therefore it is assumed that raising interest rates during the build-up of a bubble is attached to macroeconomic costs due to higher credit rates and lower investment activities. Lastly, the impact of raising policy rates is assumed to be mitigated during times of rapid increases in asset prices. Market participants expect rising prices and high returns. Higher costs of funding have little to no effect unless expectations would be altered. This however would inevitably prick the bubble and evoke a financial crisis that could have been avoided.

For advocates of this approach, central banks role is to dampen periods of economic distress but to stay neutral during upswings. Yet, the global financial crisis has revealed, that the stimulation of demand, once interest rates approach zero, is a key issue. The predominant tool for this during the global financial crisis was quantitative easing (QE). First used by the Bank of Japan (Shirakawa, 2002) in 2001, it has proven its worth throughout the last decade. Research has found different effects of QE depending on the financial structure of the relevant economy and varying implementation and announcement schemes. For the UK, Joyce et al. (2011) estimate a lowering of medium to long-term gilt rates by 100 bps. Breedon et al. (2012) extend this with a drop in long-term bond yields due to rebalanced portfolios. According to Christensen and Rudebusch (2012), this is mainly driven by reductions in term premiums for the UK. For the US, the main effect of QE was caused by lower market expectations about future short-term interest rates. D'Amico et al. (2012), Gagnon et al. (2011) and Doh (2010) detect lower term premiums for long-term treasury bonds, which is expanded by Krishnamurthy and Vissing-Jorgensen (2011) for the case of non-treasury assets. Fratzscher et al. (2013) discovere capital flows from emerging market economies towards the US due to QE rebalancing of portfolios which was followed by a appreciation of the USD. Another interesting point is the finding of Kashyap and Stein (2000) that the impact of liquidity injections on credit is higher for less liquid banks. This is confirmed by Bowman et al. (2011) and Hosono (2006) in the case of Japan. Albu et al. (2014) encounter increasing risk taking in the field of credit default swaps due to the ECBs QE program. Overall, the macroeconomic impact of the FEDs QE is found to have mitigated the decline in real GDP and inflation by 1.5 %-3 % and 1 %-1.25 % respectively and the increase in unemployment by 1.5 % (Chung et al., 2012; Kapetanios et al., 2012).

However, QE does not come without disadvantages. The low interest rate environment compresses the net interest margin, that is, banks conventional source of profit (Lambert, 2015). A problem well known from the first QE utilization in Japan which led to a liquidity trap and a subsequent lending crash (Goyal and McKinnon, 2003). In addition, the rise in liquidity leads to an increase in banks risk-taking (Kandrac and Schlusche, 2016). In summary it can be said that QE may cushion a financial crisis in the short run but creates incentives to discard the necessary purge of banks balance sheet.[32] In the end, this may lead directly into the next crisis.

The counterpart of this discussion favors the lean approach. Central banks should - under certain circumstances - try to deflate asset price bubbles (Rudebusch, 2005). Research has identified the presence of two different types of bubbles (Brunnermeier and Schnabel, 2016; Schularick and Taylor, 2012; Mishkin, 2010). They can be distin-

[32]Governments throughout Europe try to shield their private banks from the potential dangers of toxic papers and credits by transferring them into so-called 'bad banks'. These institutions are state owned banks with the sole purpose phase out those products (Schäfer and Zimmermann, 2009).

guished based on their source of funding. Price deteriorations, that are solely based on irrational expectations and in which credit lending is not involved, have limited influence on the real economy. If the bubble bursts, losses only affect the investors capital and credit lending is mostly unaffected. A credit-driven bubble on the other side creates a feedback loop between asset prices and credit lending. As a result, credit risk increases and accumulates in banks balance sheets. Once prices start to drop the feedback loop reverts and banks have to face immense depreciations. In response banks cut their lending and may - as in the case of Lehman - default. This mechanism is far more harmful for the economy (Mishkin, 2011) and justifies preventive engagement of the central bank in order to achieve its mission and ensure price stability.

The turmoil of the financial crisis has led to a paradigm shift. Previously, most central banks did not actively lean against bubbles but rather reacted to the macroeconomic consequences of the build-up. Currently, the debate shifted towards the leaning approach and many economists acknowledge the financial cycle and respectively credit market developments to be crucial for the evaluation of financial stability and respective central bank and macroprudencial interventions (Borio and Shim, 2007; Blanchard et al., 2010; Drehmann et al., 2012; Borio, 2014; Borio et al., 2016)

Our paper contributes to the existing literature by applying a two threshold VAR. While previous research focused either on credit market conditions, for example credit growth rates or financial stress indicators, or the real business cycle, proxied by output growth, we analyze non-linearities in the transmission of monetary policy arising from the financial cycle. Using the Credit-to-GDP Gap as transmission variable therefore allows us to interpret movements of the credit market in relation to the real economy. Statistical tests strongly support the existence of three regimes in the financial cycle. Generalized impulse response analysis reveal that the effectiveness of monetary policy shocks is severely weakened during the up- and downswing of the financial cycle. In addition, credit shocks turn out to be more harmful during the upswing, indicating that . With this at hand, we shed light on the powerful impact of the recent financial crisis and why central bank interventions where mostly without effect.

The remainder of our paper is structured as follows. In Chapter 4.2, we will introduce the two threshold TVAR model and test for threshold non-linearity. Chapter 4.3 describes the procedure of calculating non-linear impulse responses and analyses the regime-dependent impact of monetary and credit shocks. Chapter 4.4 assembles our results and concludes political implications.

4.2 Methodology and empirical strategy

Our model goes back to the univariate threshold autoregressive model from Tong (1978) and Tong and Lim (1980). Tsay (1989, 1998) later on propose a multivariate version and implement tests for threshold non-linearity. Simulation strategies are developed by Hansen (1996, 1999). In our model we follow the setup of Avdjiev and Zeng (2014), but deviate in respect of the identification scheme. While Avdjiev and Zeng use an A model, we apply the recursive Cholesky identification of (Sims, 1980a,b). The three-regime TVAR model can be written in compact representation by:

$$
\begin{aligned}
Y_t =& B_1(L)Y_{t-1}I(y_{t-d} \leq \gamma_1) + B_2(L)Y_{t-1}I(\gamma_1 < y_{t-d} \leq \gamma_2) \\
&+ B_3(L)Y_{t-1}I(y_{t-d} > \gamma_2) + u_t
\end{aligned}
\tag{36}
$$

where Y_t is the vector of endogenous variables, $B_1(L)$, $B_2(L)$ and $B_3(L)$ are the lag polynomial coefficient matrices, u_t is the vector of innovations. The transition variable is labeled as y_{t-d} and determines in which regime the system is in. The threshold effect is assumed to cause a regime shift with a lag of $d \geq 1$ periods.[33] The non-structural error terms are denoted by u_t. $I(.)$ is an indicator function, taking the value 1 if the expression in parenthesis is true and 0 otherwise. The threshold values γ_1 and γ_2 are estimated alongside the coefficient matrices using a grid search over all realizations of y_{t-d} included in the data.

[33] A lag of 0 would assume a direct effect of the transition variable onto Y_t, which would contradict the idea of the VAR model identification. Hence, this case is excluded.

Our dataset consists of six quarterly US variables, spanning from 1955 to 2007. A detailed description of the data set is given in table 1. The recursive ordering scheme is as follows: (1) Federal Funds Rate, (2) Credit Growth, (3) Credit-to-GDP Gap, (4) Interest Rate Spread, (5) Inflation and (6) GDP.

Table 1: Variable Description

Variable	Description	Level
Output Growth	Capacity Utilization: Manufacturing (SIC)	Change from Year Ago, Percent of Capacity
Inflation Rate	Gross Domestic Product: Implicit Price Deflator (2009=100)	Percent Change from Year Ago
Interest Rate Spread	Moody's Seasoned Baa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity	Change from Year Ago, Percent
Credit-to-GDP gap	Basel III Credit-to-GDP gap	Index
Credit Growth	Total Credit to Non-Financial Corporations, Adjusted for Breaks	Percent Change from Year Ago
Federal Funds Rate	Effective Federal Funds Rate	Change, Percent

[1] Data source: FRED Economic Data.

In accordance to Giordani (2004), we apply the capacity utilization rate to avoid a strong price puzzle. Other common methods to eliminate the price puzzle, such as the usage of a commodity price index or an external energy price variable are considered inappropriate, since adding supplementary variables to the model would dramatically reduce estimation accuracy.[34] Furthermore, the capacity utilization rate is a good proxy for the GDP gap which is the relevant variable from a theoretical point of view. Changes of the capacity utilization rate can be interpreted similar to GDP growth rates (Berndt and Fuss, 1986; Greenwood et al., 1988; Kuttner, 1994; Price, 1995; Corrado and Mattey, 1997).[35] Hence, we will refer to this as output growth rates hereafter.

[34]This is due to the combination of exponential growth in the number of estimated parameters, which VAR models in general exhibit and the fact that we have to estimate all parameters for three regimes.

[35]We chose the capacity utilization rate of the manufacturing sector since it is the only series available back up to 1955.

We choose the implicit GDP deflator as proxy of the price level. It is a broader measure for inflation, compared to the CPI and also captures shifts in consumption behavior (Alchian and Klein, 1973). Further, it responds less sensitive towards oil price shocks and does not include financial assets.

The spread between Baa corporate bond yields and 10-year treasury bills is a good proxy for the risk premium and captures the balance sheet channel of monetary policy (Bernanke and Gertler, 1995). In addition, it accounts for the compensation of systemic risk build-up (Elton et al., 2001) and has predictive power on future economic development (Bernanke, 1990).

Our transition variable is the Credit-to-GDP gap, because it has some major advantages. It captures movements of both, the financial and real economy, placing them in relation to each other. By doing so it resembles the financial cycle which is assumed to have far more influence on mid-term prices than the real cycle. Large positive values indicate a dominance of the credit market over the real economy. Such an excessively large credit aggregate indicates the build-up of a credit-driven asset price bubble. The Credit-to-GDP gap may not be the best early warning indicator from a statistical point of view (Edge and Meisenzahl, 2011; Repullo and Saurina, 2011; Buncic and Melecky, 2014) and does not necessarily represent an equilibrium notion. Nevertheless, it performs well as an indicator for credit-driven crisis (Drehmann et al., 2012; Drehmann and Tsatsaronis, 2014) and suffices the policy requirements stated by Drehmann and Juselius (Drehmann and Juselius, 2014). We calculate the Credit-to-GDP gap in accordance with the BIS guide (Bank of International Settlements, 2010). First we compute the ratio of Credit[36] to nominal GDP:

$$Ratio_t = \frac{Credit_t}{GDP_t} \cdot 100 \tag{37}$$

Afterwards we estimate the long term trend by using a two-sided Hodrick-Prescott filter (Hodrick and Prescott, 1997) with a smoothing parameter of $\lambda = 400,000$. The

[36]Credit is defined, according to the BIS, for the US as the sum of credit market debt to non-financial corporate business and household & nonprofit organizations.

λ-parameter is set to such an uncommonly high level to ensure the filter properly captures the financial cycle. As Aikman et al. (2010) and Borio (2014) have pointed out, the financial cycle is far longer than the traditional business cycle.[37] The Credit-to-GDP gap is then calculated by subtracting the trend from the actual ratio:

$$Gap_t = Ratio_t - Trend_t \tag{38}$$

For the calculation of the Credit-to-GDP gap we use the nominal GDP and a similarly broad credit aggregate as proposed by the BIS.[38] As we can see in figure 6, the long-term relationship is nearly monotonically increasing and there is no visible structural change. Therefore, the credit market is getting ever bigger in relation to the real economy. Similar to the findings of Drehmann and Tsatsaronis (2014) we discover the financial cycle to require roughly 20 years from peak to peak. Moreover the amplitude is strongly increasing which can be explained by the ongoing deregulation policy.

Credit growth resembles the credit channel and highlights the importance of credit supply for the transmission of monetary policy (Bernanke and Gertler, 1995). If banks' credit supply shrinks, borrowers have to face higher costs of funding and overall investments decrease.

As a direct measure of the monetary policy actions, we use changes in the effective Federal Funds Rate (Bernanke and Blinder, 1992; Christiano et al., 1996).

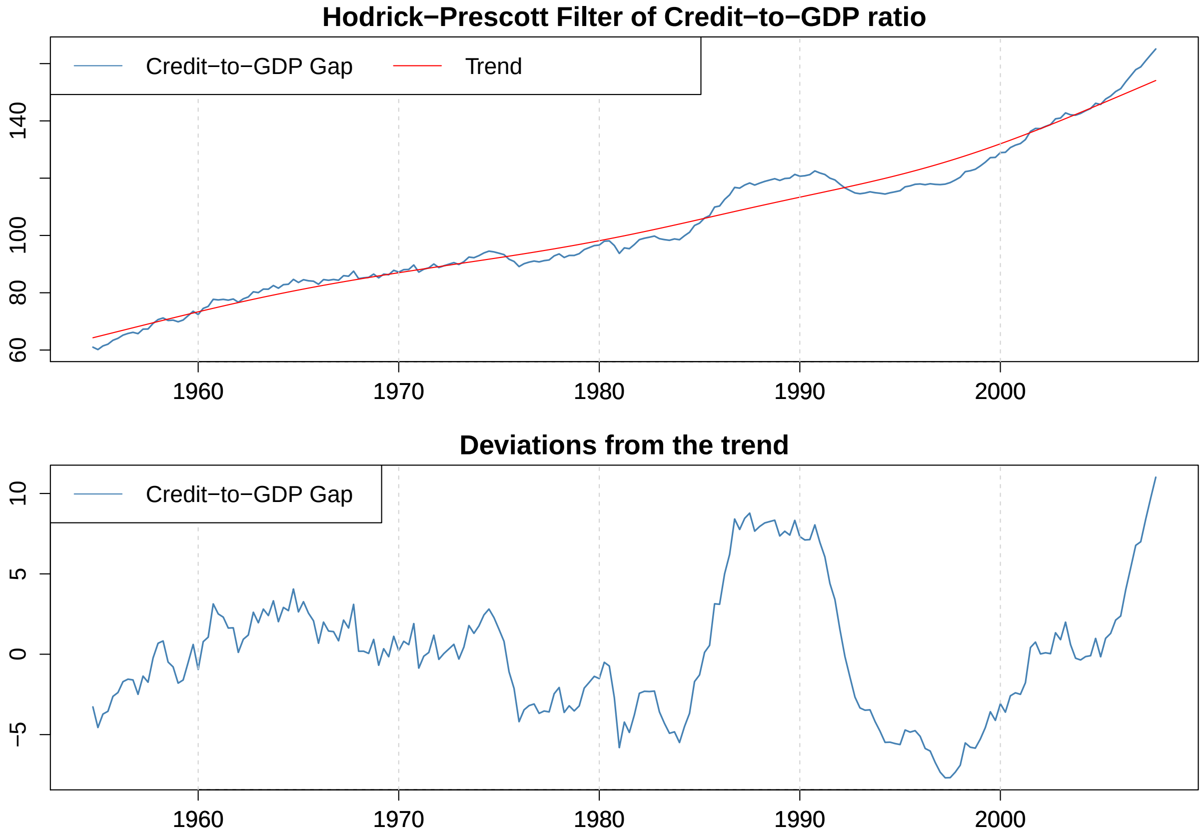
To prevent overfitting we follow Hansen (1999) and we require each regime to contain at least 15 % of all observations, equivalent to 32 data points, by setting the following restriction:

$$\frac{\sum_{t=1}^{n} I_i(\gamma, d)}{n} \geq 0.15 \tag{39}$$

[37] Drehmann and Tsatsaronis (2014) have shown that the average duration from peak to peak of the financial cycle is 20 years in contrast to 6 years for the real business cycle (National Bureau of Economic Research, 2012) for the US.

[38] Total Credit to Private Non-Financial Sector from the FRED Data Base.

Figure 6: HP-Filter of the Credit-to-GDP ratio



Following Calza and Sousa (2006) and Afonso et al. (2011), the lag length of our model is determined by using the information criteria of a linear VAR model. We assume a maximum lag length of six. The lag length of our model is set to five according to the Hannan-Quinn criterion (Hannan and Quinn, 1979). Table 2 gives a detailed overview of the AIC, BIC and HQC over the different lag lengths.

Table 2: Information Criteria

Lag	AIC	BIC	HQ
1	-889.9067	-749.9325	-833.3024
2	-1070.323	-810.3711*	-965.2008
3	-1114.961	-735.0306	-961.3202
4	-1135.171	-635.2628	-933.0122
5	-1295.244	-675.3584	-1044.568*
6	-1316.258*	-576.3948	-1017.064

[1] The * indicates the lag at which the respective criterion reaches its minimum.

