The role of credit aggregates and asset prices in the transmission mechanism

A comparison between the euro area and the US[*]

This version

January 2007

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The views presented here do not necessarily reflect those of the OeNB.

[*] This paper was partly written when M. Valderrama was a NCB Expert at the Monetary Strategy and Monetary Stance Divisions at the ECB. Many thanks go to the colleagues in these divisions. Special thanks go to Huw Pill, Thomas Westermann and Alessandro Calza for helpful comments. All remaining errors remain ours.

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Abstract

We analyze the interaction between credit and asset prices in the transmission of shocks to the real economy. We estimate a Markov switching VAR for the euro area and the US, including additionally GDP, CPI and a short-term interest rate. We find evidence for two distinct states in both regions. For the euro area, we find a regime which is correlated to the business cycle and which captures periods of very low real credit growth at the end of recessions. However, credit markets and asset price markets do not impede economic recovery during regime 1; while in regime 2, we find a procyclical effect of credit and asset price shocks on GDP. Credit shocks have a positive effect on inflation, which confirms that credit aggregates contain information about the monetary stance. For the US, regime 1 captures periods of stable GDP growth and of low but stable inflation, combined with accelerating asset price increases. We find procyclical effects of credit and asset price shocks on GDP in regime 2. In both regimes, shocks to credit and asset prices have no or even a transitory negative effect on CPI. This is consistent with the view that monetary policy may achieve price stability without at the same time necessarily achieving financial stability.

1. Introduction

We analyze the interaction between credit and asset prices in the transmission of shocks to the real economy. By comparing results for the euro area and the US we additionally obtain evidence for differences between two regions characterized mainly by a bank-based and by a market-based financial system.

The importance of credit aggregates as transmitters of monetary policy and other shocks to GDP and inflation is by now well established in the theoretical and empirical literature. Bernanke and Blinder (1988) show that when bonds and bank loans (credit) are not perfect substitutes neither for borrowers nor for lenders (banks) monetary policy actions affect the real economy not only through the money market but also through the credit market. A policy induced change in the bond rate influences indirectly the lending rate by shifting loan demand and supply. Ultimately, changes in the lending rate and in the supply of loans will influence production and thus will have an additional effect on the real side of the economy (Bernanke and Blinder 1992). This so called financial accelerator mechanism developed in Bernanke and Gertler (1989) strengthened the credit view of monetary policy transmission as opposed to the ‘money’ or monetarist view. The authors show in a neoclassical framework, how business cycles might emerge or be amplified through borrowers’ balance sheet. During business upturns, borrowers’ net worth improves, agency costs decrease and investment increases, which amplifies the business cycle. The opposite happens during periods of economic slowdown.

Another strand in the literature stresses the role of credit aggregates in the built-up of financial imbalances. In conjunction with strong economic prospects and a low and stable inflation environment, financial imbalances which put the financial sytem under stress may first materialize in strong credit growth and rapid asset price increases (Borio and Lowe, 2002, Bordo and Wheelock, 2004, Detken and Smets, 2004). These stylized facts suggest that the joint analysis of credit aggregates and asset prices helps in characterizing the economic conditions under which financial imbalances potentially build up. Due to the high economic costs incurred when the imbalances unwind the debate also focused on whether monetary policy should react preemptively to asset price increases not driven by fundamentals (see Bernanke and Gertler, 2001, and the references therein). Although we do not address the issue in the present paper, the models we estimate may help in assessing whether future credit and asset market developments bear the risks of financial imbalances.

Given their procyclical and mutually reinforcing behavior, credit aggregates and asset prices not only transmit shocks to the real economy, they also amplify the initial impulse. This implies non-linear or asymmetric responses of the variables to financial or real innovations. Kiyotaki & Moore (1997a, 1997b), Kocherlakota (2000), Boissay (2001) and Chen (2001) show that in the presence of asymmetric information and other capital market imperfections, equity plays an important role as collateral for loans, and at the same time increases in loan supply influence asset prices by improving investment prospects. These models also show that the effects of shocks are asymmetric depending on the level of economic activity.[3] During economic downturns or below-average growth periods, the effects of shocks are larger due to higher debt default probability.

To take into account the asymmetric transmission of shocks through credit and asset markets predicted by this last class of models, we use a non-linear vector autoregression which allows for time-varying parameters that switch according to an unobservable Markov process. We estimate a model for the euro area and the US separately and use the results to assess whether differences in the relationship between credit aggregates and asset prices exist between bank-based and market-based financial systems. Given the liquidity smoothing and relationship lending hypotheses in bank-based financial markets (Allen and Gale, 2000) we expect that the propagation of shocks should be smoother in bank-based systems and that therefore, the mutually reinforcing effects of credit and asset price developments should be less pronounced in the euro area.

We find regime-switching in the models of both regions. For the euro area we identify two periods which are characterized by very low real credit growth. The generalized impulse responses reveal that lending during these periods may be characterized as supply-driven (see footnote 3) while the dynamics in the other regime display features of a demand-driven lending behaviour. The mutually reinforcing effects of lending and asset prices contributing to the build-up of financial imbalances during boom periods is not confirmed in our model. Moreover, the evidence suggests that tight credit market conditions do not amplify shocks and thus do not have an amplifying effect on the business cycle of the economy. During periods of demand-driven lending, credit does have an amplifying effect on output.

For the US, the regime prevailing from the fourth quarter of 1988 to the first quarter of 1989 and from mid 1991 to the first quarter of 1997 is characterized by low volatility in GDP growth, inflation and asset price growth together with rapid credit growth. The dates correspond to a period of stable economic growth which often has been attributed to better

[3] In the framework of Bernanke and Blinder (1988), shocks may have asymmetric effects on output if e.g. the lending rate elasticity of loan supply depends on the level of economic activity. If returns on investments and therefore economic prospects are favourable, the lending rate elasticity of loan supply may be larger than the lending rate of loan demand (loan supply curve is relatively flat compared to loan demand curve), so that the amount of lending becomes mainly demand-driven. If economic prospects deteriorate, loan supply may become inelastic (nearly vertical) relative to loan demand, reflecting the increasing tightness of credit market conditions. During these periods, lending may be characterized as mainly supply-driven. Asymmetric effects of shocks at the aggregate demand level have been justified with similar arguments and investigated in Karras (1996).

monetary and fiscal policy. As we expect it for a market-based financial system, the reinforcing effects between asset prices and lending are stronger for the US.

The variance decomposition analysis for both the euro area and the US confirms the important role of asset prices and lending in the transmission mechanism. The analysis also highlights the differences between the two systems. As expected, in the US asset prices contribute more to the forecast error variance in GDP than in the euro area. Interestingly, lending explains a large fraction of the inflation forecast error variance in the euro area during the demand-driven lending regime.

Our analysis is related to Balke (2000) and Calza and Sousa (2006) who find threshold effects of credit conditions in the US and the euro area, respectively. In both investigations, non-linear impulse responses yield evidence for larger output effects during tight credit conditions which prevail before recessionary periods in the US and which are characterized by low real loan growth in the euro area. Our analysis complements the previous evidence by jointly investigating credit aggregates and asset prices.

The paper is organized as follows. Section two describes the econometric model and the Bayesian estimation method. The third section presents the results. The final section concludes and presents the policy implications of our results.

2. The econometric framework

2.1 Model and estimation

To analyze the joint behaviour of credit aggregates and asset prices and their relationship to GDP, inflation and interest rates, we use a vector autoregressive (VAR) model in which we allow the parameters to depend on an unobservable state indicator. The state indicator follows a Markov switching (MS) process and is assumed either to capture changing credit or economic regimes. Given that it is unobservable, we estimate it along with the model parameters. Therefore, we do not have to specificy a priori a variable or a combination of variables which is driving the changing process of the dynamics in the data. Nevertheless, by estimating it using the information contained in the data, we will be able to characterize the periods in which asset prices and credit aggregates were mutually reinforcing each other or not or had a weeker or a stronger effect on the economy. In this setup, it may well be that not all periods of high credit growth lead to asset price bubbles or that not all periods of low credit growth define one regime, as would be the case in a threshold model.

Let y_t be the $p \times 1$ vector containing the observable variables. The general specification of the MS-VAR model including q lags of the endogenous variables is written as:

$$y_t = \upsilon(s_t) + A_1(s_t)y_{t-1} + A_2(s_t)y_{t-2} + ... + A_q(s_t)y_{t-q} + \varepsilon_t,$$
$$\varepsilon_t \sim i.i.d.N(0, \Sigma(s_t)), \tag{1}$$

where s_t represents the unobservable state variable which takes one out of K values, $s_t = k,\ k = 1, \dots K$, in each period. The Markov switching process relates the probability that regime *j* prevails in *t* to the prevailing regime i in $t-1$, $\Pr(s_t = j | s_{t-1} = i) = \eta_{ij}$. In the following, the $K \times K$ conditional transition probabilities, of which $K(K-1)$ are unrestricted, are gathered in the transition matrix η:

$$\eta = \begin{bmatrix} \eta_{11} & \eta_{12} & \cdots & \eta_{1K} \\ \eta_{21} & \eta_{22} & \cdots & \eta_{2K} \\ \vdots & \vdots & \ddots & \vdots \\ \eta_{K1} & \eta_{K2} & \cdots & \eta_{KK} \end{bmatrix}. \tag{2}$$

We estimate the model by Bayesian simulation methods. As all conditional posterior distributions are known, we apply the Gibbs sampler. To obtain draws from the unconstrained posterior distribution, we use the random permutation sampler (Frühwirth-Schnatter, 2001), i.e. we first estimate the model without setting a state-identifying restriction on the parameters.[4] After the estimation, we explore the simulation output by means of scatter plots and marginal distributions to find a state-identifying restriction (see also appendix D of Kaufmann and Valderrama, 2006).

