Modeling Credit Aggregates[1]

Sylvia Kaufmann[2]

and

Maria Teresa Valderrama[3]

January 2004

Abstract

The purpose of this paper is to model both loans to households and to non-financial corporations and their relation to interest rates and demand variables for Austria, Germany, Netherlands and the United Kingdom. Credit aggregates are modeled using a Markov-switching vector autoregressive model, which allows testing whether shocks to the economy may have larger effects during tight credit regimes. Analyzing these four countries allows assessing the differences in the amplifying and asymmetric effects of credit aggregates between market-based or bank-based financial systems.

JEL-Code: C32, E44, E51
Keywords: Credit aggregates, financial systems, Markov switching VAR.

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

---

[1] We thank Leo de Haan, Elmar Stoess and Andreas Worms for providing us with Dutch and German series. We thank participants for comments on an earlier version of this paper presented in seminars at ECB, Bank of Canada, Bundesbank and the Annual Meeting of the Austrian Economist Association. All remaining errors are ours.

[2] Oesterreichische Nationalbank, Economic Studies Division, Otto-Wagner-Platz 3, 1090 Vienna, Austria, Phone: +43 1 40420 7222, Fax: +43 1 40420 7299; E-mail: Sylvia.Kaufmann@oenb.at.
[3] Oesterreichische Nationalbank, Economic Analysis Division, Otto-Wagner-Platz 3, 1090 Vienna, Austria, Phone: +43 1 40420 7412, Fax: +43 1 40420 7499; E-mail: Maria.Valderrama@oenb.at.

1. Introduction

The purpose of this paper is to model credit aggregates for both households and non-financial corporations and their relation to interest rates and demand variables. To profit from the availability of data, an attempt is made to construct separate models for loans-to-households and loans-to-non-financial-corporations for 4 member countries of the European Union. Credit aggregates not only play an important role in the transmission mechanism of monetary policy (Bernanke and Blinder, 1988) but they may also be important indicators of the monetary stance and liquidity conditions at the national level. This may be especially relevant for countries with an exchange rate peg or members of a monetary union where the interest rate level or "national" monetary aggregates may loose their leading indicator properties, while "national" credit aggregates may still have a more direct impact on national spending and therefore on national inflation.

There is a large body of theoretical models that relate money and credit to business cycles (Stiglitz and Weiss, 1981, Scheinkman and Weiss, 1986, Bernanke and Gertler, 1989, Kiyotaki and Moore, 1997a and 1997b, Boissay, 2001). Despite their different approaches, all these models predict that due to the existence of asymmetric information credit markets propagate shocks to the economy. Moreover, the pro-cyclicality of bank lending results in an amplification of the business cycle that is stronger during recessions and thus, leads to asymmetric effects of monetary policy.

Empirical studies for the euro area that relate money and credit to business cycles have mostly concentrated on the cyclical properties of money, prices and interest rates of the aggregate or of some large countries. There are very few studies that focus on credit aggregates and even less that cover countries like Germany and Austria. This paper fills this gap by presenting evidence for the role of credit aggregates in the transmission mechanism for Austria, Germany, the Netherlands and the United Kingdom (UK).[4] Looking at these countries allows comparing potential differences in the propagating role of credit aggregates due to the type of financial system.

Empirical evidence for these countries at the individual bank and firm level tends to confirm the hypothesis that credit aggregates are relevant for the transmission mechanisms and have asymmetric effects over the business cycle. Frühwirth-Schnatter and Kaufmann (2003) and Kaufmann (2003a) studied the behavior of bank lending and find that it reacts asymmetrically to interest rate changes over time in Austria. On the

[4] See Jacobs and Kakes (2000) and Sensier et al (2002) for similar studies done for Netherlands and UK.

other hand, Valderrama (2001 and 2003a) as well as Wesche (2000) provide evidence of a financial accelerator effect in Austria using firm level data. Vermeulen (2002), Chatelain et al. (2003) and von Kalckreuth (2003) also show that internal funds are significant determinants of investment in Germany. Similar evidence for the Netherlands is found in Van Ees and Garretsen (1994) and Van Ees et al. (1998) who find that liquidity and debt constraints matter significantly for Dutch business investment. Guariglia (1998) uses firm level data for the UK and finds that there is a significant link between financial variables and inventory investment. Moreover, the effect is stronger for firms with weak balance sheets during recessions and periods of tight monetary policy. Hall (2001) concludes that a business cycle model for the UK incorporating financial accelerator effects is consistent with observed features of corporate real and financial behavior in previous downturns.

These results suggest that credit aggregates should be modeled in a non-linear framework. To capture these asymmetries, we will use here a Markov-switching vector autoregressive model (MS-VAR). In this kind of models, parameters switch according to an unobservable state variable, that is assumed to capture changing credit or economic regimes and which is estimated along with the model parameters.