The estimation of the threshold values γ_1 and γ_2 is done by exerting the one-step-at-a-time approach (Bai, 1997; Bai and Perron, 1998; Hansen, 1999). We start by estimating a one-threshold TVAR model. To estimate $\widehat{d}$ and $\widehat{\gamma_1}$, we take every combination of each realization of the threshold-variable y_{t-d} and the possible delay parameters d and perform a complete grid search. The upper limit of d has been set to be the order of the VAR process p itself.[39] The optimal values maximize the log-determinant of the variance-covariance matrix, i. e. it minimizes the squared sum of residuals. Building on that, we imply $\widehat{d} = d$ and $\gamma_1 = \widehat{\gamma_1}$ and estimate a two-regime TVAR model and obtain an estimate $\widehat{\gamma_2}$ for γ_2. Afterwards, we reestimate the two-regime TVAR assuming $\widehat{\gamma_2} = \gamma_2$ and let $\widehat{\gamma_1}$ vary. The procedure is iterated until we have no significant change left in $\widehat{\gamma_1}$ and $\widehat{\gamma_2}$.[40] As Bai (1997) showed, this procedure leads to consistent and robust estimates of γ_1, γ_2 and d if it is iterated at least one time.

To test for threshold non-linearity in our VAR model, we apply the likelihood ratio test adaption developed by Tsay (1998), Hansen (1999) and Lo and Zivot (2001), which is the multivariate extension of the univariate likelihood ratio test proposed by Chan and Tong (1990). To test for the number of thresholds/regimes, one has to compare two models at a time with a likelihood ratio test, that is estimating a TVAR(i) with i regimes and a TVAR(j) accordingly.[41] The test value is then calculated by:

$$LR_{ij} = N \cdot (\ln(\det \widehat{\Sigma_i}) - \ln(\det \widehat{\Sigma_j})) \tag{40}$$

where N is the number of observations and $\widehat{\Sigma}$ is the respective variance-covariance matrix.

In contrast to most of the existing literature, we follow Avdjiev and Zeng (2014) and also allow for a TVAR(3). Hence, we have to calculate three test statistics: linear VAR vs. TVAR(2), linear VAR vs. TVAR(3) and TVAR(2) vs. TVAR(3). Results of the tests are given in Table 3. P-values are calculated by a bootstrap simulation with 1000 replications. Our results clearly indicate the existence of three regimes in the financial cycle.

[39]We assume $d \in [1:p]$, since $d > p$ would indicate that the lag length should be increased.
[40]We assume no significant change left if $\Delta\widehat{\gamma_1} \leq 0.0001$ and $\Delta\widehat{\gamma_2} \leq 0.0001$.
[41]A TVAR(1) model reduces to a simple linear VAR model.

Table 3: Results of likelihood ratio tests

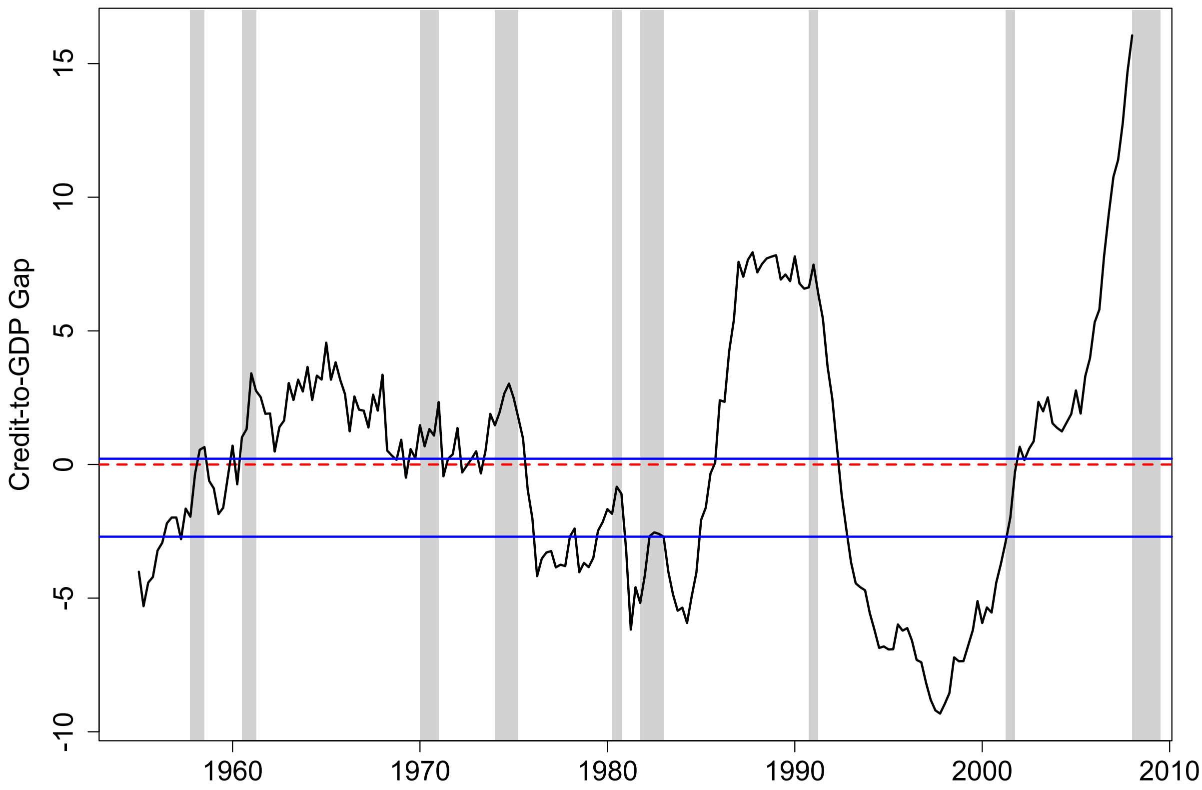
	1 vs. 2	**1 vs. 3**	**2 vs. 3**
LR value	400.1636	871.8508	471.6872
P-Value	0.001	0.000	0.007
Critical-Value ($\alpha = 0.1$)	348.1507	739.9051	417.1325
Critical-Value ($\alpha = 0.05$)	359.1258	758.9662	430.6055
Critical-Value ($\alpha = 0.01$)	376.4007	793.0095	456.7025

The estimated threshold values for our TVAR(2) model are $\widehat{\gamma_1} = -2.701505$ and $\widehat{\gamma_2} = 0.2147833$. The estimated transmission delay is $\widehat{d} = 1$. A TVAR(2) model gives an estimated threshold of -0.3455654 with the same transmission delay.

The upper threshold value $\widehat{\gamma_2} = 1.384525$ is somewhat close to the Basel III threshold value of 2 but clearly underlines a country specific adjustment to be made as proposed by the BIS. In general, we can see from figure 7 that all recessions are preceded by an increase in the Credit-to-GDP gap and succeeded by a sharp downturn. The two major crisis, the recession of the early 1990s and the global financial crisis of 2008, were both preceded by a Gap far above the threshold. Consequently, the Credit-to-GDP gap can explain these credit-driven bubbles during build-up and far before a harmful crash. Hence, the Gap is excellently suited to capture the financial cycle in our TVAR model and by endogenizing it, we can grasp interactions of both the real and financial cycle regarding different shocks.

The upper regime covers 34.6 % of all observations and resembles an overly large credit quantity in relation to the real economy or, in simpler terms, an overheated credit market. The middle regime contributes 25.6 % to the data set and indicates the normal state of the economy. As we will see when analysing the impulse response functions, when in the middle regime the economy reacts exactly like theory suggests. The low regime captures 39.9 % of the observations and represents severely weakened credit market.

Figure 7: Credit-to-GDP gap for the US (1954 to 2007)



* The blue lines represent the threshold values $\widehat{\gamma_1}$ and $\widehat{\gamma_2}$.
** Shaded areas represent NBER recessions (National Bureau of Economic Research, 2012).

4.3 Generalized Impulse Response Functions

In the following part we will explain the calculation of non-linear impulse response functions for our TVAR model and analyze the regime dependent results of shocks to federal funds rate and credit growth.

Since normal impulse response functions are not able to capture non-linearities, we apply Generalized Impulse Response Functions (GIRF) as proposed by Gallant et al. (1993) and Koop et al. (1996). The basic idea is that the GIRF is depending on the historical information set Ω_{t-1}, the sign of the shock and its size. The GIRF for horizon k is then calculated by:

$$GIRF_k = E[Y_{t+k}|\rho_j, \Omega_{t-1}] - E[Y_{t+k}|\Omega_{t-1}] \tag{41}$$

where ρ_j is a predefined shock or a variable of interest. The exact calculation is explained in Appendix B. Since impulse responses for the TVAR(3) model are extremely sensitive towards the bootstrap algorithm, we follow Avdjiev and Zeng (2014) and do not plot confidence bands.[42] The responses of the system to a unit shock of the the policy rate and credit growth are given in figures B2 and B3.

Shock of the Federal Funds Rate

Figure B2 in Appendix B shows the non-linear responses of the system to a positive unit shock of the Federal Funds Rate. The response of credit and real growth is the highest in the middle regime. The low and the high regime both yield a similarly lower response to a monetary policy shock. This finding supports the Greenspan-doctrine that the ability of central banks in deflating credit-driven asset price bubbles is indeed mitigated during boom scenarios. Interesting is that the ability of monetary policy to stimulate credit growth in the low regime is attenuated as well though being somewhat higher than in the high regime. Consequently, the stimulation of credit markets during a bust event is weaker than it might have been expected by supporters of the clean-up approach. The Credit-to-GDP Gap initially rises for all regimes and falls moderately after a period of about two years. The initial movement arises from the fact that the reaction of the credit market relative to the real economy is longer and GDP growth recovers more quickly. In the short-run, the spread reacts similar in all regimes. But after a period of one year the effect in the high regime kinks off. This goes in line with the findings of Gambacorta and Iannotti (2005). We have a price puzzle in all regimes. Interestingly, the reaction of inflation during the high regime is completely reverted. Increasing policy rates seem to further fuel inflation.

[42] In fact, the confidence bands tend to increase dramatically after few periods and do not yield much informational content as can be see figure B4 and figure B4.

The explanation may be the fact that banks profitability and hence their lending behavior is strongly influenced by the level and slope of the yield curve (Borio et al., 2015; Alessandri and Nelson, 2015). Lowering policy rates during the low regime, in which the yield curve can be assumed to be flat and at a low level, lowers banks profitability. Thereby, banks are forced to substitute their shrinking interest income by non-interest income and hence, the desired effect on the issuance of new credit lines will is small. Analogous increasing the interest level during the high regime may even enhance the net interest margin and generate reverse tendencies.

Shock of the Credit Growth Rate

Figure B3 in Appendix B shows the non-linear responses of the system to a unit shock of the Credit Growth Rate. The reaction of monetary policy is similar in all regimes, but again lower of amplitude in the two extreme regimes. The reaction of credit growth to its own shock is by far weaker in the lowest regime. This can be explained by frictions in the credit transmission channel. Companies tend to hold more liquidity and cut back their investment activities during bad times (Duchin et al., 2010; Campello et al., 2011) and banks on the other hand try to hold existing credit-lines as liquidity insurance and the issuance of new credit-lines is dampened (Acharya et al., 2014). Both mechanisms stop the positive credit shock from multiplying.

The reaction of the Credit-to-GDP gap is comparable in all the regimes. By definition, a positive shock on credit growth will increase the Credit-to-GDP ratio and heighten the respective gap. An interesting point is that the interest rate spread initially decreases in the low regime whereas it increases in the middle and high regime after two to three quarters. An increase of the spread would be the logical consequence of an increase in credit growth, that is lending standards and the risk premium should increase. A decrease of banks market power due to the negative credit shock in the low regime may explain this reverse response (Wong, 1997).

The positive credit shock takes about two years to affect the inflation rate, which can be explained due to the fact that the build-up of production capacities require time. The effect on the inflation rate is highest in the middle regime, moderate in the low regime and quite low in the high regime and covers the findings of Calza and Sousa (2006). A possible explanation is that during the two extreme regimes the transmission mechanism does not fully work. Hence, the financial sector partially absorbs increasing money supply and financial asset prices increase (Weise, 1999; Thorbecke, 1997). This however is not included in our inflation measure. The response of real GDP growth is by far highest in the normal regime and moderate in the high regime. In the low regime, the effect of close to zero which can be explained by the poor economic outlook of firms. They do less real investments and banks absorb the positive shock by increasing net interest margins.

4.4 Conclusion

In our paper, we analysed the non-linear impact of monetary policy and credit shocks throughout different stages of the credit cycle. For our empirical investigation we apply a three-regime threshold vector autoregression with a set of six variables (Output Gap, Inflation, Interest Rate Spread, Credit-to-GDP gap, Credit and Federal Funds Rate) of US data reaching from 1955 to 2007. Our approach distinguishes from recent literature in a number of points. First, we allow for three regimes of the financial cycle which is an extension of empirical literature that has long been demanded from a theoretical point. Secondly, we reflect the real as well as the financial sector by using the Credit-to-GDP gap as the transition variable of our TVAR model. Hence, we capture movements in both parts of the economy simultaneously.

Our results strongly indicate the presence of threshold nonlinearity with the existence of three regimes throughout the financial cycle. The Credit-to-GDP gap performs as a good proxy for the financial cycle and our estimated upper threshold value is close to the considered turn point of the Basel III framework in predicting the build-up of harmful credit-driven bubbles. However the financial deregulation in the United States nearly tripled the amplitude of the credit cycle and seems to have been promoting financial instability.

Analyzing generalized impulse response functions we found out that the transmission mechanisms of shocks to the policy rate and credit growth are fully effective and theory conform in the middle regime where the relationship of the credit towards the real economy is close to its long-term trend. During the two extreme regimes the responses towards shocks are damped and in some cases even reverted.

Monetary policy shocks seem to have far less effect on credit and output during the two extreme regimes and even a reverse effect on inflation during the high regime. Both effects could be observed during the recent financial crisis. The opposite accounts for monetary policy interventions during the build-up phase of credit-driven asset price bubbles. This suggests that both leaning against credit-driven bubbles and cleaning up after the burst of such a bubble may be more difficult than suggested. Another problem may arise when the credit cycle reaches its normal stance and inflation will react more sensitive on monetary policy. Central banks may want to gradually tighten their policy to prevent price hikes above their respective target rate.

Our results indicate credit shocks to be far more harmful than previously assumed. The negative effect on credit growth on itself and the impact on inflation and output growth are substantially higher during the high and middle regimes. Especially enfeeblement of the real economy is nearly doubled during normal times in relation to the high regime. Hence, deflating bubbles by provoking negative credit shocks may have undesired consequences.

Possible policy implications are that central banks alone may not be able to foreclose credit-driven asset price bubbles and smoothen the financial cycle to a harmless amplitude. A growing number of economists demand for a adjustment of the macroprudential policy framework and a better cooperation between the institutions in charge and central banks in order to whither financial stability.

4.5 Appendix B

Calculation of non-linear Generalized Impulse Response Functions

Following Avdjiev and Zeng (2014), we calculate the GIRFs in six steps:

1. Chose an initial history $\Omega_{n,t-1}$ at date n, including the lagged values of the variables at date n, and determine the starting regime.

2. Generate a random sample of shocks $u_{t,k}$ up to GIRF horizon k by taking bootstrap samples of the estimated residuals from our baseline model.

3. Calculate the evolution of all variables in the system over $k+1$ periods, assuming a recursive ordering (Cholesky). This baseline path is labeled as $Y_{t,k}(u_{t,k}, \Omega_{n,t-1})$.

4. Do the same calculation as in step 3, replacing the shock for variable j at $t = 0$ by a predefined value of ρ_j, in our case 1 for a standard deviation, and naming the vector u_j^*. The resulting path is denoted by $Y_{t,k}(u_{t,k}, u_j^*, \Omega_{n,t-1})$.

5. Steps 2 to 4 are repeated M times to avoid bias from special events in the data set and create inference for $Y_{t+k}(u_{t+k}, \Omega_{n,t-1})$ and $Y_{t+k}(u_{t+k}, u_j^*, \Omega_{n,t-1})$. The average difference of the two yields the expectation of Y_{t+k} for the n'th history $E[Y_{t+k}|\rho_j, \Omega_{t-1}] - E[Y_{t+k}|\Omega_{t-1}]$. According to Hansen (1999), we set M to 500.

6. Steps 1 to 5 are repeated N times to compute an average over N histories and obtain the non-linear impulse response for a given regime. N is also set to 500 (Hansen, 1999).