To have a concise notation, we define the vector θ which contains all model parameters, $\theta = (\upsilon(1), ..., \upsilon(K), A_1(1), ...A_q(K), \Sigma(1), ..., \Sigma(K), \eta)$ and the vector s^T which represents the path for the state indicator, $s^T = (s_T, \dots, s_0)$. The posterior distribution $\pi(\theta, s^T \mid y^T)$ is obtained by updating the prior $\pi(\theta, s^T)$ with the information contained in the data. Baye's rule yields:

$$\pi(\theta, s^T \mid y^T) = \frac{L(y^T \mid \theta, s^T)\pi(\theta, s^T)}{L(y^T)}.$$

The likelihood, conditional on s^T, may be factorized as:

$$L(y^T \mid \theta, s^T) = \prod_{t=1}^{T} f(y_t \mid y^{t-1}, \theta, s_t), \tag{3}$$

where the observation density $f(y_t \mid y^{t-1}, \theta, s_t)$ is multivariate normal:

[4] A common restriction which allows to discriminate between the states would be e.g. $\upsilon_1(1) < \upsilon_1(2)$, meaning that the first regime would relate to below-average growth periods in the first variable of the system, while the second regime would relate to above-average growth rate periods.

$$f(y_t \mid y^{t-1}, \theta, s_t) = \mid \Sigma(s_t) \mid^{-1/2} \ (2\pi)^{-p/2} \exp\left\{-\frac{1}{2}(y_t - \mu(s_t))'\Sigma(s_t)^{-1}(y_t - \mu(s_t))\right\}, \qquad (4)$$

with $\mu(s_t) = \upsilon(s_t) + A_1(s_t)y_{t-1} + A_2(s_t)y_{t-2} + ... + A_q(s_t)y_{t-q}$ and $y^{t-1} = (y_{t-1}, y_{t-2}, ..., y_1)$.

Given that the prior for s^T depends only on the transition probabilities, we can factorize the prior $\pi(\theta, s^T) = \pi(s^T \mid \eta)\pi(\theta)$, where the density of $\pi(s^T \mid \eta)$ is proportional to:

$$\pi(s^T \mid \eta) \propto \prod_{t=1}^{T} \eta_{s_t, s_{t-1}} \pi(s_0) = \prod_{j=1}^{K}\prod_{i=1}^{K} \eta_{ij}^{N_{ij}} \pi(s_0), \text{ with } N_{ij} = \#\{s_t = j \mid s_t = i\}.$$

To design the prior distribution $\pi(\theta)$, we further block the parameter vector and assume that the VAR parameters $\beta = (\upsilon(1), ..., \upsilon(K), A_1(1), ...A_q(K))$, the covariance matrices $\Sigma = (\Sigma(1), ..., \Sigma(K))$ and the transition probabilities η are independent a priori, $\pi(\theta) = \pi(\beta)\pi(\Sigma)\pi(\eta)$. We then parameterize independent normal, inverse Wishart and Dirichlet prior distributions for each state-specific set of parameters (see appendix B for details), respectively.

To obtain the inference on the joint posterior distribution $\pi(\theta, s^T \mid y^T)$, we then draw iteratively from the conditional posterior distributions $\pi(\beta \mid y^T, s^T, \Sigma)$, $\pi(\Sigma \mid y^T, s^T, \beta)$, $\pi(\eta \mid s^T)$ and $\pi(s^T \mid y^T, \theta)$. The first three distributions are conjugate to the priors, i.e. are independent state-specific normal, Wishart and Dirichlet distributions, respectively. A path s^T from $\pi(s^T \mid y^T, \theta)$ is obtained by multi-move sampling (Chib, 1996). The derivation of the posterior moments of these distributions is found in appendix B.

We draw 23,000 times from the posterior and discard the first 8,000 values to remove dependence on the starting values. We retain every 3rd draw to account for potential correlation between successive draws. After estimation, we use explorative tools like scatter plots and marginal posterior distributions to obtain a parsimonious representation of the system, in which parameters that are not switching are restricted to be equal across states or in which insignificant parameters are restricted to zero. The final model specifications are assessed by marginal likelihoods, with which we also test the switching specification against a linear model. The marginal likelihood is estimated using the optimal bridge sampler proposed in Frühwirth-Schnatter (2004).

Model inference is then obtained by averaging over the simulated parameter values to obtain the posterior mean estimate and by computing the standard deviation to estimate the standard deviation of the posterior distribution. To save space, we do not tabulate posterior estimates of the final model specification. Results are obtainable upon request, however.

The inference on the state indicator is also obtained by averaging over the simulated paths for s^T. Plotting s^T against the variables of the system and relating it to simple statistics of the data (e.g. the mean and the standard deviation) yields a characterization of the states.

2.2 Order-invariant impulse responses and variance decomposition

The parsimonious and identified models are used to compute state-dependent generalized impulse response functions (Pesaran and Shin, 1998). The advantage of the approach is that, conditional on the state, we obtain impulse responses which are independent of the ordering of the variables and also independent of views on how the variables interact at the short-term or long-term horizon.[5] Given the observed historical path of the variables and the historical distribution of the errors, we compute the state-specific response $GI_{j,d}^{h}(s_t)$ of the variables y_t at horizon h to a one standard deviation shock in variable j as

$$GI_{j,d}^{h}(s_t) = \sigma_{jj,s_t}^{-1/2} C_h(s_t)\Sigma(s_t)e_j ,$$

where σ_{jj,s_t} represents the jth diagonal element of $\Sigma(s_t)$ and e_j is a selection vector with 1 as jth element. The matrix $C_h(s_t)$ refers to the coefficient matrix at lag h of the inverted system (1). Cumulated responses are obtained with

$$GI_{j,c}^{h}(s_t) = \sigma_{jj,s_t}^{-1/2} B_h(s_t)\Sigma(s_t)e_j ,$$

where $B_h(s_t) = \sum_{l=0}^{h} C_l(s_t)$ is the cumulative effect of shocks and $C_0(s_t) = B_0(s_t) = I_p$.

Having a sample from the posterior distribution of the parameters, we can infer the distribution of the impulse responses by computing for each parameter draw the state-dependent impulse responses. By averaging over all draws and evaluating at each horizon the 90% percentile interval, we obtain the mean and a 90% confidence interval of the state-dependent impulse response distributions. In this way, we can for example, confirm whether in one regime lending is demand-driven or supply-driven as predicted by the financial accelerator model or bank lending channel; or whether in one regime there are reinforcing effects of asset prices and credit aggregates as predicted by the credit cycle literature. In general, by looking at the asymmetric dynamics of the system in different regimes we gain some insights into the transmission mechanism.

The impulse responses describe the reaction of variables to shocks and the dynamic interactions between the variables. However, they do not give an indication on the

[5] Such views are usually parameterized as restrictions on the short-term and/or long-term interaction between variables and define a structural VAR model.

importance of the shocks in explaining the variability in the variables. This answer is obtained from the variance decomposition, which we base on the state-dependent generalized impulse responses. Denote the state-dependent fraction of variable's i forecast error variance at the forecast horizon h explained by variable j by $V_{ij}^{h}(s_t)$. The state-dependent order-invariant forecast error variance decomposition is obtained with

$$V_{ij}^{h}(s_t) = \frac{\sigma_{jj,s_t}^{-1} \sum_{l=0}^{h} \left(e_i' B_l(s_t) \Sigma(s_t) e_j \right)^2}{\sum_{l=0}^{h} e_i' B_l(s_t) \Sigma(s_t) B_l'(s_t) e_i},$$

where $i, j = 1, \ldots, p$ and $h = 0, 1, \ldots$. Due to non-zero covariance between shocks, the fractions may not sum up to one. Computing the variance decomposition for each set of simulated parameters, we obtain a sample from the whole posterior distribution of the variance decomposition. We will summarize the results by reporting the posterior mean at selected time horizons for expositional convenience.

3. Empirical Evidence

The model estimated is a five-variable system which includes GDP, CPI, equity prices (DataStream Index for Euro area[6] and Standard & Poor's 500 for the US), lending to the private sector and the 3-month interest rate. We use seasonally adjusted quarterly data covering the period from the first quarter of 1980 up to the second quarter of 2004. All variables except the CPI and the short-term interest rate are expressed in real terms and in quarterly growth rates. The interest rate is differenced once. There is evidence for a non-stationary euro area inflation rate (Kugler and Kaufmann, 2005). Therefore, we difference twice the price level. Finally, the data is demeaned and standardized for computational purposes. Because of a change in the statistical definition of euro area loans, we include a dummy variable for euro area loans in the third quarter of 1990.

First, we estimate an unrestricted version of each model with two lags in which all parameters and the variance-covariance matrix of the residuals are switching. Based on this benchmark, we restrict those parameters that are not switching to be equal across regimes and those that are insignificant to be zero (see appendix D in Kaufmann and Valderrama, 2006, for the model selection procedure). The unrestricted and the restricted specifications are also tested against a linear specification by means of marginal likelihoods (see Table 1). For both the euro area and the US, the restricted specification is preferred to the others.