The methodology is used to build two credit systems, one for loans to households and one for loans to firms. The reason is that these two aggregates correspond to different spending components and may be differently affected by asymmetric informational problems and financial constraints.

Additionally, we will estimate these systems for both a large and a small country representative of a market-based[5] and a bank-based[6] system within the European Union. This allows us to get evidence of whether asymmetries propagated by credit aggregates depend on the type of financial system. For example, credit tightening during an economic downturn may be more severe in market-based systems. This is because in bank-based systems the existence of lending relationships allows borrowers to smooth liquidity shocks over the cycle.

To summarize, the contribution of the paper is first to model credit aggregates which have been rather neglected in the literature, especially for European countries. Second, it uses a non-linear methodology in order to capture the asymmetric effects predicted by theoretical models and by the evidence at the micro level. Third, it separates lending to households from lending to non-financial corporations. And finally, modeling is done for

[5] UK and the Netherlands.
[6] Germany and Austria.

four countries with diverse financial systems, which allows investigating asymmetric effects related to differences between market-based and bank-based financial systems.

The paper is organized as follows: The next section motivates the use of non-linear modeling based on theoretical models of credit cycles. Section three describes some stylized facts about the evolution of credit aggregates and the institutional framework of the four countries in this study. Section four introduces the MS-VAR model and the estimation method. Section five presents results. Conclusions follow.

2. The credit channel and non-linear models for credit aggregates

Models that focus on the credit view of monetary policy transmission (as opposed to the 'money' or monetarist view) were introduced among others by Bernanke and Blinder (1988) and Bernanke and Gertler (1989). In a simple neoclassical framework, these authors describe the financial accelerator effect by showing how business cycles might emerge or might be amplified through borrowers' balance sheets. During business upturns, borrowers' net worth improves agency costs and the cost of external finance decrease, which results in higher investment. Empirical evidence at the aggregate level for this transmission channel is found in Bernanke and Blinder (1989), Kashyap et al. (1993), Bernanke and Gertler (1995) and Christiano et al. (1996).They find that credit aggregates and the composition of external funds react to liquidity shocks and affect in turn investment behavior.

Asymmetric effects over time propagated through the credit market were introduced by Kiyotaki and Moore (1997a, 1997b) and Kocherlakota (2000). In Kiyotaki and Moore (1997a, 1997b) higher debt default during a recession leads to exaggerated responses of the economy to an initial liquidity shock. Kocherlakota (2000) demonstrates in a neoclassical framework with a tangible asset (land) as a production factor that credit constraints lead to asymmetric responses in output. Positive or small negative transitory income shocks do not affect output, while large negative shocks persistently lead to a decrease in output. This propagation mechanism is amplified when land is used as collateral.

Models with explicit switching between equilibria due to borrowing constraints or adverse selection problems in the credit market are presented in Scheinkman and Weiss (1986) and Azariadis and Smith (1998). Borrowing constraints affect economic activity through the distribution of wealth. As this distribution evolves endogenously, exogenous shocks lead to a considerable cyclical economic activity. In particular, the model solution in Azariadis and Smith leads to multiple equilibria,[7] where the switching between these states can be described by a Markov switching behavior.

In summary, these models imply that the effects of monetary policy or any other shock will have an asymmetric effect on the economy. These effects arise from the fact that lending is pro-cyclical and therefore, credit constraints become more binding during a downturn, whereas it does not have an equally symmetric positive effect during the upturn.

3. Credit aggregates in market-based and bank-based financial systems

Our choice of modeling credit aggregates for four EU countries with different financial systems allows us to investigate whether the role of credit aggregates in the transmission mechanism depends on the institutional framework. In particular, we expect that due to the existence of the "house bank" principle found in bank-based systems, credit constraints and the asymmetric propagation through credit markets may be less severe than in a market-based system.

The "house bank" principle allows both lenders and borrowers to overcome some of the asymmetric information problems found in imperfect capital markets by building long standing relationships. These lending relationships allow the borrower to be less dependent on internal funds, since the lender will provide its client with liquid funds even during an economic downturn. As a result, the borrower is able to smooth spending decisions over the cycle, since lending in this case is mostly demand driven.[8]

Evidence at the firm level confirms that the advantage of lending relationships comes from a lower dependence on internal funds and not through a lower cost of capital.[9] At the aggregate level, the presence of relationship lending should translate in smoother business cycles fluctuations. To test this hypothesis, we compare results for Austria, Germany, the Netherlands and the UK, which are two small and two large countries in the EU, representative of bank-based and market-based financial systems.