Figure B1: Macroeconomic Variables for the United States 1955-2007

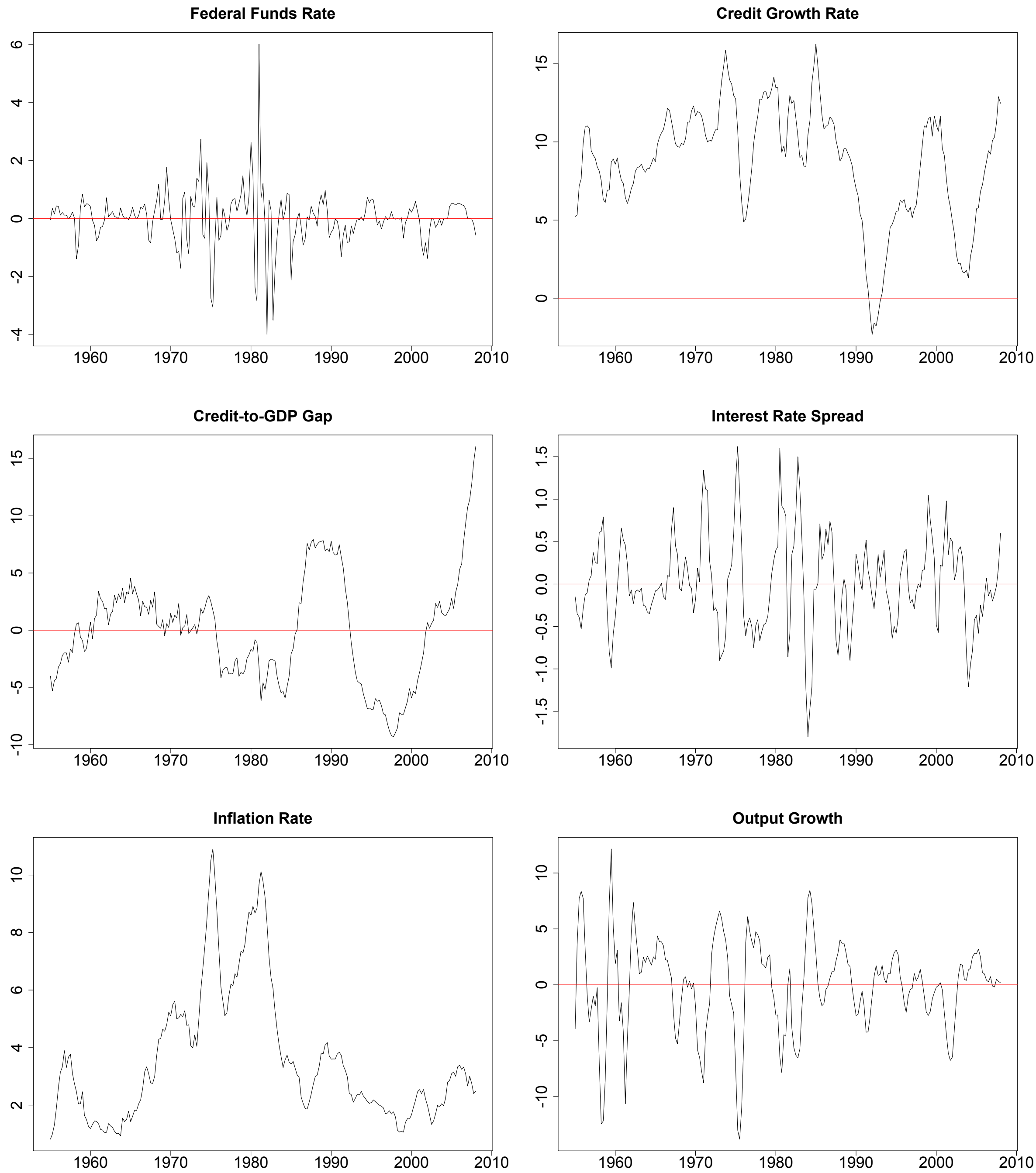
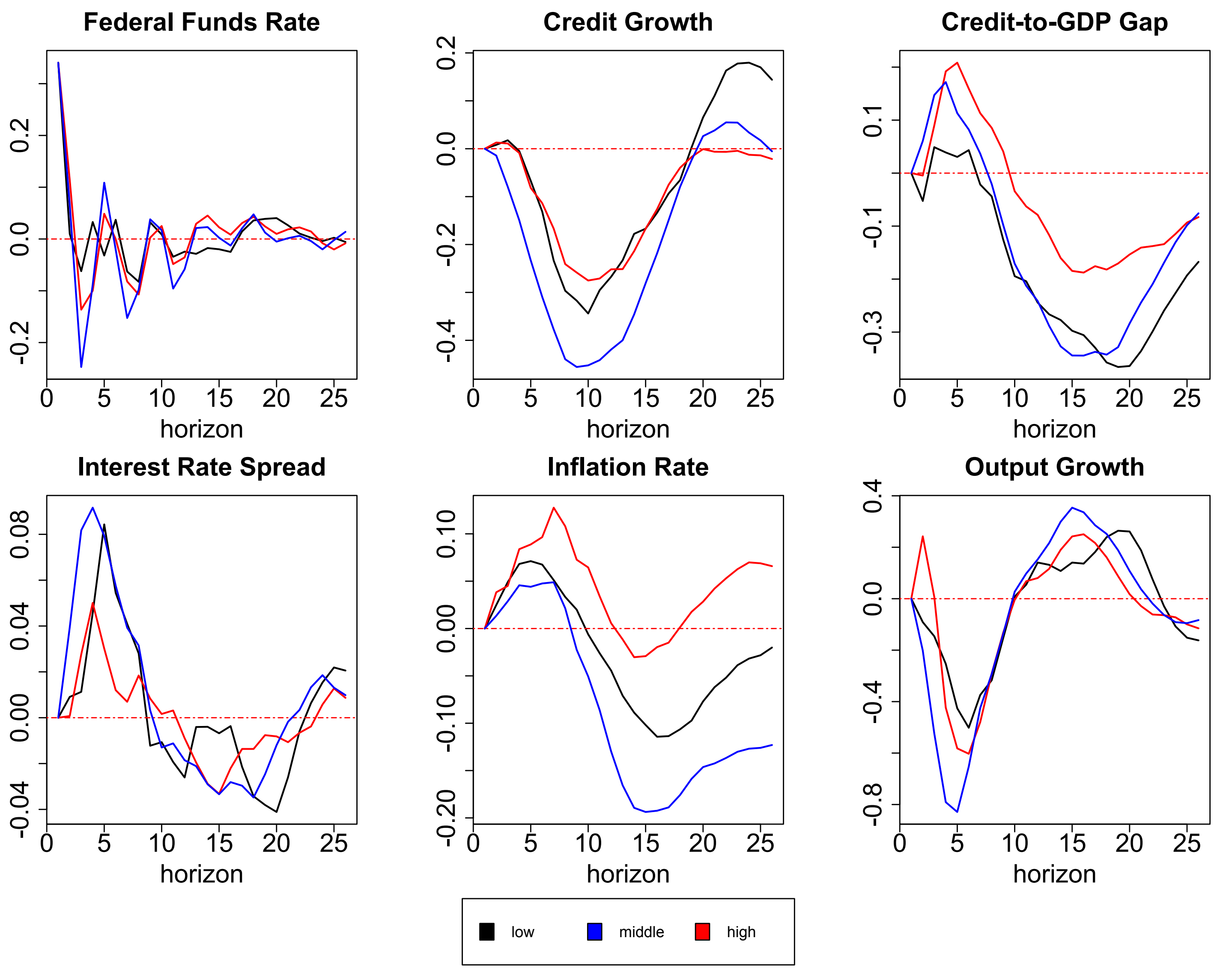
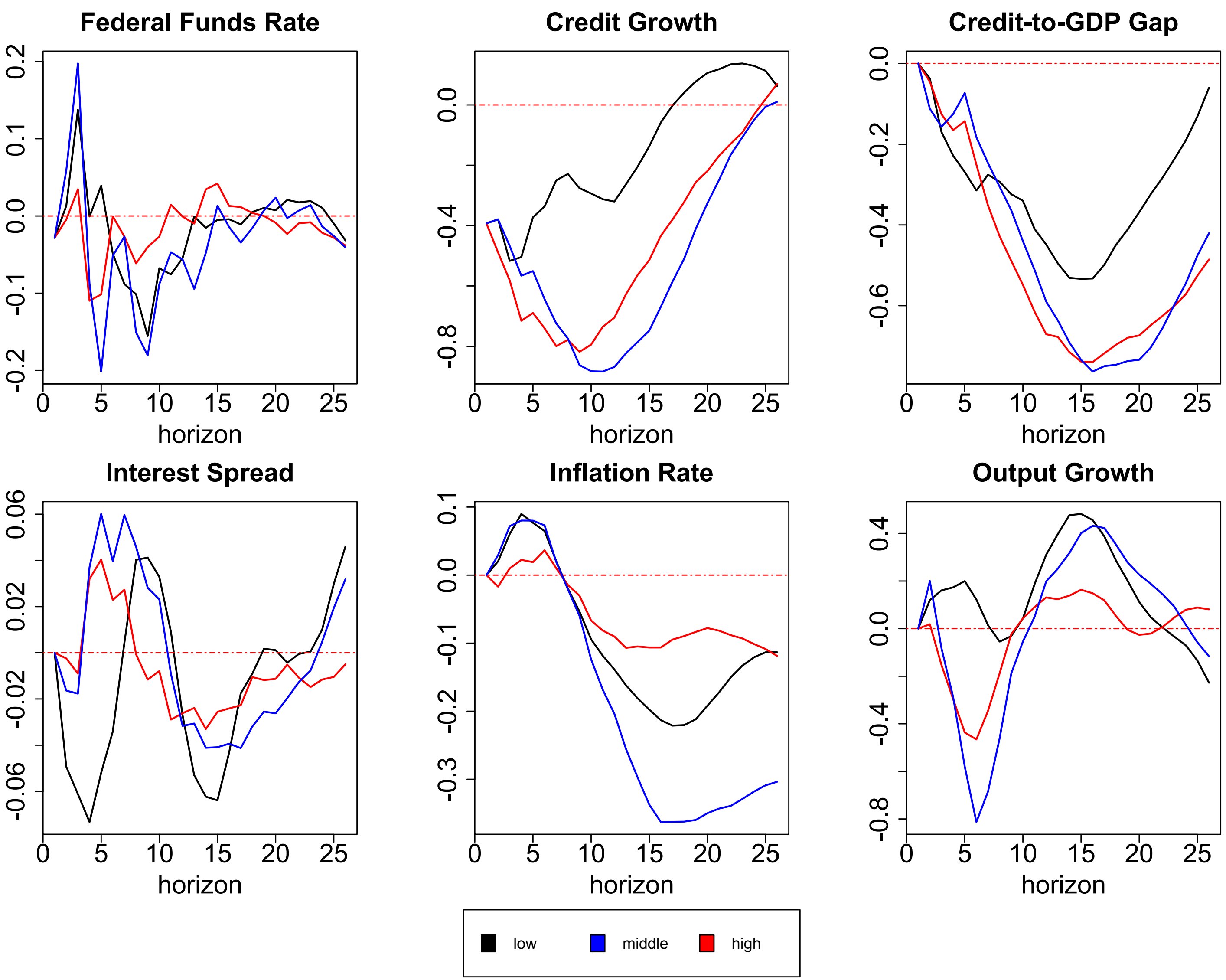


Figure B2: Non-linear impulse responses to a standard deviation shock of the Federal Funds Rate



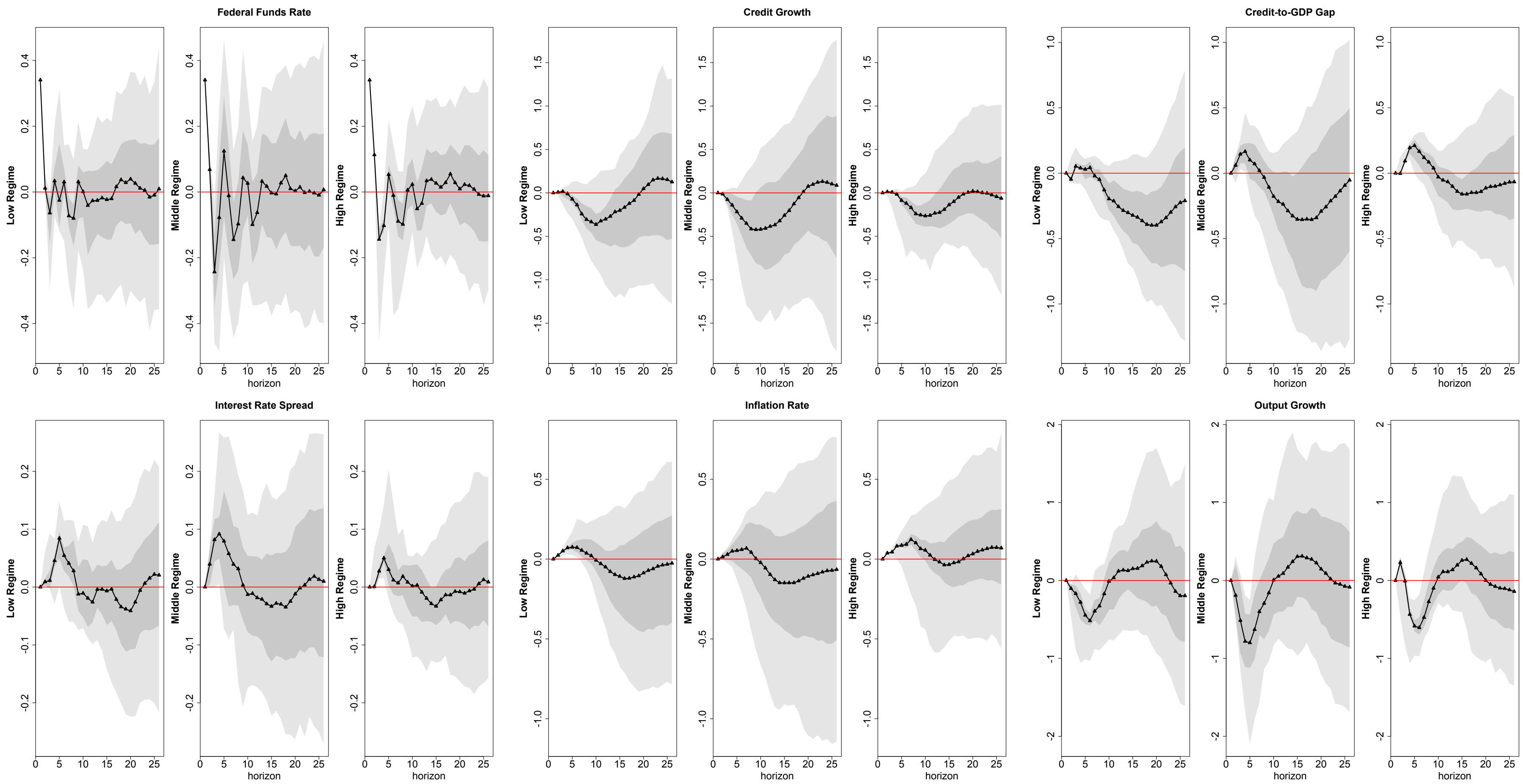
The response of the Credit-to-GDP Gap is given in units of the index, all other responses are in percent.