In the following, we discuss the results for each region separately. We first characterize the regimes relating the posterior state probabilities to the variables in the system and then

[6] This is a weighted index constructed by Datastream from country data areas dating back to 1973 covering 75-80% of stock market capitalization.

use generalized impulse responses to assess whether the relationships among the variables depend on the different credit or economic regimes. Thereby, we will characterize a credit regime as being demand-driven when the lending rate elasticity of loan supply will be larger (i.e. the supply curve is flatter) relative to loan demand and a supply-driven regime when it is lower relative to the loan demand elasticity. In the second case, monetary policy shocks (reflected in interest rate shocks) shift loan supply and have a negative effect on loans. Productivity shocks shift loan demand and have a minor effect on loans but a positive effect on the interest rate. In the first case, monetary policy shocks will have small effects on loans while productivity shocks will have positive effects on loans.

To get an idea of the information gain we obtain by taking a non-linear approach, we compare the impulse responses to those obtained from a linear VAR model.

3.1. Euro Area

3.1.1. Posterior state probabilities

The posterior state probabilities obtained for the system of the euro area are rather robust to different model specifications. In general, regime 1 prevails with a high probability at the beginning of the observation period to the end of 1981 and from the second quarter of 1993 to the first quarter of 1995 (see graph 1). The dates nearly coincide with the recession periods defined by the CEPR, albeit regime 1 ends earlier in 1981 and begins later than the recession in the first half of the 1990s. Regime 1 coincides with periods of a strong economic recovery (graph 1, top right panel) and a very low real loan growth (graph 1, bottom left panel). Our results deviate from Calza and Sousa (2006, CS henceforth), who estimate a threshold VAR model with below-average real loan growth as threshold, i.e. also the below-average growth periods in the mid 1980s and around 2002 are defining their regime.[7]

Tables 2 and 3 compare the regime-dependent average growth rates and the acceleration rates of the five variables with those obtained using the CEPR recession dates, and using the regimes identified by CS. Our estimate of regime 1 captures below-average GDP growth, 0.45% per quarter, which is nevertheless accelerating at 0.12 percentage points (pp) per quarter, verly low, decelerating real credit growth, 0.07% and -0.17pp, respectively, and decelerating asset price returns. The main difference to the regimes identified by CEPR and to those identified by CS shows up in the growth rate of real loans. During CEPR recession phases real loan growth is nearly five times larger (0.33%) and during regime 1 of CS it is six times larger (0.45%) than during regime 1 of the MS-VAR.

[7] Besides the methodology the main differences are our inclusion of asset prices and the use of a short term interest rate while Calza and Sousa (2006) include a synthetic lending rate.

GDP growth during regime 1 of the MS-VAR is seven times larger than CEPR recession growth rates of GDP (0.06%).

Table 4 contains the state-dependent standard deviations of the variables. In the MS-VAR, GDP and real loan growth are less volatile in regime 1, nearly half of regime 2 volatility. While asset prices are also less volatile in regime 1, the volatility of inflation and the interest rate is higher in regime 1. Except for GDP volatility, the state-dependent volatilities are similar whether we use regime identification by MS-VAR or by CEPR dates. Differences in state-dependent volatilities are less pronounced in the model of CS. Lower volatility of real loan growth in regime 1 is the main difference.

To summarize, regime 1 identified by MS-VAR captures periods of low credit growth which, nevertheless, does not impede economic recovery.

3.1.2. Generalized impulse responses

In general, the impulses responses obtained are also robust to different types of specifications (see graph 2). We depict the responses of regime 1 by dashed lines and the responses of regime 2 by dotted lines.

In regime 1, the response of loans to an interest rate shock is negative (marginally significant) and insignificant to an output shock, while in regime 2 the response of loans to an interest rate shock is insignificant and positive to an output shock. Therefore, regime 1, in which real credit growth is very low, may additionally be characterized as a supply-driven lending regime. In regime 2, which is prevailing otherwise, lending is mainly demand-driven.

Besides the characterization of the regimes we are also interested in evidence for reinforcing effects between credit aggregates and asset prices. The response of asset prices to a loan shock is insignificant in both regimes. On the other hand an asset price shock has a significantly positive effect on loans in regime 2. Thus, mutually reinforcing effects between asset prices and lending are not found in the data. Nevertheless, the response of loans to asset prices is consistent with the view that asset price increases reflect borrowers' net worth improvements when economic conditions are favourable and therefore obtain more easily bank loans.

We can further observe that in regime 2, the demand-driven lending regime, there is a positive response of output to shocks in asset prices and lending. Although both variables have a procyclical effect on production, the risk of rising financial imbalances may still be contained, as inflation reacts significantly positively to shocks in production and lending. Therefore, rising tensions are well reflected in prices. In regime 1, there is no procyclical effect on production of asset price and loan shocks, and no significant response of loans to an asset price shock and vice versa. This result corroborates the view that although real loan growth is very low during regime 1, it does not impede economic recovery, i.e. it does not impose financing constraints on firms.

a) Generalized impulse responses of the linear model

To assess the gains of modeling credit aggregates in a non-linear system we estimate an unrestricted linear VAR to compare the generalized impulse responses of both specifications.

In graph 3, most of the responses coincide with those obtained for regime 2 (the demand-driven lending regime) in the non-linear model. The short period of supply-driven lending and the different dynamic interactions between the variables thus remain undetected. The picture obtained is one of a procyclical economy, in which shocks to loans and asset prices have a significant positive effect on GDP and in which also shocks to GDP affect positively lending and asset prices. The non-linear model refines the picture in the sense that at the end or right after recessions, although lending standards tighten (lending becomes supply-driven) they do not impede economic recoveries. Moreover, this change in lending behaviour may pre-emptively restrain the built-up of financial imbalances in early periods of recovery.

3.1.3. Variance decomposition

Graph 4 contains the state-dependent variance decomposition of GDP and the inflation rate. Given our previous results, we expect the role of lending and asset prices being less important in regime 1. All shares reach their long-run level after 8 quarters. In regime 1, asset price, loan and interest rate shocks explain each between 10% and 15% of GDP's forecast error variance after 24 quarters. In regime 2, the shares of asset prices and loans both increase to around 20% at the 24 quarter horizon. On the other hand, in this regime the forecast error attributed to the short term interest rate is negligible. In both regimes, the forecast error variance of GDP attributed to asset prices and loans (together) is significantly higher than the contribution of the short term interest rate, which confirms the important role of both variables in the transmission mechanism.

Interestingly, the shares of asset prices, loans and interest rate shocks in the forecast error variance of the inflation rate reach about the same share as for the GDP's forecast error variance in regime 1, namely 12%, 13% and 17%, respectively. In regime 2, the variance share of asset price shocks is nearly insignificant while the share of loan shocks rises to 24% at the 8 quarter and to 36% at the 24 quarter horizon, almost 3 times as large as in regime 1. The large variance share explained by loan shocks supports the view that developments in credit aggregates contain information about future inflation prospects, which is of interest for monetary policy following a price stability target.

3.2. United States

3.2.1. Posterior state probabilities

As for the euro area, the posterior state probabilities obtained for the US are robust to different model specifications. The characterization of the regimes is not as straightforward as for the euro area. They are not obviously correlated with the business cycle (graph 5, top left panel). Regime 1 prevails twice during each recovery in the 1980s and in the 1990s, in particular during the first half year of 1985, during 1988 till the first quarter of 1989; then, more persistently, from the second quarter of 1991 to the end of 1992 and again from the second quarter of 1994 to the first quarter of 1997. After the last recession, regime 1 prevailed for half a year during the last quarter of 2001 and the first quarter of 2002. The tables 5 and 7 report the mean growth rates and the volatility of the series, respectively. We compare the state-dependent numbers with those obtained using the NBER business cycle states. The characterization of the MS regime is best based on the volatility in the series rather than on the mean growth rates. Except for asset prices and interest rates, the differences in growth rates are not that large between regimes. Asset price increases in regime 1 are about one third higher than in regime 2 and credit growth is nearly 30% lower in regime 1. On the other hand, in regime 1 the volatility of GDP growth and of inflation are about half of that in regime 2.

A further distinguishing feature of regime 1 is that growth rates in all variables but the inflation rate and real loan growth are accelerating (see table 6). Thus, regime 1 corresponds to a situation in which financial imbalances may build up given the good economic and low inflationary prospects. Whether developments in asset prices and loans reinforce each other and may get on an unsustainable growth path may be seen in the generalized impulse responses.

3.2.2. Generalized impulse responses

The state-dependent impulse responses are found in graph 6. The response of loans to an output shock is insignificant in regime 1 (dashed line) and positive in regime 2 (dotted line), while the response to an interest rate shock is marginally positive in both regimes. Thus, we again can characterize lending as demand-driven in regime 2. The responses in regime 1 do not allow a conclusion.

Loans do not react to a shock in asset prices in regime 1, while in the short run there is a positive reaction in regime 2. Asset prices react on impact marginally positively to a shock in loans. In the long-run, the reaction becomes insignificant. Thus, we find some evidence for reinforcing effects between lending and asset prices during regime 2.

Significant positive effects on GPD of shocks to asset prices and loans are present in regime 2, while the response of GDP is insignificant in regime 1. On the other hand, shocks to asset prices and loans have no effect on prices and only a marginal positive effect on interest rates in regime 2. The impulse responses obtained for the US are consistent with the view that in an environment of low and stable inflation and steadily increasing asset prices, combined with highly favourable economic prospects, inflationary pressures and the potential built-up of financial imbalances may not be primarily reflected in price increases

a) Generalized impulse responses for the linear model

The impulse responses of the linear model (graph 7) yield a picture of an economy with procyclical behaviour of loans and asset prices. Shocks to GDP and to the interest rate have a positive effect on loans. We observe on impact a positive effect of shocks to loans on asset prices and a positive effect of shocks to asset prices on loans. Shocks in both variables have a positive effect on GDP, although the effect of shock to loans is only transitory.