Austria and Germany have very similar banking systems that are characterized by narrow lending relationships.[10] In Europe, UK is well known to be a market-based

[7] One in which economic activity is slowing, interest rates are falling and credit constraints are binding, and another one of economic recovery, rising interest rates accompanied by a credit market in Walrasian equilibrium

[8] See Ongena and Smith (1998) and Boot (2000) for a more detailed account of all possible effects of lending relationships.

[9] Petersen (1994, 1995), Ongena and Smith, (1998), Houston and James (1999), Boot (2000)

[10] Evidence for Germany is extensive, see for example Chirinko and Elston (1996), Elsas and Krahnen (1998) and Harhoff and Körting (1998) and Valderrama (2001a, 2003a and 2003b) for evidence for Austria.

financial system with the highest market capitalization in Europe while the ratio of loans to non-financial corporations to GDP is low compared to other EU countries. It is not straightforward to find a small European country that has a market-based system. The best candidate are the Netherlands which, show a high share of equity issues and a large market capitalization compared to most other countries in Europe. Market capitalization in the Netherlands is the third highest of the 15 EU countries after the UK and Luxembourg[11]. Although lending relationships may also be present in the Netherlands and the UK,[12] at the aggregate level the effect should be smaller than in Austria and Germany, due to the smaller loans-to-GDP ratio.

Graphs 1 and 2 tend to confirm this perception. The ratio of loans-to-GDP for the household sector is larger in the UK and the Netherlands, reflecting the rapid liberalization of bank lending to consumers during the 1990s. In contrast, the ratio of loans-to-GDP for non-financial corporations is much higher in Austria and Germany and relatively low for the UK, while the Netherlands is somewhere in between. This is consistent with the higher market capitalization observed in both the UK and the Netherlands.

4. Model and estimation

In order to capture the non-linear dynamics predicted by theoretical models we use a Markov switching vector autoregressive (MS-VAR) model which allows for regime switching coefficients. The advantage of an MS-VAR is that it allows estimating the dates of the regime shifts and the model parameters simultaneously. Thus, there is no a priori knowledge necessary about the dates in which the economy shifts into e.g. a tight credit regime.

The most general specification of an MS-VAR model allows all model parameters to depend on the unobservable state s_t:

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

where s_t takes on one out of K values, $s_t = k, k = 1, \ldots K$, and is assumed to follow a first-order Markov process. The probability of being in regime j conditional on the past regime i, $\Pr(s_t = j | s_{t-1} = i) = \eta_{ij}$, is assumed to be exogenous and constant. In a K-state model there are $K \times K$ such conditional transition probabilities which we collect in the

[11] Data for 2000. See Rajan and Zingales (2003)

transition matrix η :

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

with the obvious restriction $\eta_{iK} = 1 - \sum_{j=1}^{K-1} \eta_{ij}$.

The estimation of model (1) yields an inference on all model parameters and the state variable s_t as well. Here, the estimation is cast into a Bayesian framework and the inference will be obtained by using Markov chain Monte Carlo (MCMC) simulation methods. Although maximum likelihood is feasible (Krolzig, 1997), MCMC methods circumvent problems that may arise when the likelihood is maximized numerically, e.g. in systems involving more than two states and a larger number of variables, one often encounters boundary problems for the transition probabilities when they get near zero or one. Moreover, the maximization proves to be sensitive to starting values. The random permutation sampler (Frühwirth-Schnatter, 2001) used here is based on the Gibbs sampler and allows the exploration of the whole unconstrained posterior distribution of the model parameters. If a suitable restriction is not known a priori to identify the states,[13] we may find an adequate one by post-processing and visualizing the output of the sampler. In general, it is sufficient to set reasonable starting values for the sampler to converge to the steady-state posterior distribution of the model parameters and of the state variable (Tierney, 1994).

To briefly expose the estimation procedure, we gather all model parameters into the vector θ for notational convenience, $\theta = (\upsilon(1),...,\upsilon(K), A_1(1),...A_q(K), \Sigma(1),...,\Sigma(K),\eta)$. Conditional on s_t, the likelihood of the data can be factorized as:

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

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

---

[12] See Van Ees and Garretsen (1994), Van Ees et al. (1998) and de Haan and Sterken (2002) for the Netherlands.

[13] A common restriction to discriminate between the states would be e.g. that $\upsilon_1(1) < \upsilon_1(2)$, 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.

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

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 $y^{t-1} = (y_{t-1}, y_{t-2}, ..., y_1)$.

Further, the prior distribution of $s^T = (s_T, s_{T-1}, ..., s_0)$ depends only on the transition probabilities and its density is proportional to $\pi(s^T \mid \eta) \propto \prod_{t=1}^{T} \eta_{s_t, s_{t-1}} \pi(s_0) = \prod_{j=1}^{K} \prod_{i=1}^{K} \eta_{ij}^{N_{ij}} \pi(s_0)$, with $N_{ij} = \# \{ s_t = j \mid s_t = i \}$.