Figure B3: Non-linear impulse responses to a standard deviation shock of the Credit Growth Rate



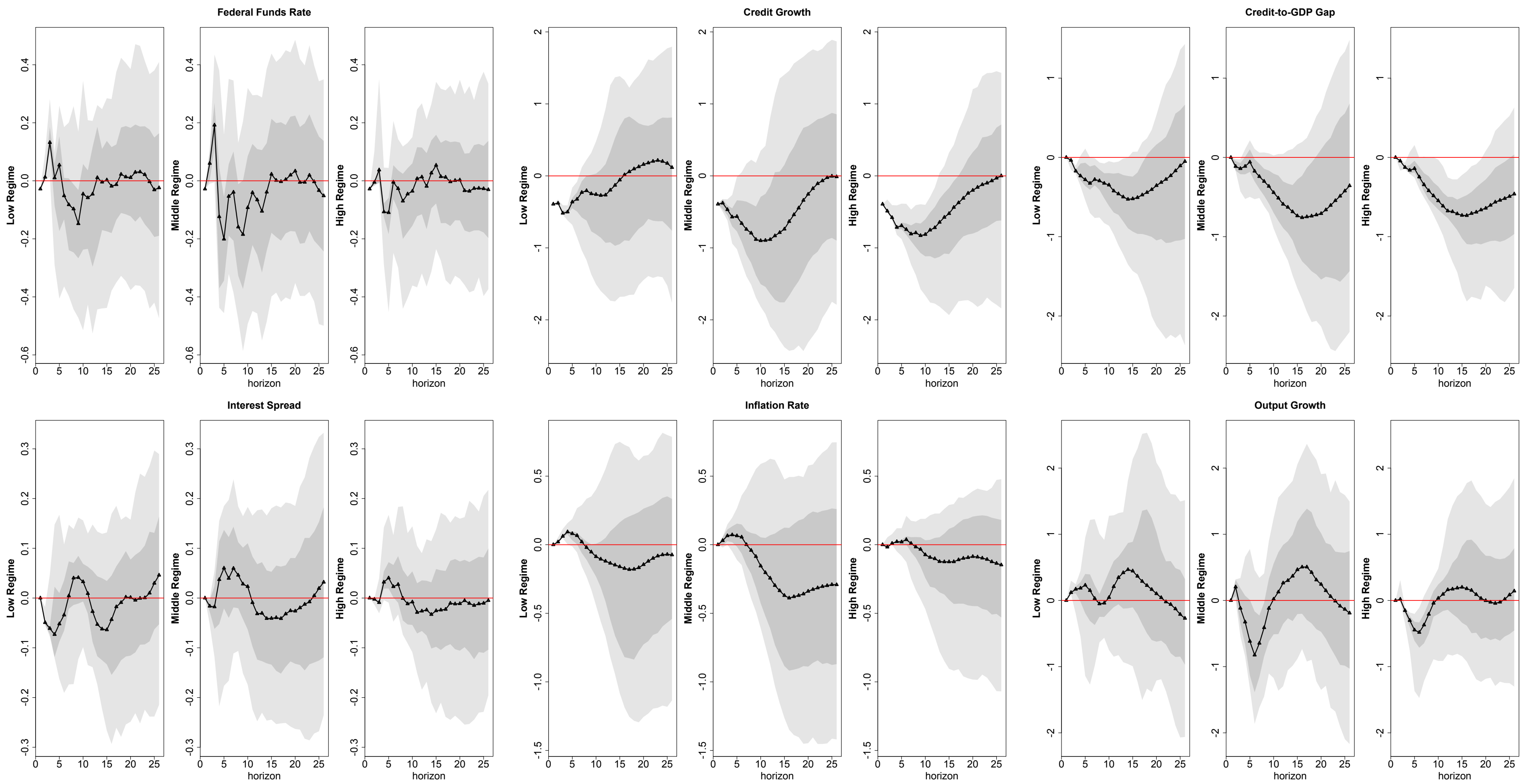
The response of the Credit-to-GDP Gap is given in units of the index, all other responses are in percent.

Figure B4: Non-linear Impulse Responses to a Standard Deviation Shock of the Federal Funds Rate (Including Confidence Bands)



Light gray shaded areas reflect the 95% confidence level, dark gray shaded areas the 68% confidence level. The response of the Credit-to-GDP Gap is given in units of the index, all other responses are in percent.

Figure B5: Non-linear Impulse Responses to a Standard Deviation Shock of the Credit Growth Rate (Including Confidence Bands)



Light gray shaded areas reflect the 95% confidence level, dark gray shaded areas the 68% confidence level. The response of the Credit-to-GDP Gap is given in units of the index, all other responses are in percent.

5 The Risk-Taking Channel of Monetary Policy Transmission in the Euro Area

Chapter Abstract

In this paper, we provide evidence for a risk-taking channel of monetary policy transmission in the Euro Area. Our dataset covers the period 2003Q1–2016Q2 and includes, in addition to the standard variables for output, prices, and policy rate, measures of lending standards and interest rate margins. Based on both, recursive identification and sign restrictions, we show that banks react fast and aggressively to monetary tightening by cutting lending standards, that is shifting towards more risk-taking, to shield their interest rate margin. Sign restrictions suggest that the initial response of the margin is positive, while banks cannot prevent a decrease in the mid run.[43]

5.1 Introduction

A growing body of literature deals with the effects of monetary policy on banks' risk-taking behavior. The idea that a changing interest rate environment is influencing banks' perception towards risk can be traced back to Hancock (1985) and Aharony et al. (1986), who find that lower short-term interest rates are related to decreased profitability of commercial banks. Asea and Blomberg (1998) point out that the credit market is subject to systematic cycles. During the bust episodes, competition for liquidity (Acharya et al., 2012) and customers increases (Beck et al., 2006). Azariadis and Smith (1998) support this finding with a dynamic model incorporating an adverse selection process in credit markets. Dell'Ariccia and Marquez (2006) as well as Lown and Morgan (2006) highlight that business cycle booms make adverse selection problems less severe and banks tend to adjust their lending standards or their loan rates downwards. Rajan (2006) connects the reduction in lending standards to low short-term

[43] This study is joint work with Matthias Neuenkirch, University of Trier.

rates[44] and argues that increased competitive pressure on financial managers during a bust leads to herding behavior, thus producing irrational deviations from fundamentals and strongly increasing the costs of a downturn.

Borio and Zhu (2012) are the first to use the term 'risk-taking channel' and to explain its different facets. The first effect operates on the basis of valuations, incomes, and cash flows. Low policy rates and a high money supply tend to raise the prices of real and financial collateral, thereby reducing the banks' risk perception and leverage (Adrian and Shin, 2013), even if lending standards are held constant. Similarly, income and wealth increase, resulting in a higher risk tolerance of borrowers (Pratt, 1964; Arrow, 1970).

The second effect arises from the impact of monetary policy actions on the banks' profitability. Nominal rate-of-return targets are relatively sticky. Negative deviations would trigger stock price declines and cause serious pressure. Lowering short-term rates drives banks to a search for higher yields in order to maintain trust of their investors (Rajan, 2006; Buch et al., 2014). Indirectly, a lower interest environment increases competition in the banking sector, which in turn also reduces the banks' ability to generate profits (Maudos and de Guevara, 2004). A corresponding flattening of the yield curve, for instance, by supplementary asset prices programs, further compresses banks' margins (Meaning and Zhu, 2011; Alessandri and Nelson, 2015). Quantitative easing in Japan can be seen as an example of the latter mechanism (Goyal and McKinnon, 2003).

The third set of effects transmits through central bank communication. By increasing the degree of transparency of its actions, central banks can remove uncertainty about the future and enforce the impact of changes in policy rates. Borio and Zhu (2012) call this the 'transparency effect.' This effect is accompanied by the 'insurance effect' arising from the anticipation that central banks are able to cut off large downside risks.

[44]Decreases in credit growth negatively affect the real economy (Kroszner et al., 2007; Reinhart and Rogoff, 2008), it is only natural that bust episodes go hand in hand with low interest rate environments, since central banks stimulate demand with expansionary interventions.

Hence, banks do not fear an intensified crisis and expansionary interventions are assumed to be more effective. However, as a side effect, banks get encouraged to take up more risk.

Recent empirical papers provide evidence for the existence of a risk-taking channel. Lower interest rates result in decreasing lending standards (Abbate and Thaler, 2015; Angeloni and Faia, 2013; Delis and Kouretas, 2011; Maddaloni and Peydró, 2011), higher leverage (de Groot, 2014; Adrian and Shin, 2013), and increased asset risks (Angeloni et al., 2015). In addition, Dell'Ariccia et al. (2014) provide a theoretical foundation for a link between the degree of risk-taking and a bank's capital structure. Indeed, small and lowly capitalized banks are empircally found to take more risk (Altunbas et al., 2010, 2014; Buch et al., 2014; Dell'Ariccia et al., forthcoming; Ioannidou et al., 2015; Jiménez et al., 2014), a finding that can be explained by their relatively higher degree of competition and their lower ability to adjust the capital structure.

However, to the best of our knowledge there is little evidence for the role of risk-taking in the monetary policy transmission for the Euro Area as a whole.[45] This paper aims at filling this gap and augments a standard monetary policy transmission model for the Euro Area and the period 2003Q1−2016Q2 with measures of lending standards and interest rate margins. We show that banks react fast and aggressively to monetary tightening by cutting lending standards, that is shifting towards more risk-taking, to shield their interest rate margin. Sign restrictions suggest that the initial response of the margin is positive, while banks cannot prevent a decrease in the mid run. As a consequence, we provide evidence for a risk-taking channel of monetary policy transmission in the Euro Area.

The remainder of this paper is structured as follows. Chapter 2 introduces the empirical methodology and the data set. Chapter 3 presents the empirical results. In Chapter 4 concludes with some policy implications.

[45] Jiménez et al. (2014) as the only exception present bank-level evidence for Spain.

5.2 Data and Econometric Methodology

Our set covers quarterly data of the Euro Area (changing composition) for the period 2003Q1–2016Q2 and consists of the following variables: the marginal refinancing rate in percent, the inflation rate based on the harmonized consumer prices index excluding energy and food, the growth rate of real GDP, interest rate margins in percentage points, and lending standards in percentage points. These five series are plotted in Figure C1 in the Appendix.

The inflation rate excludes energy and food prices to preclude exogenous price movements stemming from these two sources. The interest rate margin, defined by the European Central Bank as the difference between interest rates on new business loans and a weighted average interest rate on new deposits from households and non-financial corporations, reflects the banking sector's ability to generate profit in its core field of credit lending. Declining margins could trigger the aforementioned search for yield and are expected to be a key element in the risk-taking channel. The overall Euro Area margin is calculated as the weighted sum of country-specific interest rate margins with the countries' contribution to the ECB's capital as weighting scheme (see Table C1 in the Appendix). Lending standards are taken from the ECB's bank lending survey that includes 140 banks from all Euro Area countries. The series is calculated as the net percentage of banks reporting tighter lending standards in comparison to the previous period. The idea of this variable is to measure the change of non-financial obstacles in credit lending, such as loan-to-value restrictions, collateral, or securities.

5.2.1 Econometric Model

Our empirical strategy builds on two different identification schemes. Both methods are based on the simple linear vector autoregressive (VAR) model introduced by Sims (1980a,b). In general, a VAR(p) model with n endogenous variables can be written in reduced form as:

$$y_t = v + \sum_{i=1}^{p} A_i y_{t-i} + u_t \tag{42}$$

where y_t is the $n \times 1$ vector of endogenous variables, v is the $n \times 1$ vector of intercepts, and u_t is the $n \times 1$ vector of non-structural error terms. The A_i, $\forall i = 1, \ldots, p$, are $n \times n$ parameter matrices. We follow Sims and Uhlig (1991) to let all variables enter the system in levels or log-levels in an effort not to loose additional information by differentiating.

Both, the Bayesian information criterion and the Hannan Quinn information criterion favor a lag length of 1 for the VAR model. However, preliminary estimations shows that this is not enough to properly capture the dynamics in the system. In contrast, the use of two lags eliminates all serial correlation of the error terms according to an asymptotic Portmanteau test. Consequently, we employ a VAR(2) model.

To identify the effects of monetary policy shocks on the other variables in the system we have to transform the reduced form VAR in Eq. (42) into a structural VAR, which is given by:

$$\boldsymbol{A} y_t = A_0^* + \sum_{i=1}^{p} A_i^* y_{t-i} + \varepsilon_t \tag{43}$$

with $A_0^* = \boldsymbol{A} v$ and $A_i^* = \boldsymbol{A} A_i$, $\forall i = 1, \ldots, p$. Based on the structural errors $\varepsilon_t = \boldsymbol{A} u_t \sim (0, \boldsymbol{A} \Sigma_u \boldsymbol{A}^\top)$ we can obtain the variance-covariance matrix Σ_ε. To get unique impulse response functions, we need to set $\frac{n(n+1)}{2}$ restrictions on the matrix A (Lütkepohl, 2007). In a first step, we impose a recursive identification scheme. That is, we set A to be:

$$A = \begin{pmatrix} 1 & 0 & \ldots & 0 \\ \alpha_{21} & 1 & & 0 \\ \vdots & & \ddots & \vdots \\ \alpha_{n1} & \alpha_{n2} & \ldots & 1 \end{pmatrix} \tag{44}$$

Following Buch et al. (2014), we order the credit variables first. They argue that credit contracts do not respond immediately to monetary policy interventions or shocks to output and inflation since re-negotiations of interest rates or lending standards typically take time. In the extreme case, new interest rates and lending standards can only be applied to new contracts, which implies an even longer outside lag. In our baseline results below, we order the lending standards before interest rate margins, which is in line with the 'search-for-yield' idea. Changing interest rate margins will set incentives for changes in lending standards.

The ordering of the remaining variables follows the standard setup of a monetary policy transmission VAR as output is ordered third, prices are ordered fourth, and the short-term interest rate is ordered last. This reflects the well-known outside lag of monetary policy in its impact on prices and output and the possibility of the central bank to react instantaneously to macroeconomic shocks, that is, to preclude any inside lags in monetary policy (Kareken and Solow, 1963).

As our second identification strategy, we apply a Bayesian estimation method with sign restrictions.[46] We use a pure sign restriction approach and identify only a single impulse vector. Based on the results of our structural model, we assume that an expansionary monetary policy shock, that is, a decrease in the marginal refinancing rate, increases at least output growth. We then stepwise set further restrictions for a clearer identification. Table 4 summarizes the restrictions for each model. Following Mountford and Uhlig (2009), the restrictions are assumed to hold for at least four quarters. The detailed explanation of the estimation procedure is given in chapter 2.1.2.

Table 4: Sign Restrictions for Bayesian Estimation

Lending Standards	Interest Margin	Output Growth Rate	Inflation Rate	Marginal Refinancing Rate
Model 1				
none	none	+	none	−
Model 2				
none	none	+	+	−
Model 3				
-	none	+	+	−

[46]A detailed setup of the model is given in the seminal paper of Uhlig (2005).

5.3 Empirical Results

In the follow section, we present the results of both, recursive and Bayesian sign restrictions (Uhlig, 2005) identification. We use the results of our structural model as foundation for setting sign restrictions to obtain a clear identification.

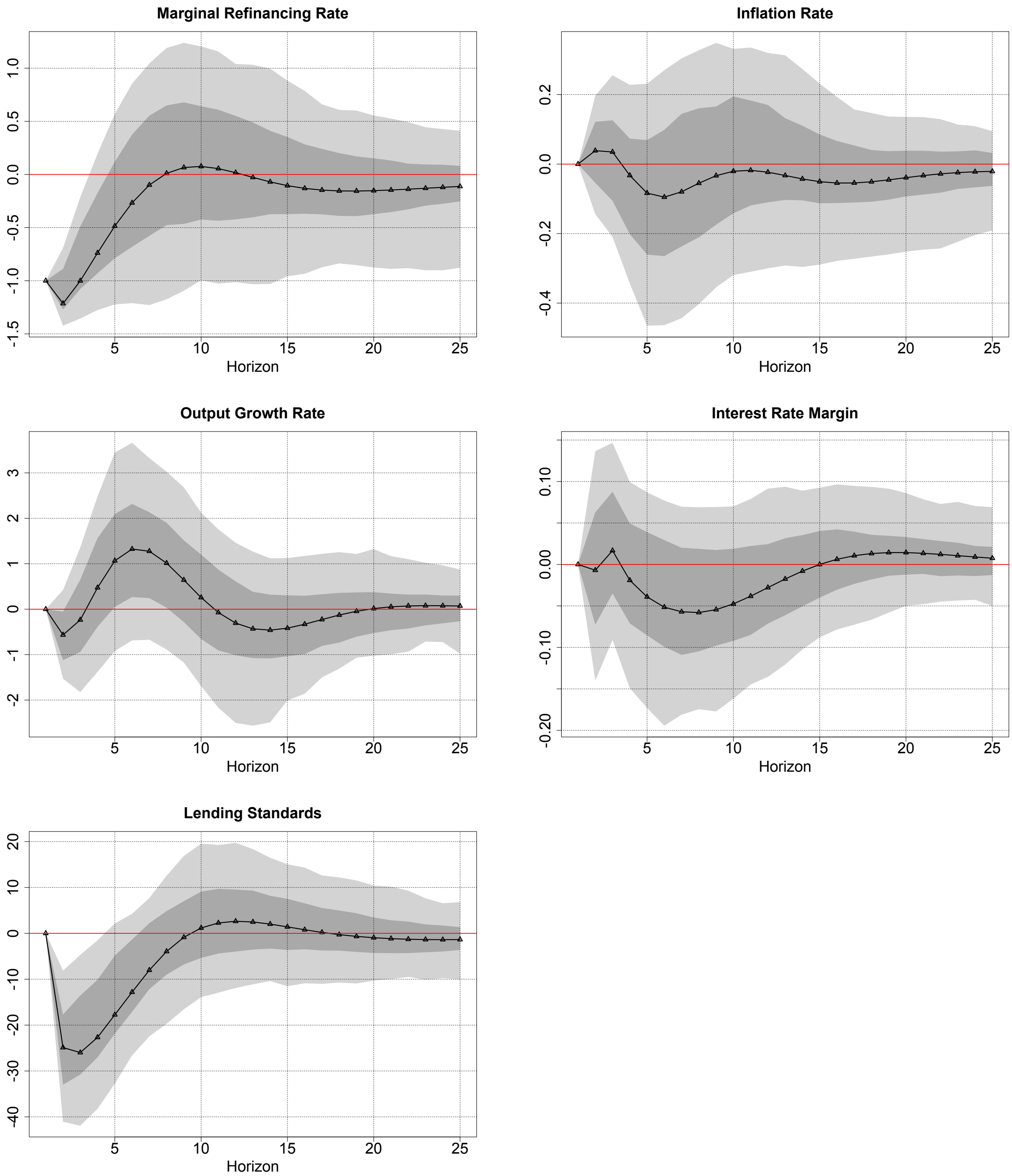
5.3.1 Results Based on Recursive Identification

The results of our recursive model are reported in figure 8. Following a negative shock of 100 base points, output growth rates increase in the medium turn. Inflation shows no significant effect, suggesting that the expansionary monetary interventions subsequent to the global financial crisis had very limited influence on inflation. This finding goes in line with, among others, Chen et al. (2012) or Joyce et al. (2012) and the references in both that inflation during this period is mainly driven by the indirect influence of oil price shocks.