Shocks to GDP have an insignificant effect on prices and a positive effect on the interest rate. Shocks to asset prices and loans lead to an increase in the interest rate but to a decrease in prices.

For monetary policy the results both in the non-linear and the linear model convey that shocks affecting credit and asset markets do not materialize into higher prices. The evidence obtained is consistent with the concerns that by achieving monetary stability, monetary policy may not necessarily achieve financial stability at the same time. Thus, the assessment whether financial imbalances are building up needs special attention.

3.1.4. Variance decomposition

Graph 9 depicts the variance decomposition for GDP and inflation. As for the euro area, the long-run level of the variance shares is nearly reached after eight quarters.

In both regimes, shocks to lending explain about the same share, around 20%, of the forecast error variance of GDP. While the share of asset price shocks remains below 10% in regime 1, it increases to 22% in regime 2. This pattern is consistent with the view that in a market-based economy firms find it easier to raise external finance other than bank loans when economic and financial conditions become favourable.

Turning to the variance decomposition of CPI we find that in regime 1 the variance shares attributable to asset price, loan and interest rate shocks are somewhat lower to those obtained for the euro area, around 10% for the first two and 14% for the interest rate shock. The main difference is observable in regime 2, in which the variance shares of shocks to loans and to asset prices are virtually the same as in regime 1 (12%), while for the euro area the variance share of loan shocks is 3 times higher and the share of asset price shocks is negligible.

4. Summary and policy implications

Based on the recent discussion in the literature, we analyze credit aggregates and asset prices jointly in a system which also includes GDP, prices and a short-term interest rate. It has been argued that in an environment of low and stable inflation rates and of favourable economic prospects, inflationary pressures may first show up in unsound developments in financial markets and materialize in prices only with a substantial delay. Given that lenders' net worth usually serves as collateral for new bank loans, an improvement in net worth leads to an increase in bank loans which increase investment prospects. In turn, improved investment prospects lead to increases in asset prices. These mutual reinforcing effects lead to the built-up of financial imbalances. The predictions of the theoretical literature also suggest that asset prices and credit aggregates together with real and price variables should empirically be modelled in a non-linear framework. We estimate the model for two regions, the euro area and the US. By comparing the results we can assess whether there are differences in the role of asset prices and loans in the transmission mechanism in economies mainly characterized by a bank-based and a market-based financial system, respectively.

For the euro area we are able to characterize the two regimes as periods in which lending is either demand-driven or in which it is supply-driven. We define periods of demand-driven lending by a situation in which the lending rate elasticity of loan supply is larger relative to the elasticity of loan demand. The situation where the lending rate elasticity of loan supply is lower than the elasticity of loan demand is defined as supply-driven lending. For the euro area, regime 1 prevails from the beginning of the observation sample to the end of 1981 and from the first quarter of 1993 to the first quarter of 1995. Regime 1 relates to periods of supply-driven lending, during which, nevertheless, no amplifying effects of asset price and loan shocks on GPD are observable. We also cannot observe a mutually reinforcing behaviour between asset prices and loans during this regime. During the demand-driven lending regime (regime 2), shocks to asset prices and to lending have a procyclical effect on output. However, the unsound built-up of financial imbalances is contained, as shocks to asset prices and loans have a positive impact on inflation and the interest rate. Moreover, there is no evidence that asset prices and lending reinforce each other in regime 2, either.

In the US, regime 1 prevails twice during the recoveries of the 1980s and the 1990s. The distinguishing feature of the regimes for the US is the lower volatility of GDP growth and inflation in regime 1, which is about half of volatility in regime 2. Moreover, all variables except the inflation and real loans grow at an accelerating rate during regime 1. The generalized impulse responses show a transitory positive effect of asset price shocks on loans and vice versa in regime 2. In regime 2, shocks to asset prices and loans have a positive effect on GDP, too. In both regimes, shocks in these two variables do not materialize in higher prices and only marginally positively affect the interest rate. The impulse responses are consistent with the view that in an environment of low and stable inflation and steadily increasing asset prices, combined with highly favourable economic prospects, inflationary pressures and the potential built-up of financial imbalances may not be primarily reflected in price increases. Thus, monetary policy, by achieving monetary stability, may not necessarily achieve financial stability at the same time, which calls for a special assessment of developments in financial markets.

The variance decomposition analysis highlights the differing roles of both asset prices and lending in the transmission mechanism of the euro area and the US. In regime 2, the share of GDP's forecast error variance attributable to loan shocks is 20% in both regions. Asset price shocks account for 19% of GDP's forecast error variance in the euro area and 22% in the US, whereas in regime 1 the shares are 13% and 8%, respectively. This reflects the fact that in an economy with a market-based financial sector, firms have easier access to external finance other than bank loans when economic conditions are favourable. The importance of loans in the euro area is corroborated by the result that lending shocks account for 36% of the inflation's forecast error variance in regime 2, while the share of asset price shocks is negligible. The policy conclusion for the euro area is that credit growth contains information about inflation prospects and may serve as an indicator of the monetary stance.

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APPENDIX A: Tables and Graphs

Table 1. Log of the marginal likelihoods of various model specifications

	Euro area	U. S.
Linear with 1 lag	-1208.6	-1178.5
Linear with 2 lags	-1180.1	-1152.1
Switching unrestricted with 1 lag	-1158.0	-1101.1
Switching unrestricted with 2 lags	-1121.8	-1045.1
Switching restricted	**-1118.9**	**-1039.8**

Table 2. Euro area: Average growth rates*

	MS VAR		CEPR		Calza and Sousa		
	regime 1	regime 2	reces-sions	other-wise	regime 1	regime 2	whole sample
GDP	0.45%	0.52%	0.06%	0.60%	0.43%	0.60%	0.51%
Inflation**	-0.20%	-0.09%	-0.26%	-0.07%	-0.31%	0.03%	-0.10%
Asset prices	1.19%	2.61%	1.33%	2.64%	2.63%	2.39%	2.43%
Loans	**0.07%**	0.94%	0.33%	0.93%	0.45%	1.15%	0.83%
Interest rate**	-8	-11	-10	-11	-15	-7	-11

*Averages during periods in which the probability of being in regime 1 or 2 is more than 50%
**Inflation: Change in percentage points, interest rate: Change in basis points

Table 3. Euro area: Average acceleration rates (in percentage points) *

	MS VAR		CEPR		Calza and Sousa		
	regime 1	regime 2	reces-sions	other-wise	regime 1	regime 2	whole sample
GDP	0.12%	-0.01%	-0.08%	0.02%	-0.02%	0.03%	0.00%
Asset prices	-1.52%	0.17%	0.34%	0.34%	-0.10%	-0.59%	-0.04%
Loans	**-0.17%**	0.02%	-0.08%	-0.08%	-0.02%	0.00%	-0.01%
Interest rate**	0	-1	-19	3	-9	11	0

*Averages during periods in which the probability of being in regime 1 or 2 is more than 50%
**Change in basis points

Table 4. Euro Area: Standard deviations of growth rates*

	MS VAR		CEPR		Calza and Sousa		
	regime 1	regime 2	reces-sions	other-wise	regime 1	regime 2	whole sample
GDP	0.28%	0.54%	0.53%	0.47%	0.56%	0.49%	0.51%
Inflation	0.71%	0.36%	0.67%	0.35%	0.47%	0.33%	0.42%
Asset prices	4.72%	7.98%	5.27%	8.02%	6.68%	8.49%	7.64%
Loans	0.54%	0.63%	0.69%	0.64%	0.47%	0.70%	0.68%
Interest rate**	99	46	98	43	61	54	55

*Averages during periods in which the probability of being in regime 1 or 2 is more than 50%
**Inflation: Change in percentage points, interest rate: Change in basis points

Table 5. USA: Average growth rates*

	MS VAR		NBER		
	regime 1	regime 2	recessions	otherwise	whole sample
GDP	0.78%	0.77%	-0.19%	0.93%	0.77%
CPI	0.77%	0.88%	1.13%	0.79%	0.84%
Asset prices	**2.76%**	2.02%	-0.18%	2.66	2.26%
Loans	**0.78%**	1.12%	0.41%	1.10%	1.01%
Interest rate**	-11	-14	-99	0	-13

*Averages during periods in which the probability of being in regime 1 or 2 is more than 50%
**Change in basis points

Table 6. USA: Average acceleration rates (in percentage points)*

	MS VAR		NBER		
	regime 1	regime 2	recessions	otherwise	whole sample
GDP	0.08%	-0.06%	0.00%	-0.01%	-0.01%
CPI	-0.04%	0.00%	-0.22%	0.02%	-0.02%
Asset prices	**0.07%**	-0.02%	3.46%	-0.54%	0,01%
Loans	**-0.07%**	0.07%	-0.18%	0.05%	0.02%
Interest rate	2	0	-32	4	-1

*Averages during periods in which the probability of being in regime 1 or 2 is more than 50%
**Change in basis points