Finally, the specification of the prior distribution of the model parameters, $\pi(\theta)$, completes the Bayesian setup:

- 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, $\pi(\theta) = \pi(\beta)\pi(\Sigma)\pi(\eta)$.
- β is assumed multivariate normal $N(b_0, B_0^{-1})$. For the constant terms $(\upsilon(1), ..., \upsilon(K))$ we assume a non-informative prior that is independent of the autoregressive parameters, B_0^{-1} is therefore block-diagonal. The prior covariance matrix of the autoregressive parameters $A_1(1), ... A_q(K)$ is designed in a way that takes into account the possible different scales of the system variables and tightens the prior for the standard errors of higher order lags (see Litterman, 1986, and Hamilton, 1994, pp.360-362).
- $(\Sigma(1), ..., \Sigma(K))$ are independent a priori and have each an inverse Wishart distribution, $\Sigma^{-1}(k) \sim W(\nu_0, S_0)$, $k = 1, ..., K$.
- $\eta_{1\cdot}, ..., \eta_{K\cdot}$ are independent a priori and are assumed to have a Dirichlet prior distribution, $\eta_{k\cdot} \sim D(e_1, ..., e_K)$, $k = 1, ..., K$.

The inference on the *joint* posterior distribution of the model parameters and the state variable, $\pi(\theta, s^T \mid y^T)$, is then obtained by successively simulating the parameters and the path of the state variable out of their *conditional* posterior distribution. The sampling scheme includes the following steps (see Appendix B for details):

- $\pi(\beta \mid y^T, s^T, \Sigma)$, simulating the VAR parameters given the data, the state variable and the covariance matrices out of a multivariate normal distribution. We check in each iteration, whether the simulated parameters define a stationary system. If this is not the case, we reject the draw and retain the current values for the next sampling step.

- $\pi(\Sigma \mid y^T, s^T, \beta)$, simulating the covariance matrices given the data, the state variable and the VAR parameters out of *K* independent Wishart distributions.
- $\pi(s^T \mid y^T, \theta)$, simulating the state variable given the data and all model parameters using the multi-move sampler described in Chib (1996).
- $\pi(\eta \mid s^T)$, simulating the transition probabilities, which in fact depend only on s^T, from *K* independent Dirichlet distributions.
- A *permutation step* completes each iteration of the sampler in which the simulated parameters are permuted randomly to explore the unconstrained posterior distribution. In the presence of two states, this amounts to interchange all state-specific parameters and the state variable with a probability of 0.5 and to leave them unchanged otherwise: $(\beta(1), \beta(2)) := (\beta(2), \beta(1))$, $(\Sigma(1), \Sigma(2)) := (\Sigma(2), \Sigma(1))$, $s^T = 3 - s^T$, $\eta_{ij} := \eta_{3-i,3-j}, i, j = 1,2$.

Based on explorative tools like scatter plots and marginal posterior distributions of the simulated values of the state-specific parameters, we can then find a restriction that identifies the states[14] and according to which we reorder all simulated values to obtain the posterior inference on the model. With these tools, we also find a parsimonious representation of the system, i.e. which parameters are not switching or which are insignificant and can be restricted to zero (see appendix C).

To assess our model specification, we estimate the marginal likelihoods with which we can test the switching specification against a linear alternative by means of the Bayes factor. The marginal or model likelihood is estimated using the optimal bridge sampler derived in detail in Frühwirth-Schnatter (1999, see also Appendix C for technical details).

The appropriate parsimonious and identified model is then used to compute state-dependent impulse response functions, whereby the structural model is identified by means of a Cholesky decomposition of the respective (state-dependent) covariance matrix. We obtain the distribution (mean and confidence interval) of the impulse

[14] In the empirical investigation, it turned out that for some systems one of the constants, in particular the growth rate of consumption or of investment, could be used to identify the states. In these cases, the states relate primarily to periods of above- and below-average growth in one variable. In other systems, the states can be discriminated on the basis of an autoregressive coefficient (see appendix D).

responses by using draws of the MCMC simulations of the model parameters and computing the related impulse responses.

5. Results

(a) Data and Model Selection

The model outlined in section 4 is used to build a five-variable system of loans to non-financial corporations and loans to households. We use quarterly seasonally adjusted data covering the period from the first quarter of 1980 up to the last quarter of 2002. The effective sample period is adjusted to the country-specific data length (see graphs 3 to 10 in appendix A). Due to the well-known identification problem, we do not distinguish between credit demand and supply. The system describing loans to non-financial corporations includes (in that order) investment, imports, CPI and the 3-months interest rate.[15] Households' consumption, net disposable income, CPI, loans to households and the short-term interest rate form the second system. All variables are expressed in real terms (except for the CPI and the short term interest rate) and in quarterly percentage growth rates. Interest rate changes are expressed in basis points (the first difference of the level times 100). The data is demeaned for computational purposes.