The responses of both credit variables are consistent with the findings of other VAR papers (Abbate and Thaler, 2015; Afanasyeva and Güntner, 2014). The response of lending standards shows two interesting features. The downward adjustment happens immediately, indicating that banks quickly adjust their lending behavior and take more risk to prevent their interest rate margins from falling. However, this adjustment becomes insignificant after four quarters. Interest Rate margins decrease after an expansionary monetary policy shock, yet this reaction is insignificant, even at the 68% confidence level. This shows that banks are mostly able to shield their interest rate margins, and hence their profitability concerning conventional credit business, from decreasing short-term rates.

Finally, it is worth noticing that figure 8 also shows that inclusion of the two credit variables to the monetary policy transmission VAR yields theory-consistent responses. Leaving these variables out of the system generates the well-known price puzzle (Balke and Emery, 1994), as illustrated in figure C2.

Figure 8: Impulse Responses Based on Recursive Identification



Notes: Figure shows impulse responses to an expansionary monetary policy shock of 100 base points based on recursive identification as outlined above. Light shaded areas reflect the 95% confidence level; dark shaded areas the 68% confidence level. All responses are given in percent.

5.3.2 Results Based on Sign Restrictions

The main disadvantage of the structural VAR model based on recursive ordering is that the contemporaneous response of interest rate margins and lending standards to the monetary policy shock are set to zero. This could only be avoided by ordering these variables after the policy rate, which is economically not reasonable. The sign-restricted VAR solves this issue by leaving the responses of both variables open.[47] Consequently, Figure 9 presents impulse responses of an expansionary monetary policy for model 3, that is the most restrictive one as defined in Table 4. The sign restriction models 1 and 2 show similar results, yet the identification is less sharp and thus the response of the interest rate margin is less pronounced.

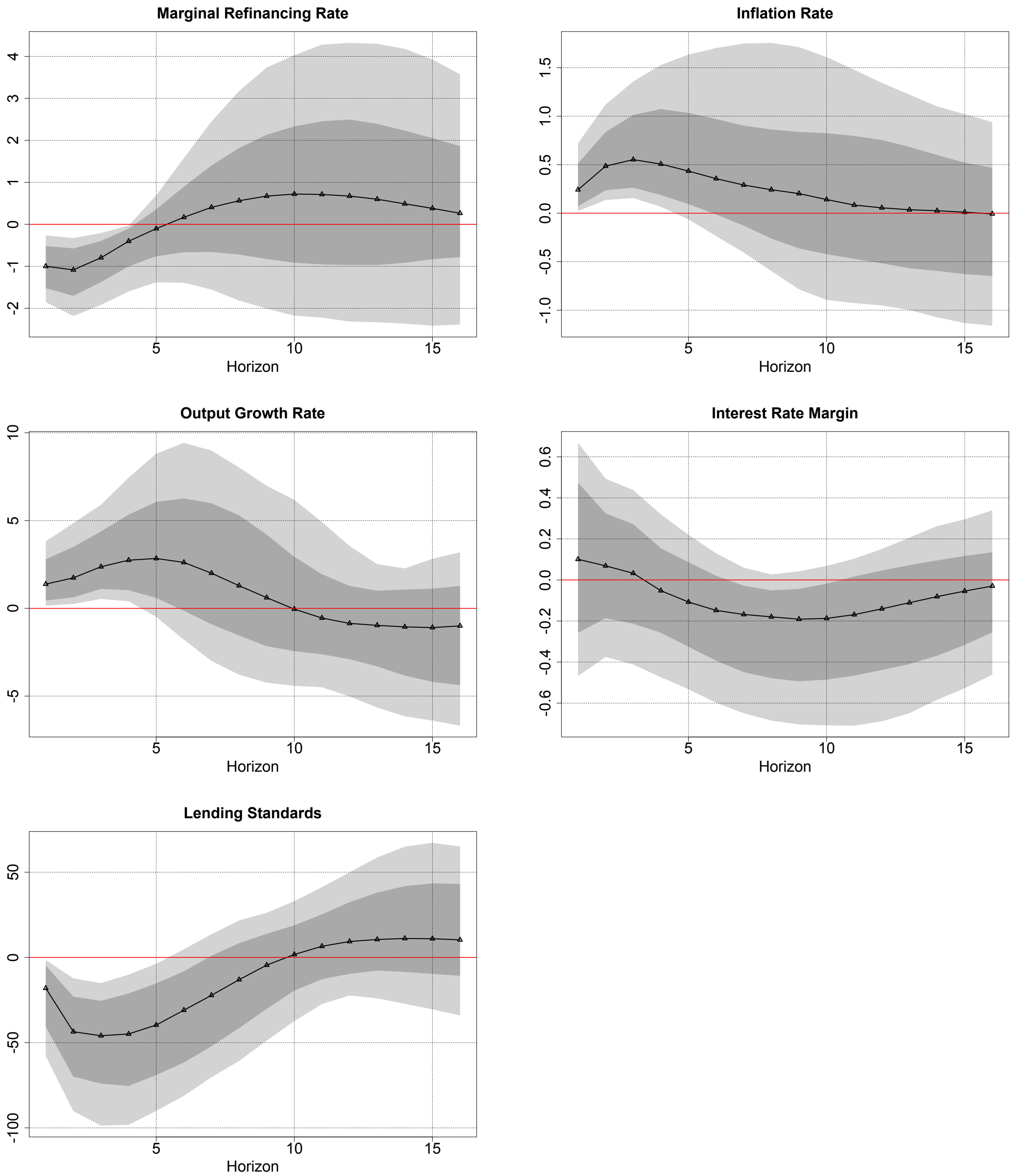
Our key results concerning the reaction of output and prices remain robust, although the response of inflation only becomes significant after setting the respective restriction. However, the significance of the impulse responses is somewhat lower compared to the recursive identification scheme. In case of the credit variables, we observe that banks react fast and aggressively towards an expansionary monetary policy shock by decreasing their lending standards. By doing so, they are able to shield their interest rate margin from declining in the short run. However, the response of interest rate margins becomes significantly negative during 7-10 quarters after the shock occurs. The initial tendency of margins is positive, yet insignificant, indicating that European banks tend to overshoot with their risk-taking behavior. Inflation and output growth react theory conform and increase for 6 quarters after the shock and are non-transitory.

5.4 Conclusions and Policy Implications

In this paper, we augment a standard monetary policy transmission model for the period 2003Q1–2016Q2 with measures of lending standards and interest rate margins to investigate the risk-taking channel of monetary policy in the Euro Area. Based on both, recursive identification and sign restrictions, we show that expansionary monetary policy initially lead to an increased risk-taking behavior of banks for 6 quarters. The sign restricted model suggests that the initial reaction of interest Rate margins tends to be positive, indicating an overshooting of lending standards reaction. How-

[47]Note that this comes at some cost as Uhlig (2005) states that sign restrictions can be seen as more restrictive than a recursive scheme.

Figure 9: Impulse Responses Based on Sign Restricted Model 3



Notes: Figure shows impulse responses to an expansionary monetary policy shock based on sign restrictions. Light shaded areas reflect the 95% credible set; dark shaded areas the 68% credible set. All responses are given in percent.

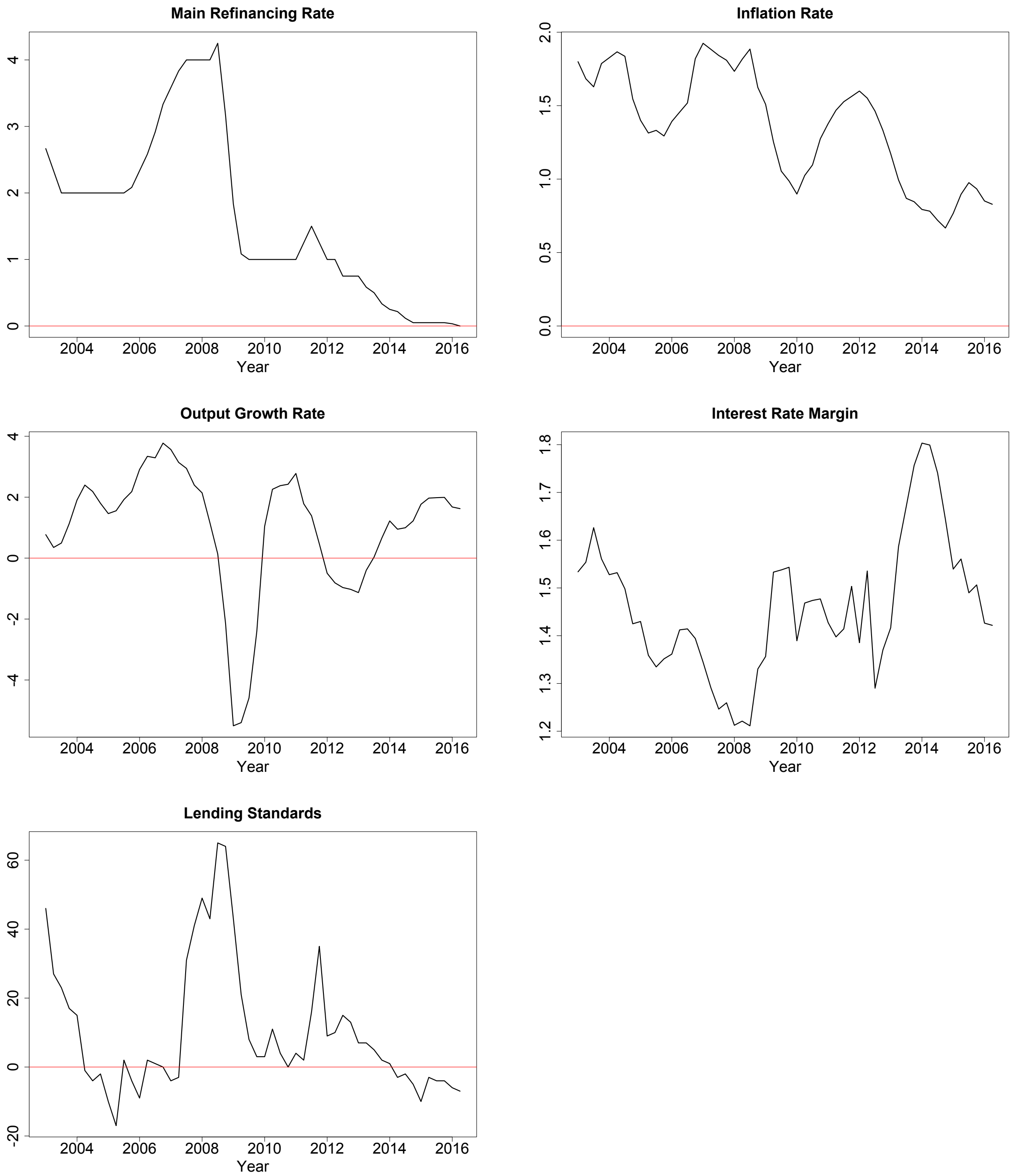
ever, banks do not seem to be able to fully shield their interest rate margin from expansionary monetary policy, leading to a decrease in the mid run. Thus, our paper provides evidence for a risk-taking channel of monetary policy transmission in the Euro Area. Our findings are in line with previous results for the US. Furthermore, we verify the theoretical idea of a credit margin compression due to monetary policy loosening in the Euro Area.

Our paper has several policy implications. First, central bankers should keep the risk-taking channel in mind when setting monetary policy. The case of Japan has shown that prolonged periods of low interest rates may lead to the build-up of risk in the credit system. The supporting effect of expansionary monetary policy is, if significant at all, only present in the short-run. Excessive risk-taking, however, might provide the foundation for the next financial crisis. Currently, the Euro Area (and other economies) is facing the longest and most pronounced era of expansionary monetary policy interventions. But all Euro Area countries except for Greece and Finland face a moderate economic upswing, making the continued loose monetary policy questionable. Even worse, the massive liquidity surplus led to a period of ever decreasing lending standards and the build-up of extreme balance sheet risks in the banking sector. As demonstrated by the Federal Reserve's interest rate increase in December 2015, a minor adjustment of the policy rate might dampen this unwanted risk-taking.

Second, we provide some implications for macroprudential policy. The German Financial Stability Committee recently proposed the implementation of several prudential policy instruments in order to prevent credit misallocation, in particular in the real estate sector (Financial Stability Committee, 2015). The proposal includes four main instruments: (a) loan-to-value restrictions, (b) amortization requirements or maximum maturities, (c) debt service coverage ratios, and (d) debt-to-income ratios. Such instruments try to counteract the banks' risk-taking behavior. Nevertheless, lowering interest rates while restricting lending standards at the same time will come at some costs. If banks cannot shield their interest rate margins by taking more risk, profits will fall, ultimately making the financial system more unstable. Another consequence might be a restructuring of financial intermediaries away from interest-based activities. Hence, macroprudential policy interventions accompanied by low interest rates may even amplify a negative shock on banks' balance sheets, if tougher regulation is implemented procyclical.