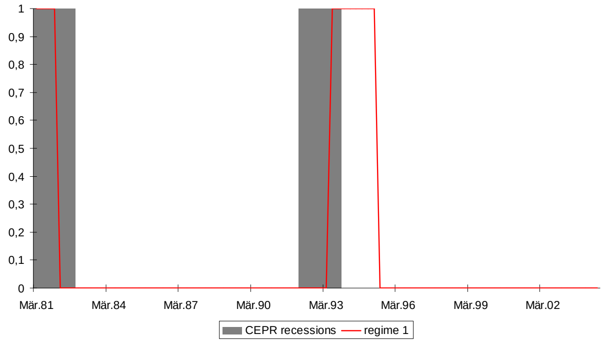
Table 7. USA: Standard deviation of growth rates*

	MS VAR		NBER		
	regime 1	Regime 2	recessions	otherwise	whole sample
GDP	0.49%	0.77%	0.76%	0.53%	0.68%
CPI	0.28%	0.57%	0.78%	0.42%	0.50%
Asset prices	8.06%	8.25%	11.60%	7.48%	8.15%
Loans	**1.10%**	0.99%	0.75%	1.05%	1.03%
Interest rate**	59	72	119	42	68

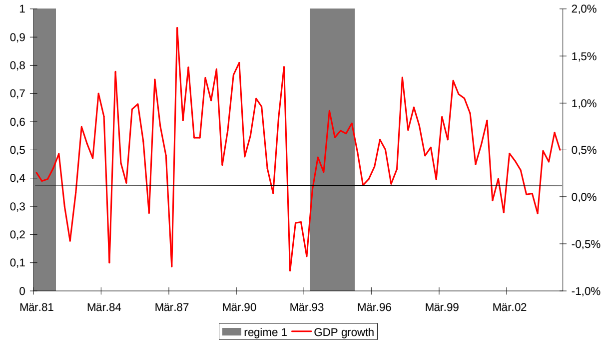
*Averages during periods in which the probability of being in regime 1 or 2 is more than 50%
**Change in basis points

Graph 1. Euro area posterior state probabilities $P(s^T = 1 \mid y^T)$

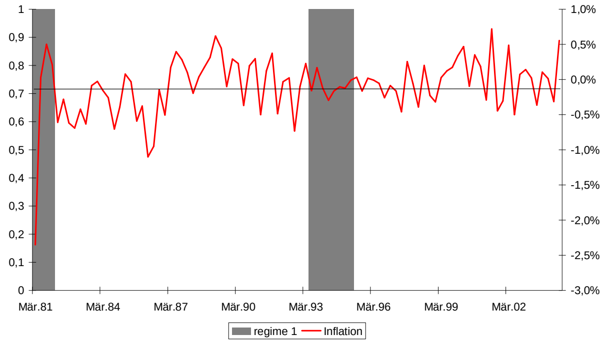
CEPR Recessions



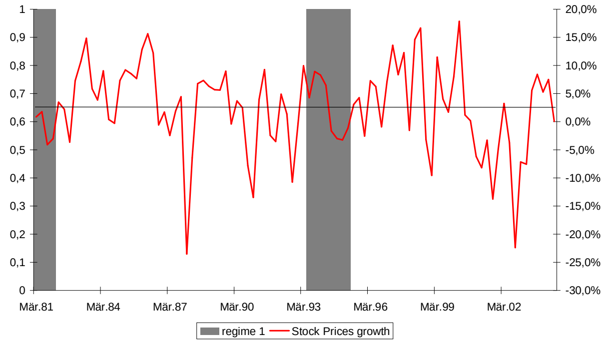
GDP growth



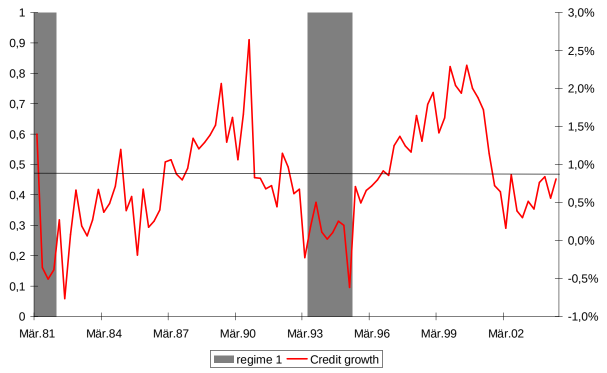
Inflation growth



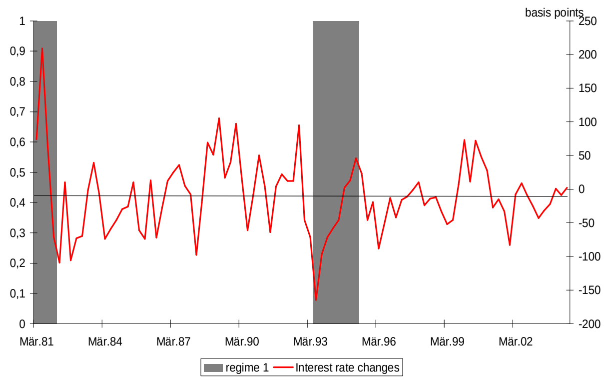
Stock Prices growth



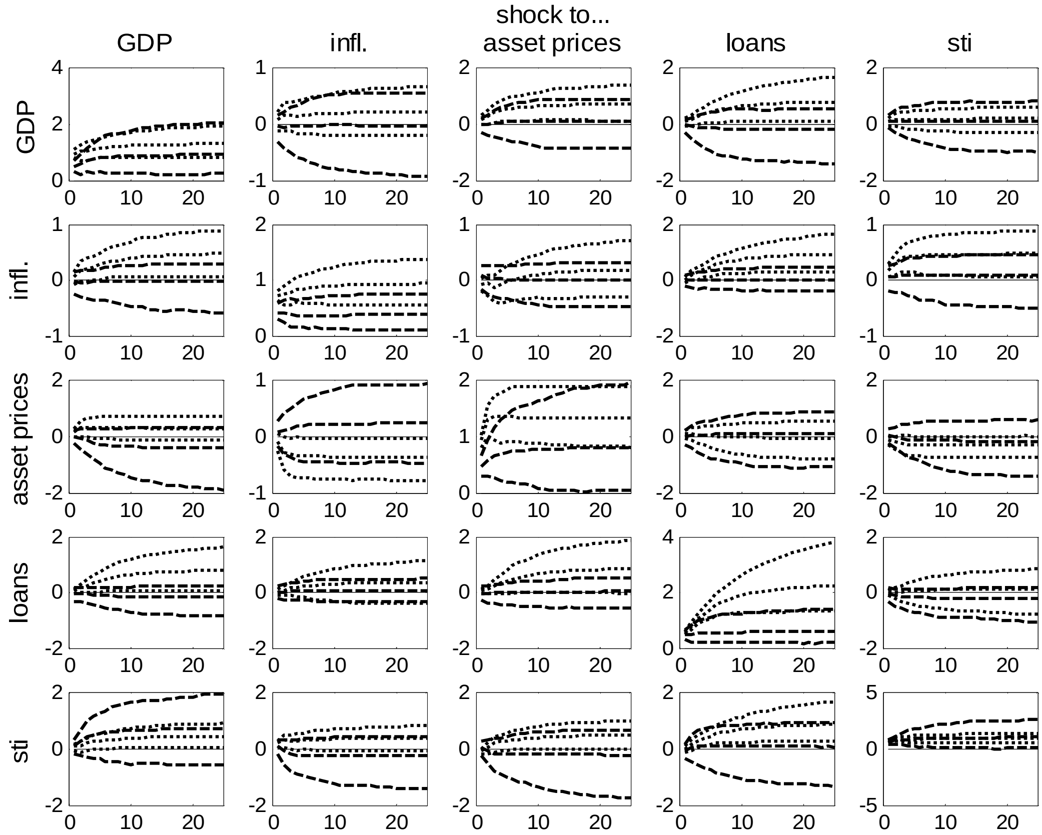
Loans growth



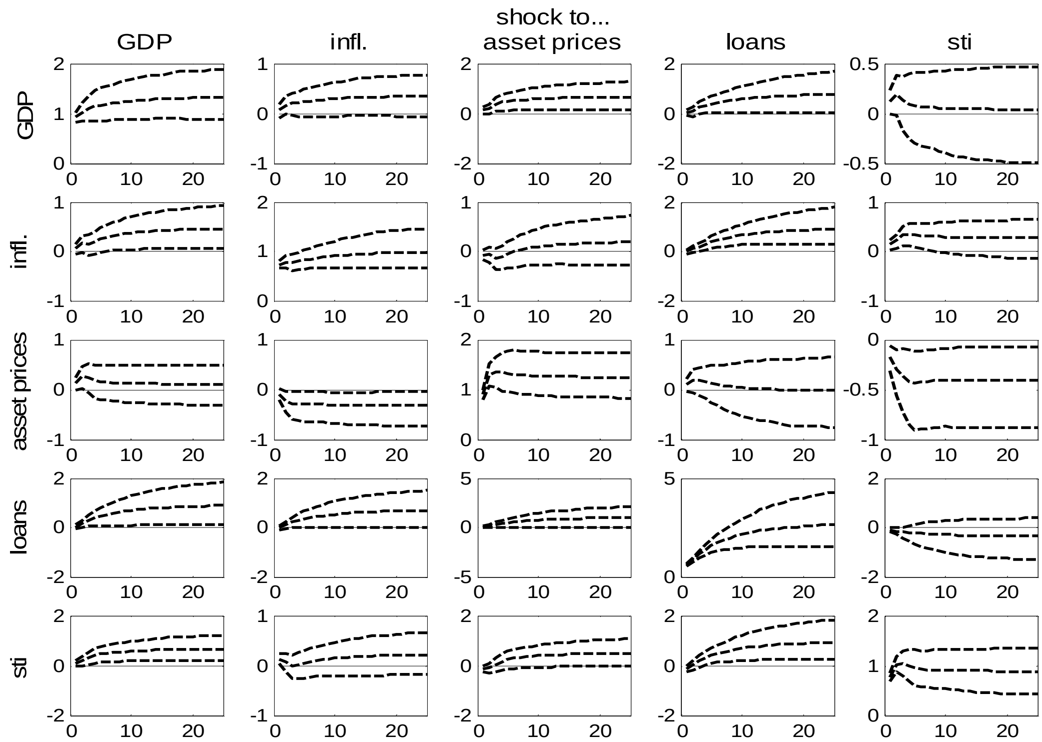
Short term interest rate



Graph 2. Euro area. Cumulated generalized impulse responses. Dashed: regime 1, dotted: regime 2 (with 90% conf.int.)