First we estimate an unrestricted version of each model with two lags, where all parameters are switching. Based on this benchmark estimation, we restrict those parameters which are not switching to be equal across regimes and those which are insignificant to be zero (see appendix C for the model selection procedure). The unrestricted and the final specifications are also tested against a non-switching specification by means of marginal likelihoods, i.e. using the Bayes factor.[16] Table 1 shows the results also for the case of an unrestricted switching and a non-switching (linear) specification of the VAR model with one lag. In all cases, the final specification is preferred to all others .

Table 1: Log of the marginal likelihood of various model specifications.

	Austria	Germany	Netherlands	United Kingdom

[15] The choice of the short term interest rate is driven by our interest in studying the effects of monetary policy and also by the fact that a substantial part of loans are extended with a variable interest rate clause. In particular for Austria, the data show that lending rates (unfortunately available only since 1995) follow more closely the short term interest rate than the long-term interest rate.

[16] Twice the difference of the log of the marginal likelihood is interpretable on the same scale as the well-known likelihood ratio test with X^2 distribution.

Loans to non-financial corporations				
Non-switching 2 lags	-1334.37	-1384.90	-1295.41	-1757.52
Unrestricted 2 lags	-1321.79	-1383.04	-1264.11	-1736.24
Non-switching 1 lag	-1308.32	-1369.76	-1284.32	-1816.69
Unrestricted 1 lag	-1326.08	-1371.36	-1267.53	-1768.60
Final specification	**-1291.24**	**-1351.26**	**-1230.40**	**-1724.98**
Loans to households				
Non-switching 2 lags	-813.69	-882.97	-769.35	-1580.96
Unrestricted 2 lags	-734.21	-1027.06	-726.25	-1438.77
Non-switching 1 lag	-797.36	-853.27	-748.02	-1539.65
Unrestricted 1 lag	-762.64	-1051.17	-743.26	-1434.37
Final specification	**-715.85**	**-799.92**	**-708.31**	**-1409.40**

In the following, we discuss the results for each country. We expect to relate the posterior state probabilities to specific economic periods and/or to specific credit regimes. In addition, we can assess asymmetric responses to shocks between regimes. The difference in responses should be smaller for countries characterized by a bank-based financial system (Austria and Germany).

(b) Austria

The posterior state probabilities obtained from the system for loans to non-financial corporations are depicted in graph 11. Regime 1, depicted in the upper panel, can be broadly related to economic conditions. In particular it prevails during 1982/83, 1986/87, 1992/93, 1995/97, 1998/99 and from mid 2001 through end of 2002, which correspond to periods of below average growth that have been identified in Kaufmann (2001, 2003b) for the 1990s and are consistent with euro-wide business cycle dating as in ECB (2002).

The impulses responses depicted in graph 12 show that lending is not a significant determinant of investment since in both regimes the response of investment to a shock in loans is insignificant. The reaction of investment to an interest rate shock is almost identical in both regimes, but it is slightly larger in regime 1. Loans react significantly positively to both an investment and an interest rate shock in both regimes, whereby the response in regime 1 is again larger. These results suggest that lending is demand driven rather than supply driven, which is consistent with the weak microeconomic evidence for a bank lending channel in Austria (Frühwirth-Schnatter and Kaufmann, 2003, and Kaufmann, 2003a). Moreover, the much smaller response of loans to investment in regime 2 reflects the fact that substitutes to bank loans, such as retained earnings, are preferred during an economic upturn, which is also consistent with evidence of a balance sheet channel in Austria (Valderrama 2001, 2003a, 2003b). Since investment does not seem to react to lending in any regime, there is no evidence that credit aggregates amplify the business cycle. These results reflect that due to the “house bank” principle investment does not face credit constraints in any regime.

The posterior state probabilities for the system of loans to households (see graph 13) are not obviously related to economic conditions as it is the case for loans to firms. Regime 1 is mostly prevailing during the period 1987/88 and 1995/96. The period 1987/88 corresponds to the beginning of the Austrian financial market liberalization and an increase in real estate prices (Braumann, 2002). The period 1995/96 coincides with a strong increase in consumer credit as commercial banks were trying to compensate for the decrease in public debt. Thus, regime 1 can be characterized by periods of rapid loan growth. The impulse response functions (see graph 14) are different from those of the firms’ loans system. In regime 2, consumption reacts, as expected, significantly positively to a shock in loans. In regime 1, the reaction is insignificant, which implies that monetary policy does not restrict consumption during these periods. Consumption does not react significantly to interest rate shocks in any regime. Loans, however, do not react significantly to consumption shocks nor to interest rate shocks in any regime. This could be explained by the fact that a large percentage of lending to households is used for residential investment.[17]