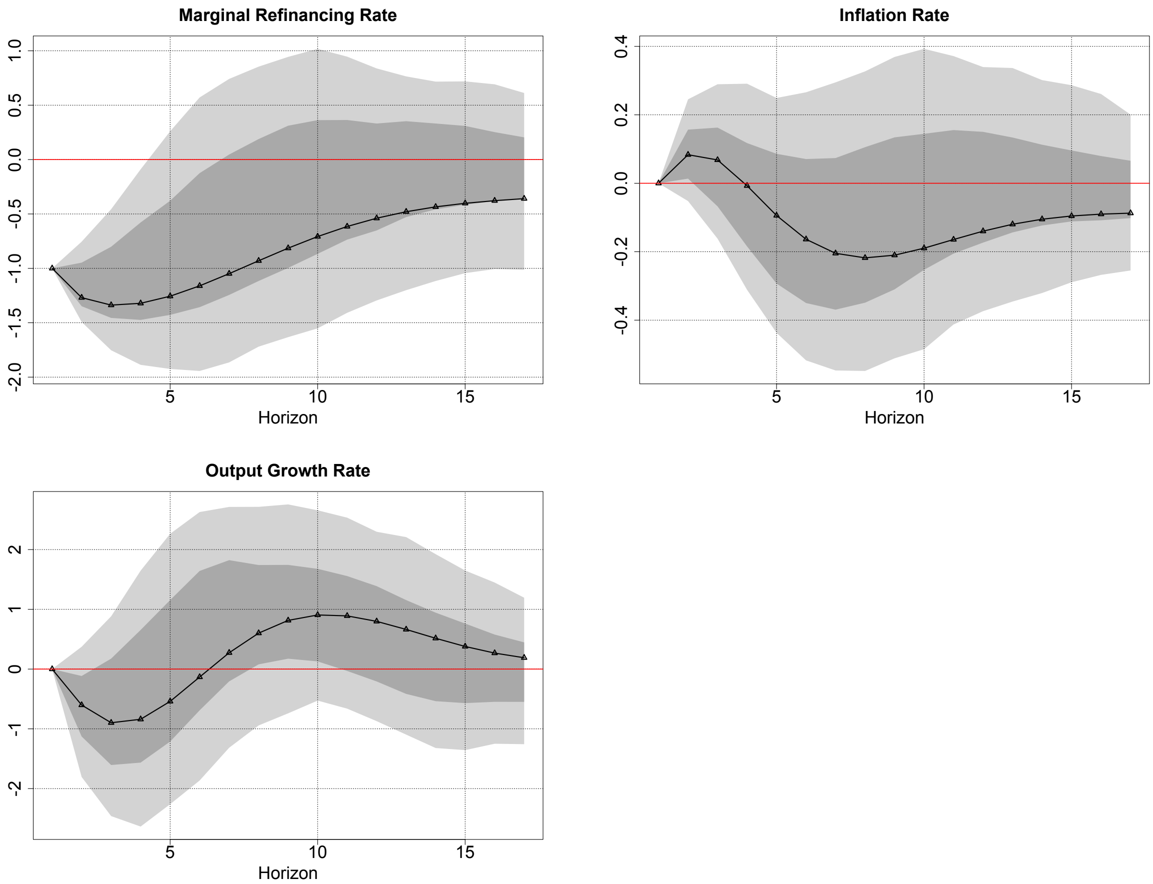
5.5 Appendix C

Figure C1: Macroeconomic Variables for the Euro Area



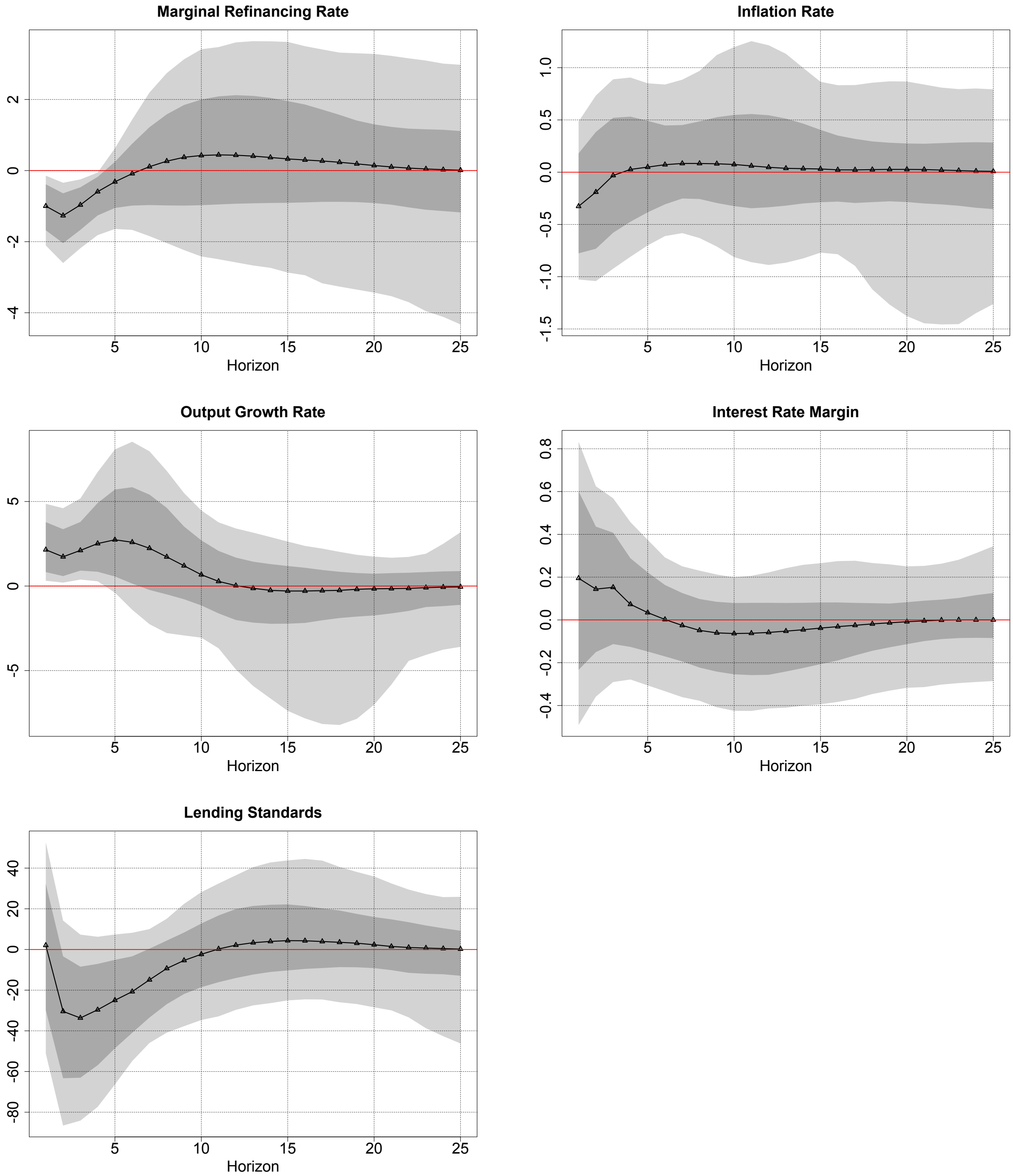
Notes: MRR: main refinancing rate in percent; P: harmonized index of consumer prices in logs; Y: industrial production in logs; MAR: interest rate margin in percentage points; LS: lending standards in percentage points.

Figure C2: Three Variable VAR Model with Prize Puzzle



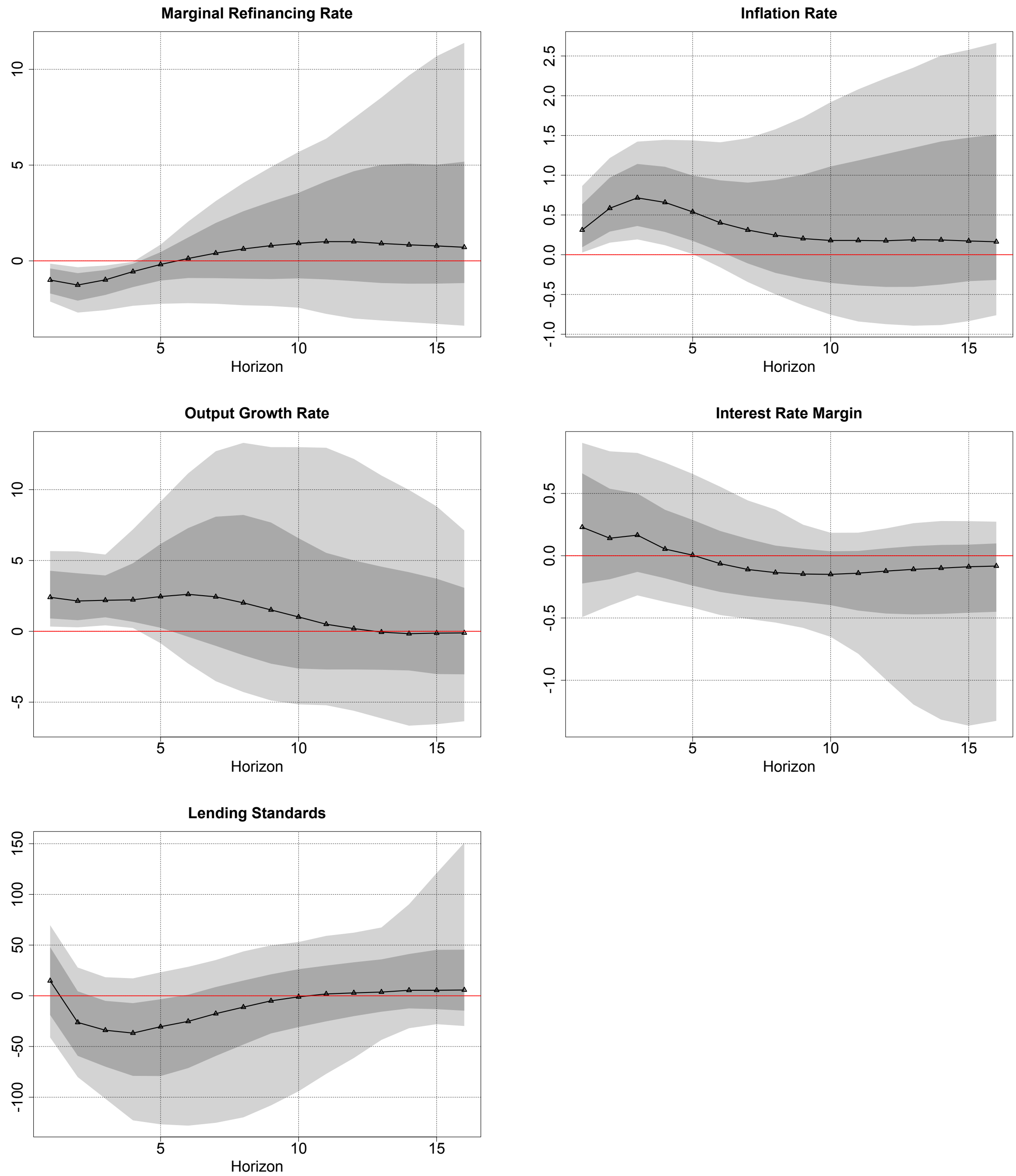
Notes: Figure shows impulse responses to an expansionary monetary policy shock of 100 base points based on recursive identification. Light shaded areas reflect the 95% confidence level; dark shaded areas the 68% confidence level. All responses are given in percent.

Figure C3: Impulse Responses Based on Sign Restricted Model 1



Notes: Figure shows impulse responses to an expansionary monetary policy shock based on sign restrictions. Light shaded areas reflect the 95% credible set; dark shaded areas the 68% credible set. All responses are given in percent.

Figure C4: Impulse Responses Based on Sign Restricted Model 2



Notes: Figure shows impulse responses to an expansionary monetary policy shock based on sign restrictions. Light shaded areas reflect the 95% credible set; dark shaded areas the 68% credible set. All responses are given in percent.

Table C1: Weighting Scheme of Lending Margins (in Percent)

	03Q1−06Q4	07Q1−07Q4	08Q1−08Q4	09Q1−10Q4	11Q1−13Q4	14Q1−14Q4	15Q1−16Q2
Austria	2.88	2.87	2.86	2.82	2.82	2.81	2.79
Belgium	3.63	3.62	3.61	3.56	3.56	3.54	3.52
Cyprus	0.00	0.00	0.22	0.22	0.22	0.22	0.21
Estonia	0.00	0.00	0.00	0.00	0.28	0.28	0.27
Finland	1.84	1.83	1.83	1.81	1.80	1.80	1.78
France	20.80	20.70	20.63	20.40	20.34	20.26	20.14
Germany	26.40	26.27	26.19	25.89	25.82	25.72	25.57
Greece	2.98	2.97	2.96	2.93	2.92	2.91	2.89
Ireland	1.70	1.69	1.69	1.67	1.67	1.66	1.65
Italy	18.06	17.97	17.91	17.71	17.66	17.59	17.49
Latvia	0.00	0.00	0.00	0.00	0.00	0.40	0.40
Lithuania	0.00	0.00	0.00	0.00	0.00	0.00	0.59
Luxembourg	0.30	0.30	0.30	0.29	0.29	0.29	0.29
Malta	0.00	0.00	0.09	0.09	0.09	0.09	0.09
Netherlands	5.87	5.84	5.82	5.76	5.74	5.72	5.69
Portugal	2.56	2.54	2.54	2.51	2.50	2.49	2.48
Slovakia	0.00	0.00	0.00	1.11	1.11	1.10	1.10
Slovenia	0.00	0.50	0.50	0.50	0.50	0.49	0.49
Spain	12.97	12.90	12.86	12.72	12.68	12.63	12.56

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

Chapter 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 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 indeed can be described as a mixture of two states. The first (second) state with an overall share of 80% (20%) can be interpreted as "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 as 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.[48]

6.1 Introduction

There is an ongoing discussion 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 (European Central Bank, 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

[48] This study is joint work with Jan Pablo Burgard and Matthias Neuenkirch, both University of Trier.

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.[49]

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 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.

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

[49] Tenreyro and Thwaites (2016) find the opposite as in their paper US monetary policy is less powerful during recessions.

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 20% can be interpreted as "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 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.

6.2 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 on 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) aim at filling this gap. Nevertheless, outside of the short transition period, the economy remains rigidly in one state in this class of models.

6.2.1 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[50], 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:

$$F(y_t|\mathcal{F}_{t-1}) = \sum_{k=1}^{K} \alpha_k \Phi\left(\Omega_k^{-\frac{1}{2}}\left(Y_t - \Theta_{k0} - \Theta_{k1}Y_{t-1} - \Theta_{k2}Y_{t-2} - \ldots - \Theta_{kp_k}Y_{t-p_k}\right)\right) \tag{45}$$

$\mathcal{F}$ 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. Θ_{k1},...,Θ_{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 an 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.

[50]Component is the equivalent terminus to a regime that is commonly used in the mixture model literature.

6.2.2 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:

$$Z_{t,i} = \begin{cases} 1 & \text{if } Y_t \text{ comes from the } i^{th} \text{ component}; 1 \le i \le K \\ 0 & \text{otherwise.} \end{cases} \tag{46}$$

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

$$l_t = \sum_{k=1}^{K} Z_{t,k} \log(\alpha_k) - \frac{1}{2}\sum_{k=1}^{K} Z_{t,k} \log|\Omega_k| - \frac{1}{2}\sum_{k=1}^{K} Z_{t,k}(e_{kt}^\top \Omega_k^{-1} e_{kt}) \tag{47}$$

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:

$$l = \sum_{t=p+1}^{T} l_t = \sum_{t=p+1}^{T} \left(\sum_{k=1}^{K} Z_{t,k} \log(\alpha_k) - \frac{1}{2}\sum_{k=1}^{K} Z_{t,k} \log|\Omega_k| - \frac{1}{2}\sum_{k=1}^{K} Z_{t,k}(e_{kt}^\top \Omega_k^{-1} e_{kt}) \right) \tag{48}$$

Expectation Step

Since we cannot directly observe the vectors $Z_1,\ldots,Z_T$, 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} component of Z_t, we obtain the mixture weights:

$$\widetilde{\tau}_{t,k} = \frac{\alpha_k |\Omega_k|^{\frac{1}{2}} \mathrm{e}^{-\frac{1}{2} e_{kt}^{\top} \Omega_k^{-1} e_{kt}}}{\sum_{k=1}^{K} \alpha_k |\Omega_k|^{\frac{1}{2}} \mathrm{e}^{-\frac{1}{2} e_{kt}^{\top} \Omega_k^{-1} e_{kt}}}, \quad \forall k = 1, \ldots, K \tag{49}$$

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 (Thompson et al., 1998; Wedel and Kamakura, 2000; McLachlan and Peel, 2000; Grun, 2008; Dang and McNicholas, 2015).

Similar to Thompson et al. (1998), we use a multinomial logit model for the transition process. The mixture weights obtained in Eq. (49) 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:

$$\widetilde{\tau}_{t,k} = \frac{\mathrm{e}^{\zeta_t^T \gamma_k}}{\sum_{j=1}^{K} \mathrm{e}^{\zeta_t^T \gamma_j}} \tag{50}$$

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 submodel, which simplifies Eq. (50) as follows:

$$\widetilde{\tau}_{t,k} = \frac{1}{1 + \mathrm{e}^{-(\sum_{j=0}^{n} \beta_{j,k} x_{t,j})}} \tag{51}$$

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. (49) with the expected value of the logit model in Eq. (51), conditional on the results of the estimated logit model of equation (51):

$$\widehat{\tau}_{t,k} = E\left[\frac{1}{1+\mathrm{e}^{-(\sum_{j=0}^{n}\beta_j x_{t,j})}} \mid x_{kt}, \beta_{j,k}\right] \quad \forall k = 1,\ldots,K, \forall j = 1,\ldots,n \tag{52}$$

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

$$\widehat{\alpha}_k = \frac{1}{T-p}\sum_{t=p+1}^{T}\widehat{\tau}_{t,k} \tag{53}$$

$$\widehat{\widetilde{\Theta}}_k^{\top} = \left(\sum_{t=p+1}^{T}\widehat{\tau}_{t,k}X_{kt}X_{kt}^{\top}\right)^{-1}\left(\sum_{t=p+1}^{T}\widehat{\tau}_{t,k}X_{kt}Y_t^{\top}\right) \tag{54}$$

$$\widehat{\Omega}_k = \frac{\sum_{t=p+1}^{T}\widehat{\tau}_{t,k}\widehat{e}_{kt}\widehat{e}_{kt}^{\top}}{\sum_{t=p+1}^{T}\widehat{\tau}_{t,k}} \tag{55}$$

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

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. Until October 2008, we use the ECB's main refinancing rate (MRR).[51] After that date, we replace the MRR with the shadow interest rate by Wu and Xia (2016), which provides

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

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.

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 puts some emphasis on the 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.[52] Figure D1 in the Appendix shows all five variables over the sample period.