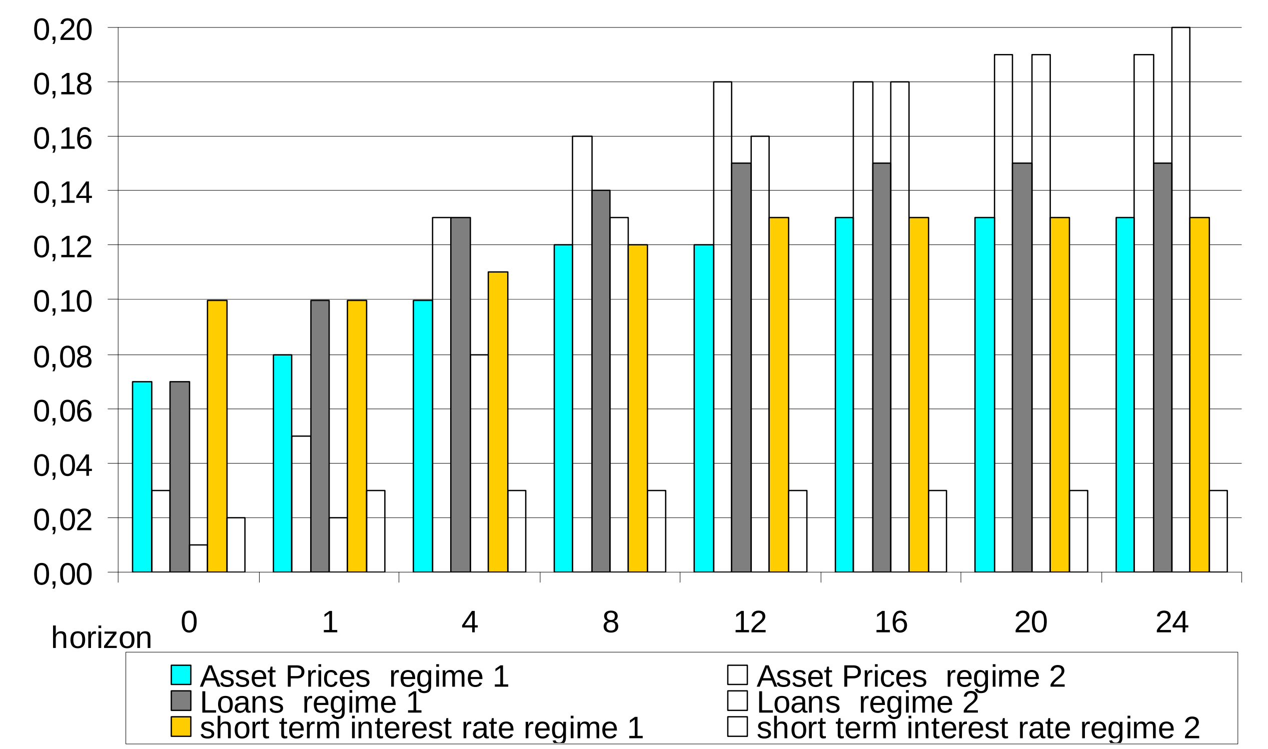


Graph 3. Euro area. Generalized impulse responses (linear model)

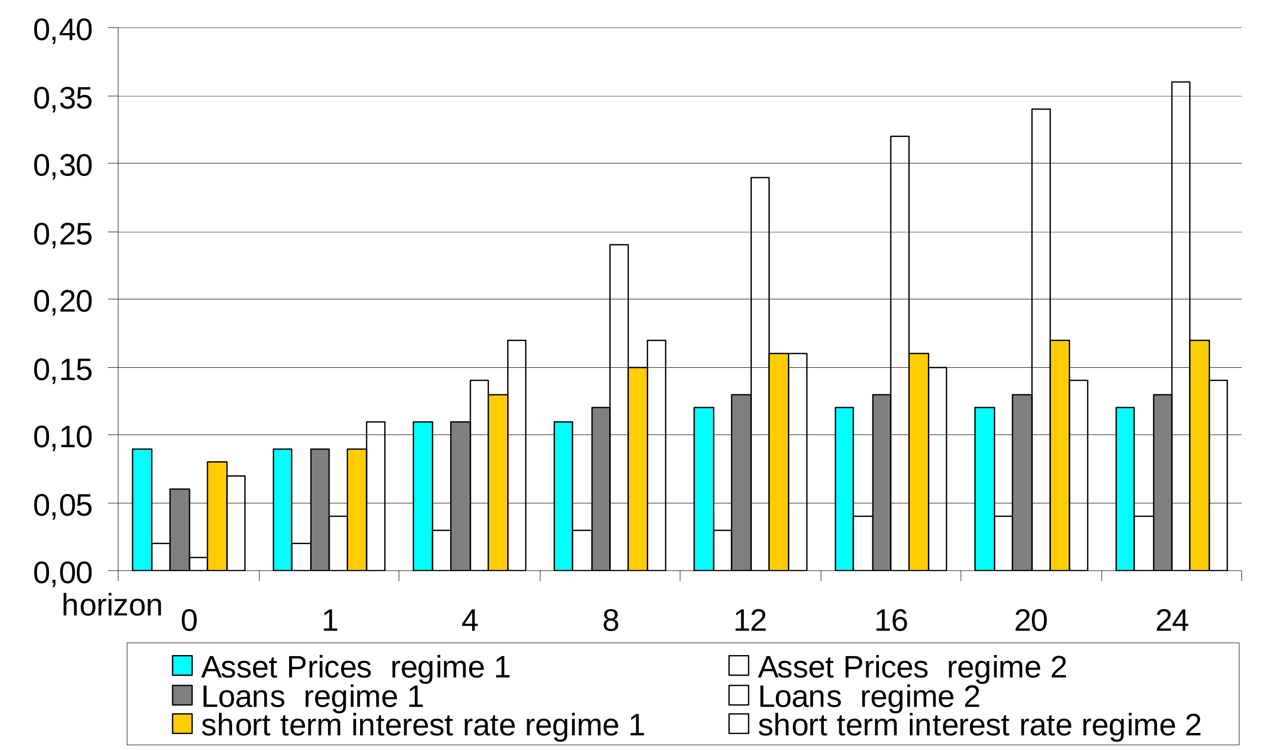


Graph 4. Euro area: variance decomposition

Forecast error variance in GDP attributable to changes in:

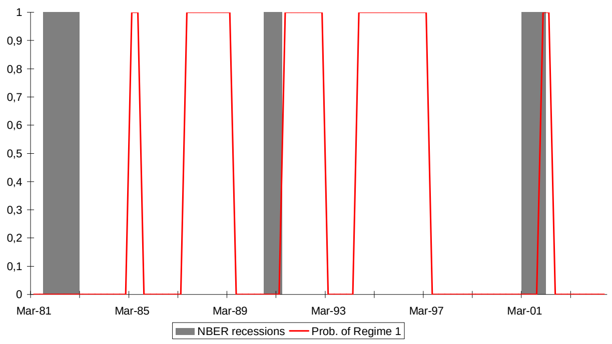


Forecast error variance in CPI attributable to changes in:

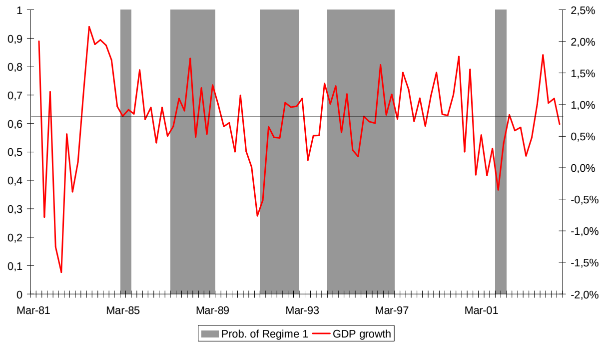


Graph 5. US. Posterior state probabilities $P(s^T = 1 \mid y^T)$

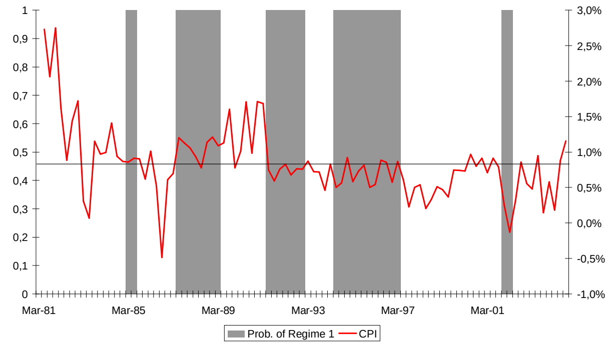
NBER Recessions



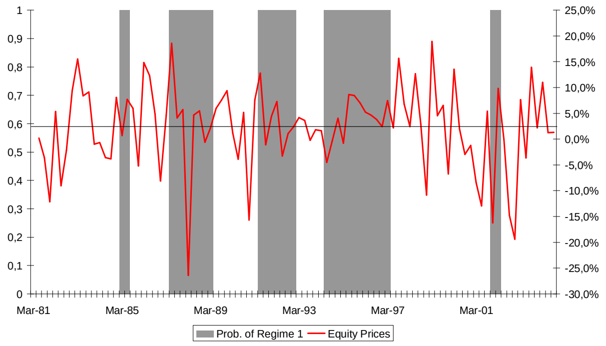
GDP growth



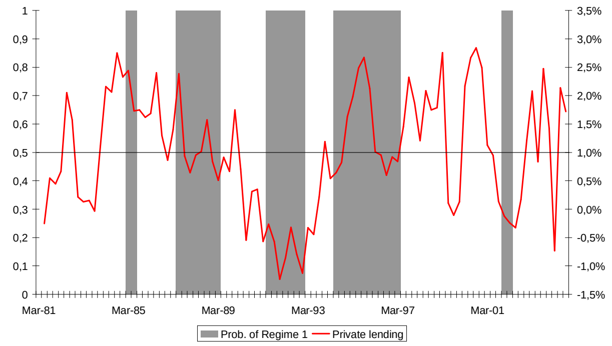
Inflation



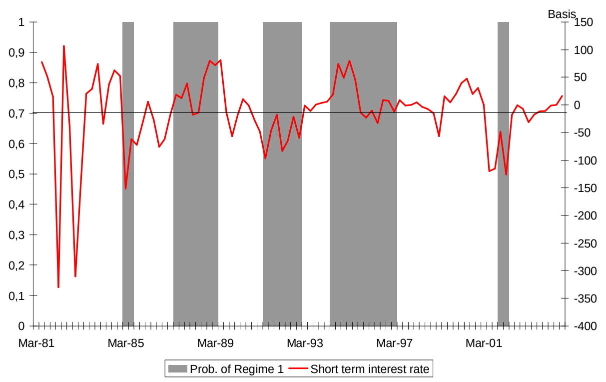
Stock Prices



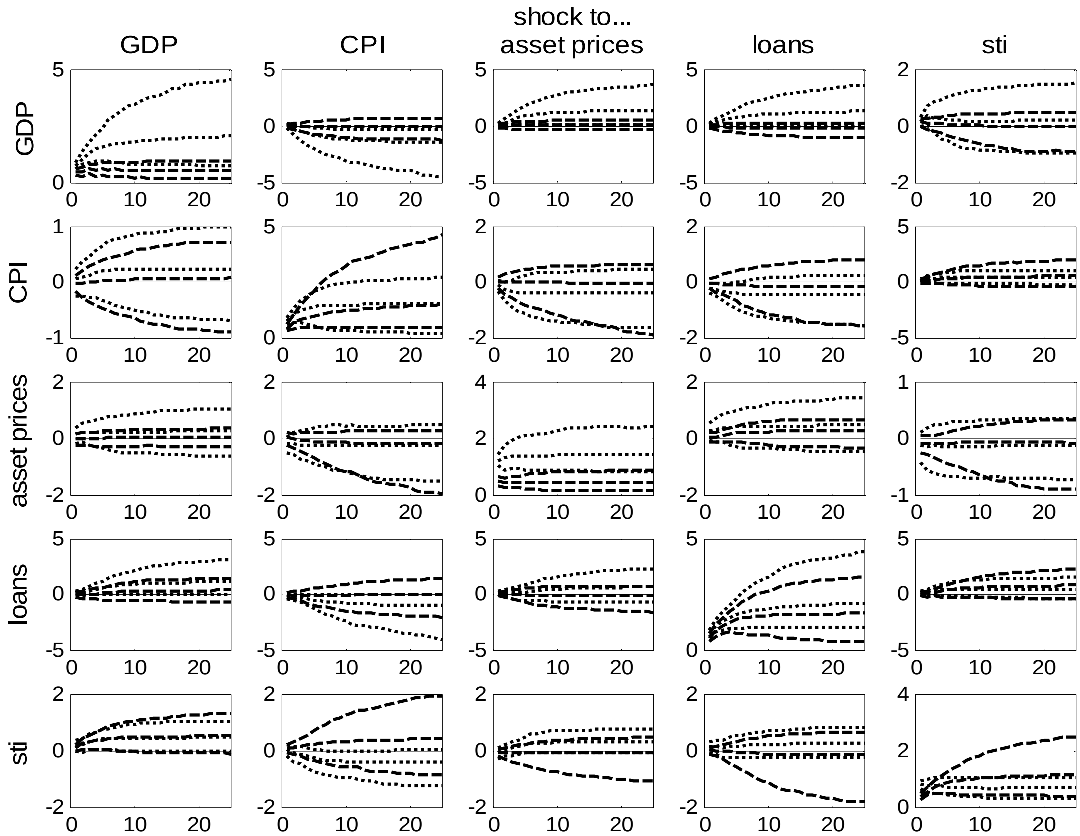
Loans



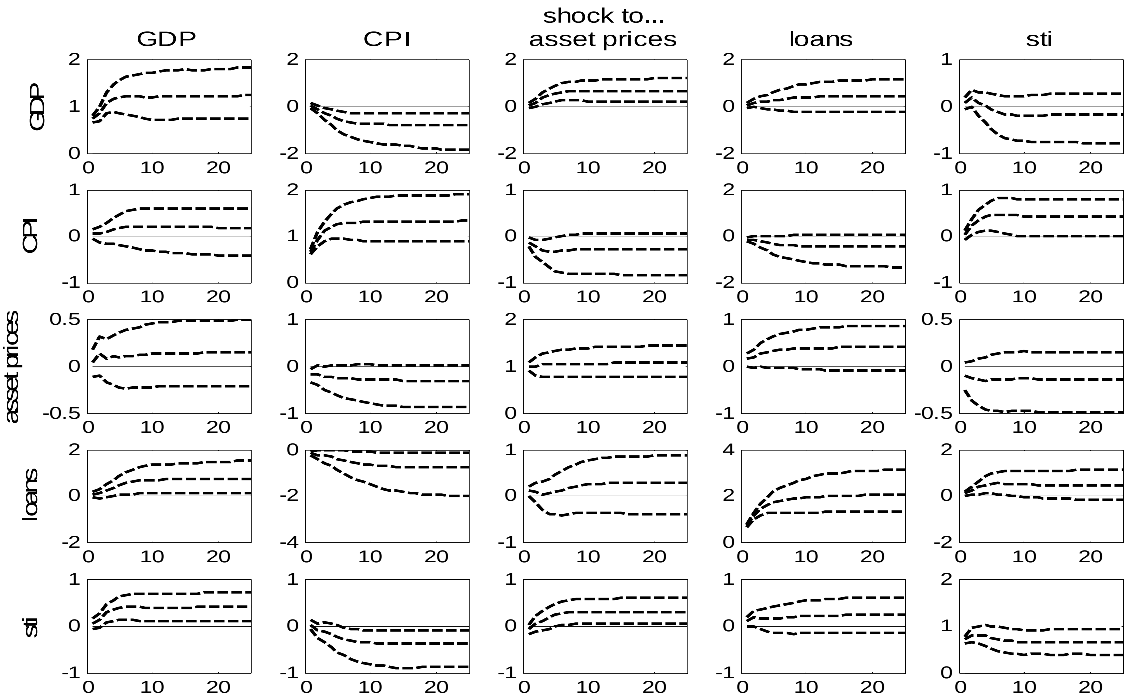
Short term interest rate



Graph 6. US. Cumulated generalized impulse responses. Dashed: regime 1, dotted: regime 2 (with 90% conf.int.)