Overall, the evidence for Austria suggests that monetary policy effects and their transmission through credit aggregates differ between regimes. In the case of non-financial corporations, the asymmetry does not imply that credit markets amplify shocks, but rather, that they smooth them. This is consistent with the “house bank” principle, where during periods of below average growth banks provide liquidity to non-financial corporations. In the case of the household sector, lending decisions do not react to monetary policy, implying that credit markets do not restrict household consumption. Thus, the considerable slow down in lending to non-financial corporations observed during the last 2 years is a result of lower demand, while households’ consumption has

[17] Unfortunately, it is not possible to extract consumer credit from this data

not been negatively affected by lower lending during the same period (see graphs 3 and 4).

(c) Germany

The posterior probabilities of regime 1 (graph 15) are indicative of economic slowdowns. The analysis of the impulse responses in graph 16 shows that investment does not react significantly to loans in either regime, although the response in regime 1 tends to be larger. Investment does react positively and marginally significant to a shock in the interest rate in regime 2 while there is no significant response in regime 1. Loans respond positively to a shock to investment in both regimes, while the response to an interest rate shock is significant but differs between regimes: it is positive in regime 2 and negative in regime 1, indicating that in regime 2 bank lending is demand driven.

The posterior state probabilities estimated for the system of loans to households (graph 17) reveals that regime 2 is prevailing most of the time until 1995 and thus, a meaningful relation to economic conditions cannot be made. After 1995, however, the posterior state probabilities are similar to those found for non-financial corporations. Given the high growth in lending to households observed since 1995, regime 1 can be characterized as a state in which access to credit was not constrained for households. The response of consumption to lending is insignificant in regime 1 and negative and significant in regime 2 (graph 18). This result appears counterintuitive, but as the data includes mortgage loans, it may reflect the cautious behavior of German households, which decrease consumption as their residential debt increases. Another reason might be that traditionally, consumer credit was not widely used until the mid-1990s. On the other hand, consumption does not react significantly to shocks in the short term interest rate in any regime. The responses of lending to consumption and an interest rate shock are always insignificant in regime 1 while in regime 2 lending reacts positively to consumption shocks and negatively to interest rate shocks. The response is consistent with the expected reaction of credit markets under the bank lending channel. However, we can not observe the expected amplifying effect of lending on consumption.

Overall, these findings show that credit aggregates do not amplify negative shocks since investment is not significantly affected by bank lending in either regime. There is evidence that the house bank principle plays a role during regime 2, because of the asymmetric response of loans to an interest rate shock and the fact that lending is demand driven. In the case of households, consumption reacts negatively to lending in regime 2, while lending reacts positively to consumption in the same regime, suggesting an asymmetric effect that works by dampening rather than by amplifying negative shocks.

Thus, the fall in both lending to firms and to households, observed since 2000, is also the result of the fall in aggregate demand rather than a lower supply of credit.

(d) Netherlands

The posterior state probabilities for non-financial corporations reveal that one state prevails most of the time and it is therefore difficult to give an economic meaningful interpretation related to usual dating of business cycles in the Netherlands[18] (graph 19). Regime 2, on the other hand, captures periods in which loan growth relative to investment growth was low (see graph 7) - which is characteristic of a state in which access to credit is constrained - and periods of falling interest rates.

The analysis of the impulse responses (graph 20) shows some asymmetries between regimes. Although, investment always reacts positively and significantly to a loan's shock as well as to an interest rate shock, the response is significantly larger (in both cases) in regime 2. This indicates that the negative effects of a fall in lending will be amplified in regime 2, which is consistent with the financial accelerator view of the credit channel. , On the other hand loans do not react significantly to an investment shock in regime 2 and react negatively to it in regime 1. In regime 1 the evidence shows a behavior that is characteristic of a marked-based financial system in which firms prefer to finance themselves with retained earnings or other sources of external funds.[19] Although in regime 2 credit growth does not react to investment it can not be identified as supply driven since lending reacts positively to an interest rate shock.[20]

The posterior state probabilities for loans to households depicted in graph 21 show that regime 1 can be related to the troughs of the business cycle as dated by the Dutch central bank (DNB).[21] Although most impulse responses are insignificant, we can observe some asymmetries across regimes (see graph 22). The reaction of consumption to a loans shock is insignificant in both regimes, but in regime 1 the response is larger and positive, indicating that credit aggregates have on average pro-cyclical effects in regime 1. This is confirmed by the insignificant reaction of loans to consumption and interest rate shocks in regime 1. In regime 2, loans react on average positively to a consumption shock and negatively to an interest rate shock. Overall these responses are insignificant, which may be explained by the large share of mortgage loans in these series and that

[18] See for example, DNB Quarterly Bulletin, December 2002

[19] See de Haan and Hinloopen (2002) who show that the most-preferred financing of Dutch firms is internal financing.