6.2.4 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:

$$\log \mathcal{L} = \sum_{t=1}^{T} \log \sum_{k=1}^{K} \alpha_k \left\{ |\Omega_k|^{-\frac{1}{2}} \, \mathrm{e}^{-\frac{1}{2} e_{kt}^{\top} \Omega_k^{-1} e_{kt}} \right\} \tag{56}$$

The information criteria are then defined as:

$$BIC = -2 \log \mathcal{L} + \log(T - p_{\max}) \left\{ \left(n^2 \sum_{k=1}^{K} p_k \right) + K \left[\frac{n(n+1)}{2} + n + 1 \right] - 1 \right\} \tag{57}$$

[52]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.

$$AIC = -2\log\mathcal{L} + 2\left\{\left(n^2\sum_{k=1}^{K} p_k\right) + K\left[\frac{n(n+1)}{2} + n + 1\right] - 1\right\} \tag{58}$$

$$HQ = -2\log\mathcal{L} + 2\log\left[\log(T - p_{\max})\right]\left\{\left(n^2\sum_{k=1}^{K} p_k\right) + K\left[\frac{n(n+1)}{2} + n + 1\right] - 1\right\} \tag{59}$$

Table 5 shows the information criteria for different lag combinations.[53] 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 5: 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

In contrast to Fong et al. (2007), who assume that Y_t only follows one component in each period by determining the largest value of $\tau_{t,1} \ldots, \tau_{t,K}$, we imply that every component is present with a proportion $\widehat{\tau_{t,k}}$ in each period. Hence, the regime-independent error series $\mathbf{e}_t$ of the model is calculated by:

$$\widehat{\mathbf{e}_t} = \sum_{k=1}^{K} \widehat{\tau_{t,k}} \cdot \widehat{e_{kt}} \tag{60}$$

To test for the presence of autocorrelation, a Portemonteau statistic up to order $h = 8$ is calculated by:

$$Q_h = T\sum_{j=1}^{h} tr\left(\widehat{C_j}^{\top}\widehat{C_0}^{-1}\widehat{C_j}\widehat{C_0}^{-1}\right) \tag{61}$$

[53]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.

where $\widehat{C_i} = \frac{1}{T}\sum_{t=i+1}^{T} \widehat{\mathbf{e}_t}\widehat{\mathbf{e}_{t-i}^{\top}}$ and $Q_h \sim \chi^2\Big(n^2[h - \min(p_1, \ldots, p_k)]\Big)$. The null hypothesis of autocorrelation is thereby rejected.

6.2.5 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 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.

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 four 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. (53)–(55). Second, we calculate the regime-independent error series $\widehat{\mathbf{e}_t}$ as of equation (60), from which we randomly draw 500 bootstrap samples. Third, 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.

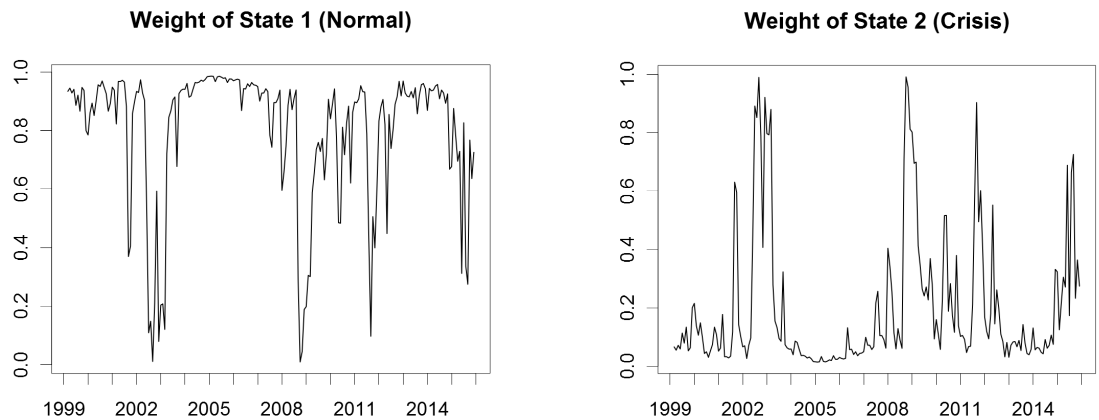
It is worth highlighting that for the calculation of the impulse responses we do not have to assume that the economy remains in a single state as done in many Markov-switching VAR applications. The overall impulse response function is a continuously varying mixture of the impulse responses for both states,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

6.3 Empirical Results

6.3.1 State Weights

In a first step, we present the weights of the different states obtained with the help of the logit submodel. Figure 10 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 "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 10: Weights of Both States



Notes: Weights of both states over time are obtained by estimation of Eq. (50).

Figure D2 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 10. Higher levels of inflation and the interest rate are associated with a larger probability to be in normal times. In contrast, larger figures for industrial production lead to a higher probability to be 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 ($\rho = 0.48$).[54]

6.3.2 Impulse Response Functions

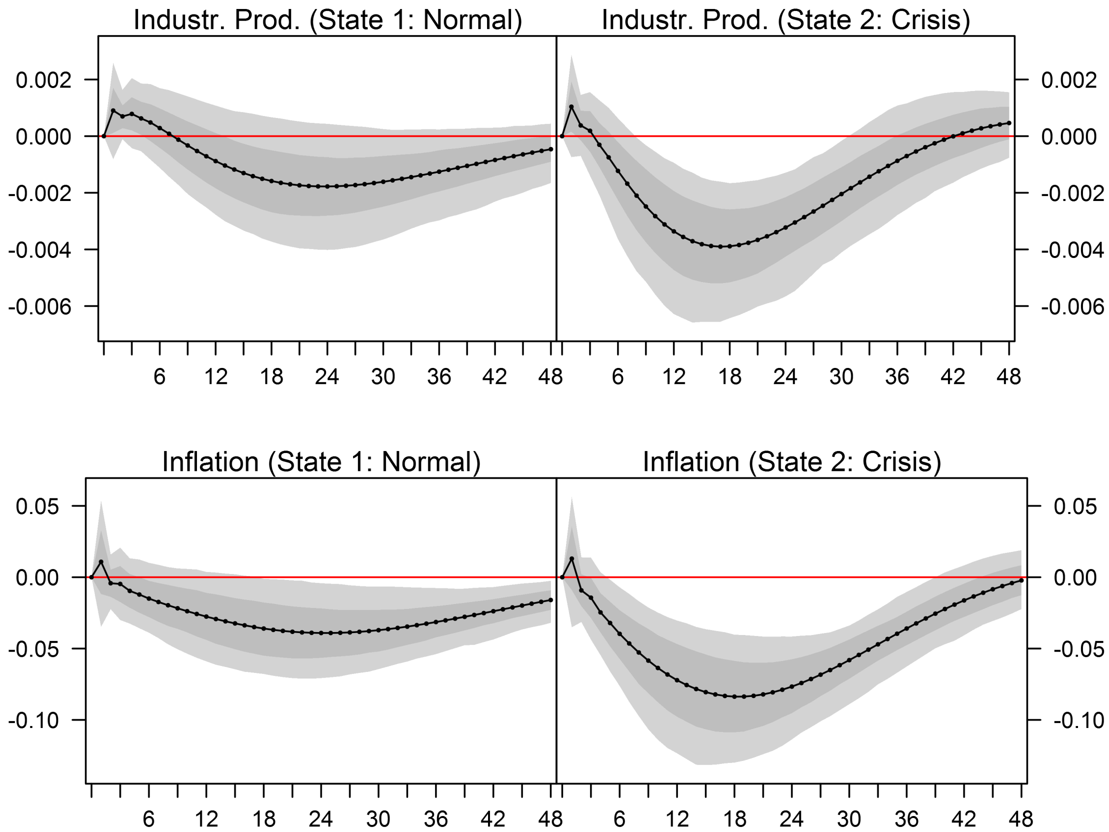
In a second step, we derive the impulse response after a one standard deviation shock in the error terms of the interest rate equation, which corresponds to 40.37 basis points.[55] The results for output and prices are presented in Figure 11.

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 ones for inflation become significant for the first time 16 months after the interest rate shock. Second, the contractionary effects are stronger 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

[54]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 10 and the impulse responses in Figure 11 are less distinct in such a parsimonious setting. Therefore, we stick to the setup with the four-variable logit submodel.

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

Figure 11: 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.

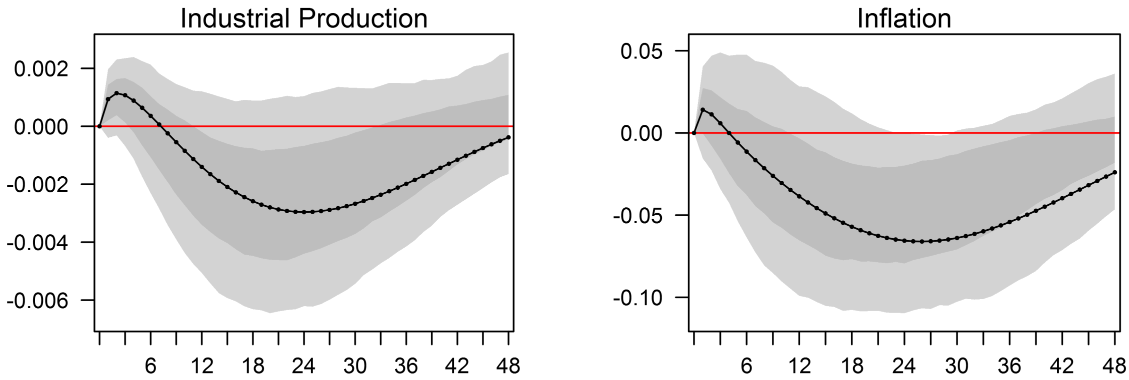
in the normal state the influence on IP becomes insignificant after 47 months and the impact on inflation is significant even beyond 48 months.[56]

6.3.3 Discussion

One crucial advantage of the Logit-MVAR model is the gain in efficiency, for instance, compared to a standard linear VAR model. Figure 12 shows the corresponding impulse responses for such a linear VAR model obtained using the identification strategy described in Section 2.5.

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

Figure 12: Impulse Reponses for Linear VAR

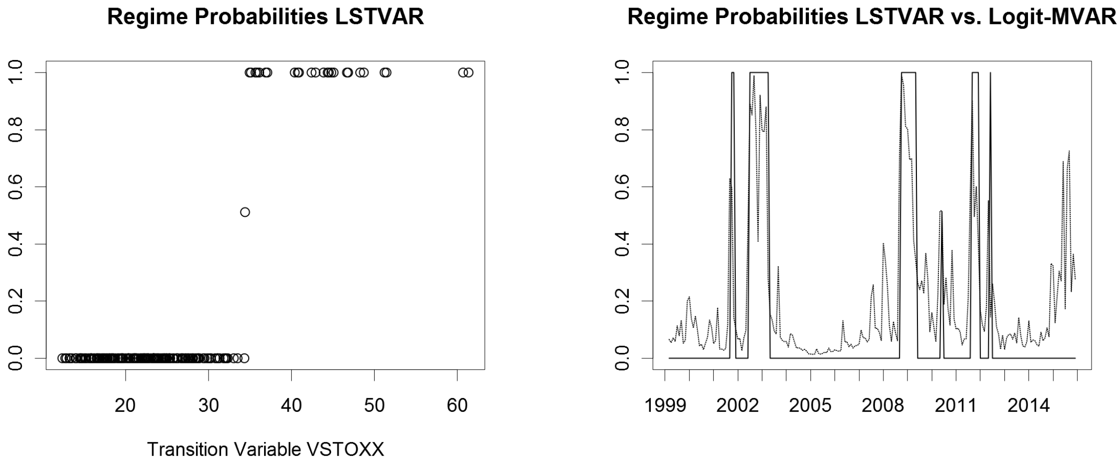


Notes: The figure shows selected impulse responses to a one standard deviation shock in the interest rate indicator for a linear VAR. Dark grey-shaded areas indicate 68% confidence bands and light grey-shaded areas indicate 95% confidence bands that are created by bootstrapping and 500 replications.

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 D2), we use the VSTOXX as transition variable for the LSTVAR model. In such a model, the estimated smoothness parameter ($\gamma = 174.8$) is even larger than in the original paper of Weise (1999). The left panel of Figure 13 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 13: 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 10.

The right panel of Figure 13 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 10. 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 10 and 11). 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.

6.4 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 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 non-linear 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.

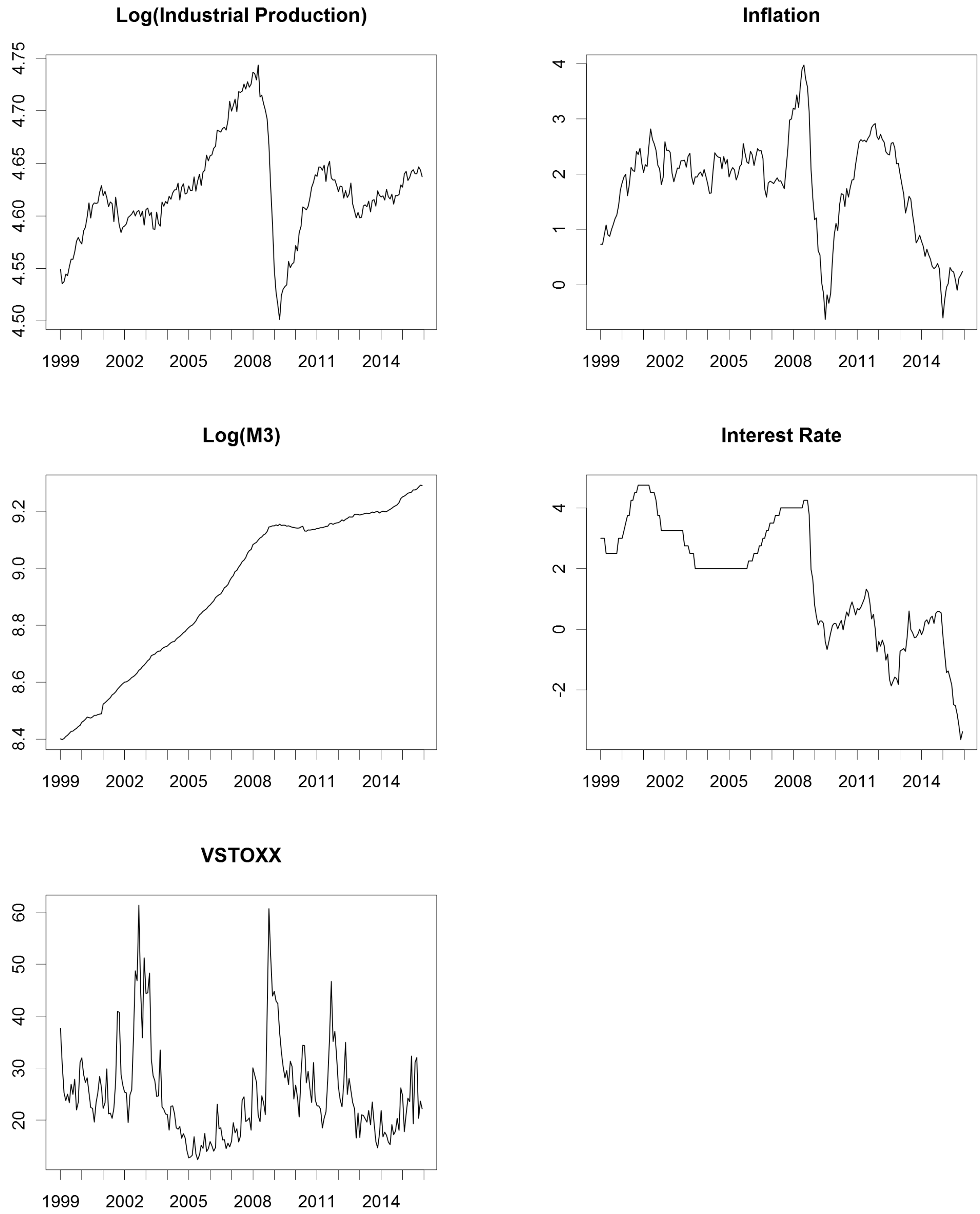
We show that monetary policy transmission in the euro area indeed can be described as a mixture of two states. The second state with an overall share of 20% can be interpreted as "crisis state" as its weights are particularly large during the recession in 2002–2003, after the Lehman collapse in 2008,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