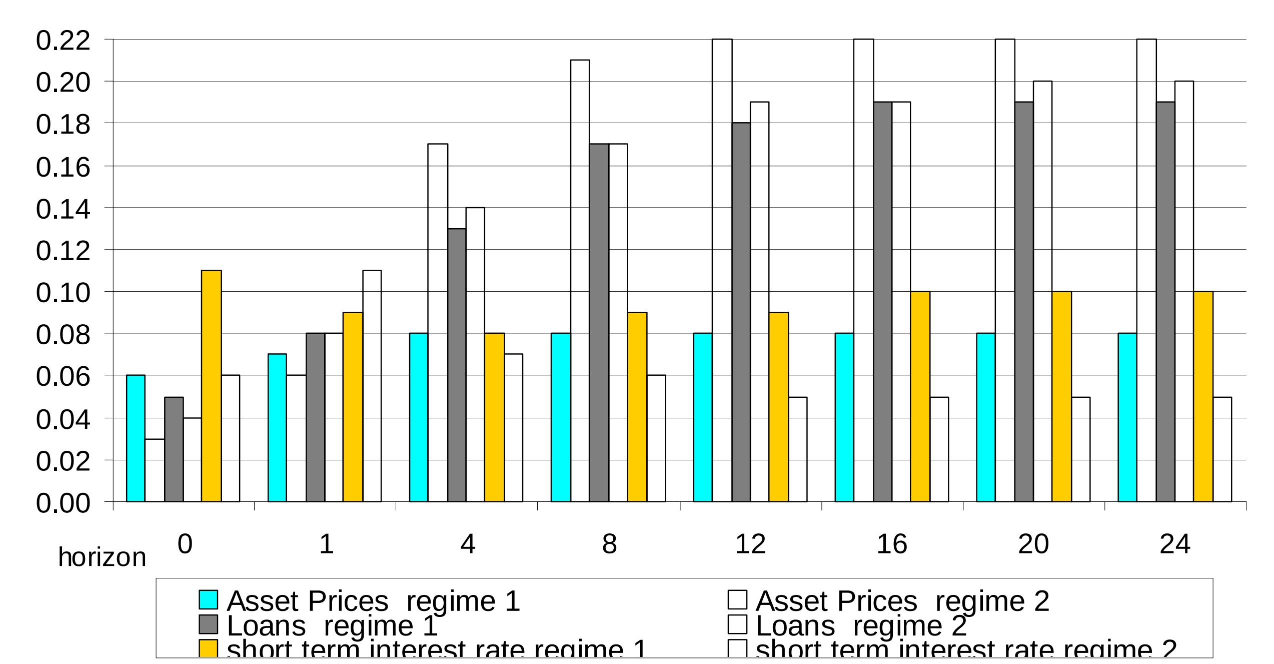


Graph 7. US. Generalized impulse responses (linear model)

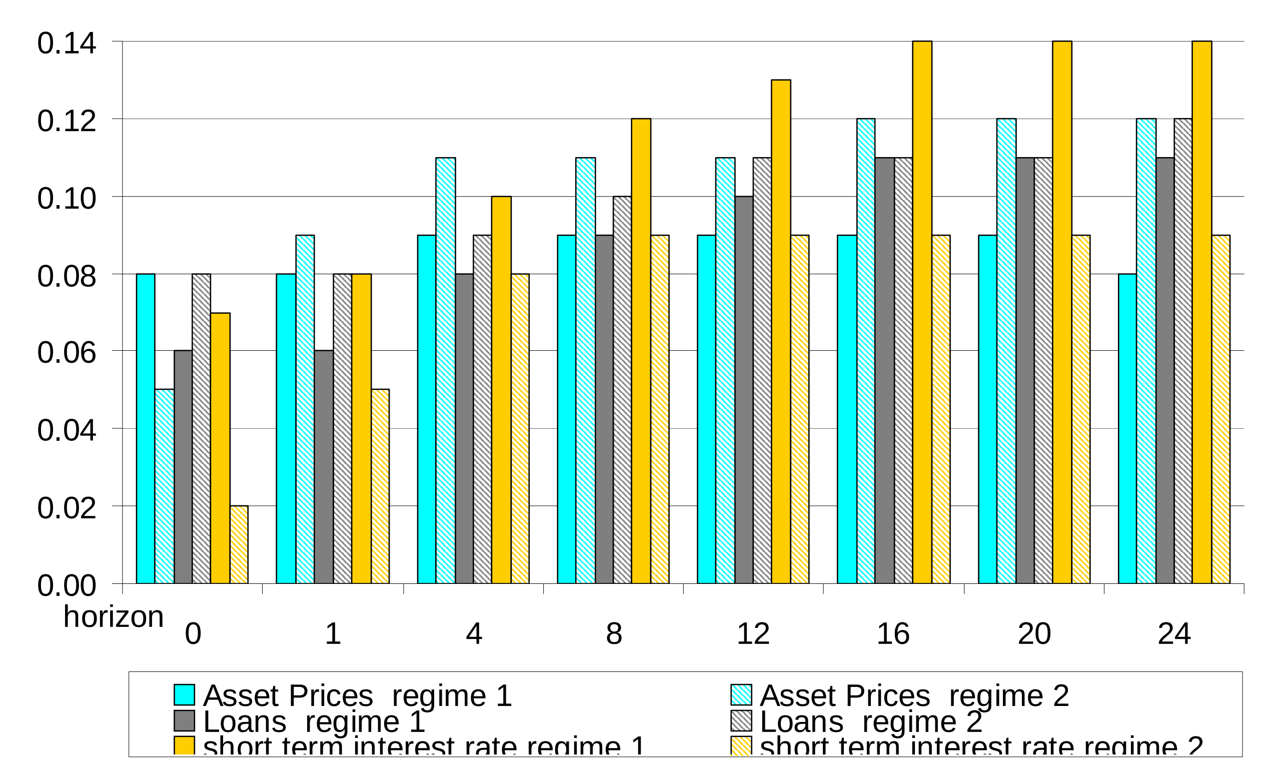


Graph 8. USA: variance decomposition

Forecast error variance in GDP attributable to changes in:



Forecast error variance in CPI attributable to changes in:



APPENDIX B: Prior specification and conditional posterior distributions

For expositional convenience we assume that $q = 1$ in the MS-VAR model (1). We can then write concisely:

$$y_t = y_{t-1}^* \beta(s_t) + \varepsilon_t, \quad \varepsilon_t \sim i.i.d.N\big(0, \Sigma(s_t)\big), \tag{1'}$$

where $y_{t-1}^* = \big(I_p \otimes [1\ y_{t-1}']\big)$ and $\beta(s_t) = vec\big([\iota_p\ \ A(s_t)]'\big)$ with ι_p being a $p \times 1$ vector of ones.

We assume that the prior distribution of the VAR parameters $\beta = vec(\beta(1),...,\beta(K))$, the residual covariance matrices $\Sigma = (\Sigma(1),...,\Sigma(K))$ and the transition probabilities η are independent, $\pi(\theta) = \pi(\beta)\pi(\Sigma)\pi(\eta)$. Specifically,

- β is assumed to be state-invariant and multivariate normal $N(b_0, B_0^{-1})$, i.e. B_0^{-1} is block-diagonal across states and block-diagonal within states as we assume independence between the intercept term and the autoregressive parameters. For all parameters, we assume a prior mean of 0. The prior information for the intercept terms $(\upsilon(1),...,\upsilon(K))$ is set to 1. The prior covariance matrix of the autoregressive parameters $A(1),...A(K)$ is designed in a way that takes into account the possible different scales of the system variables and that tightens the prior standard errors of higher order lags (see Litterman, 1986, and Hamilton, 1994, pp.360–362). The overall tightness parameter is set to 0.4 and the weight for off-diagonal elements to 0.5.
- $(\Sigma(1),...,\Sigma(K))$ are independent a priori and have an inverse Wishart distribution, $\Sigma^{-1}(k) \sim W(\nu_0, S_0)$, for $k = 1,...,K$, where $\nu_0 = p + 2$ and $S_0 = I_p$.
- $\eta_{1\cdot},...,\eta_{K\cdot}$ are independent a priori and are assumed to have a Dirichlet prior distribution, $\eta_{k\cdot} \sim D(e_{k1},...,e_{kK})$, $k = 1,...,K$, where $e_{kk} = 2$ and $e_{kj} = 1$ for $k \neq j$.

The conditional posterior distributions can now be derived as:

- $\pi(\beta \mid y^T, s^T, \Sigma) = N(b, B^{-1})$, with $B = Y'WY + B_0$, $b = B^{-1}(Y'Wy + B_0 b_0)$ and $y = vec(y_2, \ldots, y_T)$. The matrices Y and W are the predictor and the weighting matrices of model (1'), respectively:

$$Y = \begin{bmatrix} y_1^* D_2^1 & \cdots & y_1^* D_2^K \\ \vdots & \ddots & \vdots \\ y_{T-1}^* D_T^1 & \cdots & y_{T-1}^* D_T^K \end{bmatrix}, \quad W = diag\big(\Sigma(s_2)^{-1}, \cdots, \Sigma(s_T)^{-1}\big),$$

where $D_t^k = 1$ if $s_t = k$ and 0 otherwise. The draw is accepted, if the simulated parameter values define a stationary system; if this is not the case, we reject the draw and retain the current values to continue with the next sampling step.

- $\pi(\Sigma^{-1} \mid y^T, s^T, \beta) = \prod_{k=1}^{K} W(\nu_k, S_k)$, where $\nu_k = \nu_0 + N_k$ and $S_k = S_0 + \sum_{s_t=k} \varepsilon_t ' \varepsilon_t$ with $N_k = \#\{s_t = k\}$ being the number of periods in which state k was prevailing.
- $\pi(\eta \mid s^T) = \prod_{k=1}^{K} D(e_{k1} + N_{k1}, \ldots, e_{kK} + N_{kK})$, where $N_{kj} = \#\{s_t = j \mid s_{t-1} = k\}$.

Finally, we draw s^T from $\pi(s^T \mid y^T, \theta)$ by applying the multi-move sampler described in Chib (1996). As we start the sampler by simulating the VAR parameters, we need a starting value for s^T. We define it to be $s_t = 1$, if y_t is below average, and $s_t = 2$, if y_t is above average.

When iterating over the sampling steps, we first do not restrict the parameters to fulfill a state-identification restriction. Rather, we first explore the unconstrained posterior distribution using the random permutation sampler (Frühwirth-Schnatter, 2001) and define a state-identifying restriction by post-processing the simulation ouput, e.g. by looking at scatter plots of the VAR parameters against the persistence probabilities or by estimating marginal parameter distributions. On the basis of such graphical devices, it is usually straightforward to define a state-identifying restriction (see also Kaufmann and Valderrama, 1996).