[20] This is consistent with the evidence found by others for the Netherlands in which the bank lending channel is weakened due to customer relationships and the possibility of banks to isolate monetary shocks. See Kakes (1998), Jacobs and Kakes (2000) and de Haan (2003)

growth in household lending has been accompanied by a housing market boom, which is not captured in our model and does not have a one-to-one effect on consumption.[22]

At least for firms these results point to the existence of a financial accelerator effect and suggest that credit aggregates introduce some asymmetries by amplifying shocks in regime 2. Thus, the slow down in bank lending observed in the last two years may have contributed to an even stronger slow down in economic activity. The same amplifying effect of credit aggregates can be observed in the case of loans to households, albeit the uncertainty is very large.

(e) United Kingdom

The posterior state probabilities obtained from the system for loans to non-financial corporations (graph 23) are closely correlated to economic conditions in the UK. In particular, regime 1 captures nicely the recession during the years 1990-93, while regime 2 captures periods of "normal" economic conditions.

The response of investment (graph 24) to a shock in loans is positive and significant in regime 2 and insignificant in regime 1. On the other hand, investment reacts significantly negatively to an interest rate shock in regime 2, while the response is insignificant in regime 1. Loans to non-financial corporations react significantly positively to shocks to investment and to the interest rate in regime 2 but insignificantly to both variables in regime 1. It is worth mentioning, that in regime 2 the interest rate responds positively to an inflation shock and in regime 1 the response is insignificant. Overall these results document the pro-cyclicality of credit markets in regime 2, i.e. during normal economic conditions.

The regimes identified for the system of loans to households are not as nicely correlated to the business cycle as the model discussed before. Nevertheless, the posterior state probabilities of regime 1 (graph 25) were weakly correlated to economic conditions until 1992. . Regime 2 prevails most of the time after 1992, which coincides with periods of rapid credit growth relative to GDP (see graph 1).

Although the sign of the response differs across regimes, the response of consumption to both a lending and an interest rate shock is insignificant in both regimes (graph 26). On the other hand, the response of loans to a consumption shock is insignificant in regime 1 but positively significant in regime 2. Lending in regime 1 reacts positively to an interest rate shock and it does not in regime 2; indicating that lending is

[21] See DNB, 2002.
[22] See DNB, 2000

demand driven in regime 2. These responses may reflect the fact that the acceleration in lending observed since the mid-1990s has not been used to finance consumption but residential or financial investment.

Overall, the evidence for loans to non-financial corporations obtained here suggests that monetary policy and credit markets have asymmetric effects across regimes. We find a strong pro-cyclical effect of credit markets during periods of normal economic conditions, while lending does not amplify shocks on investment in regime 1. Also, the effects of credit aggregates and monetary policy on spending seem to be weaker in periods of subdued economic growth. Thus, the slow down in lending observed in the last two years has not constrained investment, as the financial accelerator view predicts. The dynamics obtained from the model describing loans to households, capture the liberalization of the credit market and the increased availability of credit to households. Accordingly, high credit growth observed in the last quarters of the sample has not been accompanied by high growth in consumption.

6. Conclusions

In this paper we use a Markov-switching VAR model in order to test the following hypotheses derived from theoretical models that relate credit aggregates to economic activity: First, due to market imperfections arising from asymmetric information, credit aggregates propagate or amplify shocks to the economy. Second, these imperfections become more stringent under certain economic conditions, i.e. during a recession or tight credit conditions. By comparing results for different countries, we can test whether these effects are stronger in market-based financial systems.

We obtain results that show evidence for two regimes in each country, which can be related to periods of different economic conditions or to periods of different conditions on the credit market.

For Austria and Germany, the two countries that represent bank-based financial systems, we find that lending to non-financial corporations propagates shocks to the economy, but does not amplify them nor constrain economic activity in periods of subdued growth or tight liquidity conditions. This confirms the smoothing role of the house bank principle. In the case of households we find that lending is not binding. However, the evidence is less clear cut due to the inclusion of mortgage loans in lending to households.

In the two countries representing market-based financial systems we find evidence for a financial accelerator effect in the firm sector and, particularly for the UK also a strong pro-cyclical effect of credit markets during periods of economic recovery. The evidence for the household sector is less significant, the acceleration of lending during the 1990s has been used to finance residential and financial investment, rather than consumption.

In summary, the hypotheses are partially confirmed. Credit aggregates act as propagators and have non-linear effects on the real economy. In bank-based systems the effects of negative shocks are smoothed, while in market-based systems we observe an amplifying effect during good economic conditions. However, we find that in periods of subdued economic growth or tight credit conditions, the responses are similar to those found in the case of bank-based financial systems, i.e. credit constraints do not become binding.