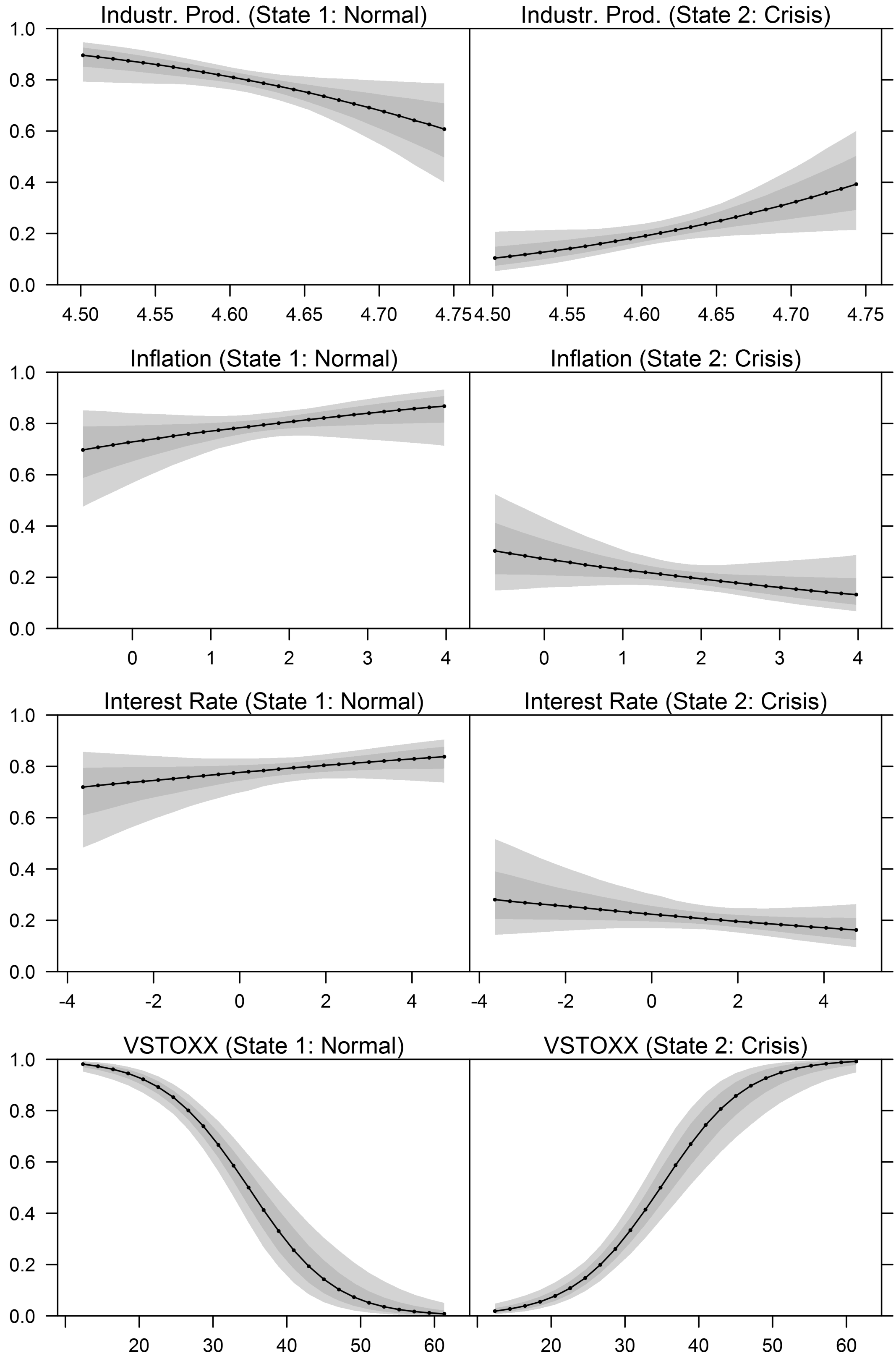
6.5 Appendix D

Figure D1: 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).

Figure D2: 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.

7 Conclusion and Policy Outlook

The aim of this thesis is to investigate the transmission mechanism of monetary policy and analyze its scope. To do so, we applied different empirical models and shed light on non-linearities and facets of the transmission mechanism that have not gotten much attention so far.

We started in chapter 1 by exemplifying what has changed since the era of the Great Moderation has ended and why monetary policy was able to stabilize inflation and economic growth during the latter one. On this occasion, we identified structural changes in the economy. New developments in the goods producing and financial sector have led to the stabilization of economic and credit growth rates. Apart from that, rule based monetary policy and inflation targeting have been identified to stabilize inflation by increasing the transparency of monetary policy decisions. Lastly, the transmission mechanism seems to have changed in the sense that the economies reaction towards monetary shocks has decreased. Yet, the global financial crisis of 2008 has ended the era of Great Moderation and prompted the question of non-linearities in the transmission mechanism.

Chapter 2 and 3 have established a theoretical and empirical foundation for the analysis of the transmission mechanism by introducing common time series methods and examining the traditional channels of monetary policy transmissions.

In chapter 4, we analyzed non-linear behavior in the transmission arising from the financial cycle, that is the cyclical movement of the Credit-to-GDP gap. The financial cycle is known to render the build-up of credit-driven asset price bubbles and serves as indicator variable for macroprudential policy in the Basel III framework. We used a data set of six US variables, that is output growth, the inflation rate, the interest rate spread, Credit-to-GDP gap, credit growth and the federal funds rate, ranging from 1955Q1 to 2007Q4. By applying a TVAR model with three regimes, we were able to identify the existence of a non-linear relationship in the system. Our main findings are that restrictive monetary policy is less potent during the upper phase of the cycle that is associated to credit overheating behavior and negative credit shocks are more harmful during this phase. We emphasize that monetary policy alone does not seem to be able to lean against credit-driven bubbles by deflating them and advise the combined use of restrictive monetary and prudential policy to smooth the amplitude of the financial cycle and temper the build-up of credit-driven bubbles.

Chapter 5 takes a deeper look at the risk-taking channel of monetary policy in the Euro Area. We propose the calculation of a joint Euro Area interest rate margin according to the ECB capital key and the usage of lending standards from the ECB bank lending survey as a proxy for risk-taking behavior. The rest of the data set includes the marginal refinancing rate, inflation and output growth, covering the period 2003Q1 to 2016Q2. Applying structural and sign restrictive identification, we verify the existence of a risk-taking channel in the Euro Area. Following a negative interest rate shock, banks react swiftly by decreasing their lending standards. The initial response of the interest rate margin tends to be positive, indicating a supportive effect for banks, but in the mid-run, banks cannot shield their interest rate margins from the associated negative effect of low short-term interest rates. Our results point out that long-lasting expansionary policy interventions have negative effects on banks' profitability and lead to excessive risk-taking. Further, we advice to coordinate monetary and prudential policy, since implementing procyclical regulation and lowering interest rates at the same tame may leave the financial system more fragile instead of fostering stability.

In chapter 6, we develop a logit mixture vector autoregressive model and apply it to monthly Euro Area data from 1999 to 2015. Our data set is composed of the industrial production index, inflation, the money aggregate M3 and the VSTOXX index. We use a composite indicator of the shadow rate and the main refinancing rate according to Wu and Xia (2016). Our model is the first to allow for a metric transition between different economic regimes and is able to capture multiple sources to determine the regime affiliation. Impulse response analysis support previous findings (Weise, 1999; Garcia and Schaller, 2002; Lo and Piger, 2005; Mishkin, 2009; Neuenkirch, 2013; Jannsen et al., 2015) that monetary policy is more potent during 'crisis times'.

Addressing our research question on the scope of monetary policy, we have different conclusions. As Borio and Shim (2007) have stated, monetary policy cannot to the job alone. As we have analyzed, central banks ability to lean against credit-driven bubbles during their build-up is limited and we advise the combined use of prudential and monetary policy as demanded by Borio (2011). Still, it is questionable of central banks are able to completely smooth out financial crisis. More likely, we can only weaken the cyclical behavior.

During crisis periods, monetary policy is found to be more potent and lowering interest rates positively affects banks' profitability in the short-run, giving banks the ability to better cope with large depreciations. Yet, this comes at the cost of excessive risk-taking and weakens their position as low short-term rates stay persistent. Hence, we advice swift and strong expansionary interventions with a gradual exit from low interest rates.

Regarding the quotation of Ben Bernanke, research has made major progress in studying the monetary policy transmission process and identified negative consequences resulting in its behavior. However, central banks still cannot do much more than try to smooth out periods of economic distress by stimulate demand and at the same time, attempt to limit the negative side effects of expansionary interventions.

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Deutsche Zusammenfassung

Monetary policy cannot do much about long-run growth, all we can try to do is to try to smooth out periods where the economy is depressed because of lack of demand.

Ben S. Bernanke, Hearing of the House Financial Services Committee, 18$^{\text{th}}$ July 2012.

Für lange Zeit glaubte man, dass Geldpolitik fähig wäre, Preisstabilität und wirtschaftliches Wachstums während allen Phasen des Wirtschaftskreislaufes zu gewähren. Die ra der 'Great Moderation', oft auch Volcker-Greenspan Periode genannt, beginnend in der Mitte der 1980er Jahre, war durch verringerte Volatilitt des Wirtschaftswachstums und der Inflation unter den Industrienationen. Der Ausdruck Terminus wurde allerdings das erste Mal von Stock and Watson (2003) verwendet.

konomen haben lange studiert, was diesen Rückgang der Volatilität erzeugt hat und mehrere Faktoren besonders hervorgehoben. Ein wichtiger Forschungsstrang erklärt, dass es strukturelle Veränderungen in der Wirtschaft gab, beispielsweise eine geringere Volatilität in den Güter produzierenden Sektoren durch bessere Kontrollen in der Inventarisierung, technische Entwicklungen im Finanzsektor sowie eine Stabilisierung der Staatsausgaben (McConnell and Perez-Quiros, 2000; Blanchard and Simon, 2001; Stock and Watson, 2003; Kim et al., 2004; Davis and Kahn, 2008). Während Viele der berzeugung waren, dass die Geldpolitik lediglich Glück hatte, was Ihre Reaktionen gegenüber Inflation oder anderer exogener Schocks angeht (Stock and Watson, 2003; Primiceri, 2005; Sims and Zha, 2006; Gambetti et al., 2008), decken Andere auf, dass die Geschichte weitaus komplizierter ist.

Regelbasierte Geldpolitik (Taylor, 1993), welche die 'inflation targeting' beinhaltet (**?**) wird als eine der Hauptquellen bei der Stabilisierung der Inflation identifiziert (Clarida et al., 2000; Davis and Kahn, 2008; Benati and Surico, 2009; Coibion and Gorodnichenko, 2011). Abgesehen davon, haben sich die Mechanismen der geldpolitischen

Transmission verändert. Giannone et al. (2008) vergleichen hierzu die ra der 'Great Moderation' mit der vorherigen Periode und kommen zu dem Schluss, dass Reaktion der Wirtschaft auf geldpolitische Schocks abgenommen hat. Diese Erkenntnis wird unter Anderem von Boivin et al. (2011) gestützt. hnlich dazu zeigen Herrera and Pesavento (2009), dass die Geldpolitik während der Volcker-Greenspan Periode sehr effektiv darin war, die wirtschaftlichen Auswirkungen von exogenen lpreisschocks auszubügeln. Dieses Ergebnis kann für die darauf folgende Periode nicht reproduziert werden.

Jedoch hat die Subprime Krise die Volkswirtschaften weltweit unerwartet stark getroffen und die ra der 'Great Moderation' damit beendet. Innovationen im Finanzsektor und Deregulierung haben dazu geführt, dass Banken exzessiv Risiken aufnehmen konnten und die Finanzstabilität wurde dramatisch geschwächt (Crotty, 2009; Calomiris, 2009). Dies führte zum Aufbau von kreditfinanzierten Preisblasen (Schularick and Taylor, 2012). Die Federal Reserve Bank, welche als allmächtiger Gewährleister von Preisstabilität und Wirtschaftswachstum während der 'Great Moderation' angesehen wurde, konnte eine harte Krise nicht verhindern. Noch mehr, Sie verstärkte die Preisblase durch niedrige Zinsen als Reaktion auf die Dotcom Blase Anfang der 2000er Jahre und hat die Auswirkungen seiner Interventionen falsch eingeschätzt (Taylor, 2009; Obstfeld et al., 2009).

Neue Forschungsergebnisse ermöglichen eine detailliertere Erklärung zu der von Ben Bernanke gestellten Frage, welchen Handlungsspielraum die Geldpolitik überhaupt besitzt und deuten die Existenz von Nichtlinearitäten in der geldpolitischen Transmission an. Weise (1999), Garcia and Schaller (2002), Lo and Piger (2005), Mishkin (2009), Neuenkirch (2013) und Jannsen et al. (2015) finden heraus, dass Geldpolitik wirksamer während Zeiten finanzieller Anspannung bzw. Rezessionen ist. Die Effektivität während wirtschaftlich 'normalen' Zeiten hingegen ist weitaus geringer, teilweise sogar unsignifikant. Dies veranlasst die Frage, ob diese Nichtlinearitäten die Fähigkeit von Zentralbanken, sich gegen Preisblasen und finanzielle Ungleichgewichte zu lehnen, einschränkt (White, 2009; Walsh, 2009; Boivin et al., 2010; Mishkin, 2011).[57] Wie Ben S. Bernanke in dem zu Anfang erwähnten Zitat anmerkt, denken heutzutage viele konomen, dass Geldpolitik nur dazu dienen kann, Perioden, in denen die wirtschaftliche Lage schwach ist, zu glätten, indem Sie die Nachfrage stimuliert.

Das Ziel dieser Arbeit ist es, die Reichweite und Möglichkeiten von Geldpolitik zu analysieren. Um dies zu tun, wenden wir verschiedene empirische Modelle an, zeigen Nichtlinearitäten im geldpolitischen Transmissionsmechanismus auf und erläutern die makroökonomicshen Auswirkungen der Geldpolitik detailliert. In Kapitel 2 führen wir die gängigen Zeitreihenmethoden, linear und nicht-linear, zur quantitativen Analyse der geldpolitischen Transmission ein. In Kapitel 3 werfen wir darauf basierend einen detaillierten Blick auf die gängigen Transmissionskanäle.

In Kapitel 4 analysieren wir die nicht-lineare Auswirkung von Geldpolitik während verschiedenen Phasen des sogenannten Finanzzyklus. Neben dem realen Konjunkturzyklus und dem Kreditzyklus, die in der Regel durch Wachstumsraten des BIP oder von Kreditaggregaten dargestellt werden, gelangt der Finanzzyklus zu immer mehr Bedeutung (Drehmann et al., 2012; Borio, 2014; Borio et al., 2016). Er basiert auf der Kredit-zu-BIP Lücke und gibt den Aufbau von kreditfinanzierten Preisblasen wieder, welche die gefährlichsten für die Realwirtschaft sind, indem Sie den Bankensektor destabilisieren (Shin and Adrian, 2008; Schularick and Taylor, 2012; Brunnermeier and Schnabel, 2016). Unsere Ergebnisse zeigen, dass Geldpolitik während Phasen der Kreditüberhitzung weitestgehend ohne Effekt ist.

Kapitel 5 betrachtet tiefer gehend den Risiko-Kanal der geldpolitischen Transmission im Euroraum. Banken tendieren dazu, Ihre Kreditvergabestandards zu senken und riskantere Kredite, welche mit einer höheren erwarteten Rendite assoziiert werden, in Ihr Portfolio aufzunehmen, um die negativen Effekte von sinkenden Zinsen auf Ihre Kreditmarge auszugleichen. Dieses Verhalten wird auch als Risiko-Kanal bezeichnet (Gambacorta, 2009; Borio and Zhu, 2012). Unsere Ergebnisse stützen die Exis-

[57] Wir werden dies im Detail in Kapitel 4 diskutieren und hierbei den Einfluss des sogenannten Finanzzyklus und Kreditüberhitzung auf die Effektivität von geldpolitischen Interventionen erläutern.

tenz dieses Risiko-Kanals in der Eurozone für die Periode von 2003 bis 2016. Außerdem heben wir hervor, dass expansionäre Geldpolitik tendenziell eine initial positive auf die Kreditmarge von Banken hat, welche vor allem durch eine berreaktion der Kreditvergabestandards hervorgerufen wird. Allerdings scheinen Banken mittelfristig nicht fähig zu sein, die negativen Konsequenzen für Ihre Kreditmargen verhindern zu können.

In Kapitel 6 untersuchen wir die bereits oben genannte zustandsabhängige Transmission von Geldpolitik für den Euroraum und entwickeln hierzu ein neues empirisches Modell, ein logistisches, Vektor autoregressives Mischverteilungsmodell. Unsere Ergebnisse unterstützen bisherige Ergebnisse aus der Literatur und ermöglichen es erstmals, metrische bergänge zwischen verschiedenen Phasen, sowie den gleichzeitigen Einfluss verschiedener ökonomischer Quellen zuzulassen. Hierdurch erweitern wir die bisherige Forschung, welche sich lediglich auf binäre Sprünge zwischen den Phasen konzentriert.