References

Azariadis, C. and B. Smith, 1998, Financial intermediation and regime switching in business cycles, The American Economic Review 88, 516-536.

Bernanke, B.S. and A.S. Blinder, 1988, Credit, money, and aggregate demand, American Economic Review 78, 2, 435-439.

Bernanke, B.S. and A.S. Blinder, 1989, The Federal funds rate and the channels of monetary transmission, American Economic Review 82, 901-921.

Bernanke, B.S. and M. Gertler, 1989, Agency costs, net worth, and business fluctuations, American Economic Review 79, 1, 14-31.

Bernanke, B.S. and M. Gertler, 1995, Inside the black box: the credit channel of monetary policy transmission, Journal of Economic Perspectives 9, 1, 27-48.

Boot, A.W.A, 2000. Relationship banking: What do we know?, Journal of Financial Intermediation, 9, 7-25.

Braumann, B., 2002, Financial Liberalization in Austria, mimeo, Oesterreichische Nationalbank

Chatelain, J. B., A. Generale, I. Hernando, U. von Kalckreuth and P. Vermeulen, 2003, Firm investment and monetary transmission in the euro area, in: Monetary Policy transmission in the Euro Area, I Angeloni, A Kashyap and B Mojon (eds), Cambridge University Press (forthcoming) and also in Oxford Review of Economic Policy 2003.

Chib, S., 1996, Calculating posterior distributions and modal estimates in Markov mixture models, Journal of Econometrics 75, 79-97.

Christiano, L.J., M. Eichenbaum, and C. Evans, 1996, The effects of monetary policy shocks: Evidence from the flow of funds, The Review of Economics and Statistics, 16-34.

De Haan, L. de, 2003, The credit channel in the Netherlands: evidence from bank balance sheets, in: Monetary Policy Transmission in the Euro Area", I Angeloni, A Kashyap and B Mojon (eds), 2003, Cambridge University Press (forthcoming).

De Haan, L. and J. Hinloopen 2002 "Preference hierarchies for internal finance, bank loans, bond and share issues: evidence for Dutch firms" Mimeo

De Haan, L. de and E. Sterken, 2002, Corporate governance, relationship lending and monetary policy: firm-level evidence for the Euro area, University of Groningen CCSO Working Paper No. 12.

DNB, 2000, Survey among Dutch mortgage-holders on the use of mortgage credit, Quarterly Bulletin, June.

DNB, 2002, Just a normal cyclical downturn in the Netherlands, Quarterly Bulletin, December.

Elsas, R. and J. P. Krahnen, 1998, Is Relationship Lending Special? Evidence from Credit-File Data in Germany, Journal of Banking and Finance 22, 1283–1316.

Ees, H. van and H. Garretsen (1994), "Liquidity and Business Investment: Evidence from Dutch Panel Data", Journal of Macroeconomics, 16:613-627.

Ees, H. van, H. Garretsen, L. de Haan and E. Sterken (1998), "Investment and Debt Constraints: Evidence from Dutch Panel Data", in S. Brakman, H. van Ees and S.K. Kuipers (editors), Market Behavior and Macroeconomic Modelling, London: MacMillan,159-179.

European Central Bank, 2002, Characteristics of the euro area business cycle in the 1990s, Monthly Bulletin, July, 39-49.

Frühwirth-Schnatter, S., 2001, MCMC estimation of classical and dynamic switching and mixture models. Journal of the American Statistical Association 96, 194-209.

Frühwirth-Schnatter, S., 1999, Model likelihoods and Bayes factors for switching and mixture models, Vienna University of Economics and Business Administration, Technical Report 1999-71, revised version January 2001.

Frühwirth-Schnatter, S. and S. Kaufmann, 2003, Investigating asymmetries in the bank lending channel. An analysis using Austrian banks' balance sheet data, Oesterreichische Nationalbank, Working Paper 85.

Guariglia, A. 1999, "The effects of financial constraints on inventory investment: evidence from a panel from UK firms", Economica, 66, pp.43-62.

Hamilton, J. D., 1994, Time Series Analysis, Princeton University Press.

Harhoff, D. and T. Körting, 1998 Lending Relationships in Germany: Empirical Results from Survey Data, Journal of Banking and Finance, Vol. 22, S. 1317-1353.

Hall, S. 2001 Financial accelerator effects in UK business cycle, Bank of England Working Paper. No. 150

Houston, J., and C.M. James, 1999. Do Relationships have Limits? Banking Relationships, Financial Constraints and Investment, Working Paper, University of Florida.

Jacobs, J. and J. Kakes, 2000, Credit demand asymmetry in the Netherlands, Mimeo

Kakes, J. 1998, Monetary transmission and bank lending in the Netherlands, Mimeo

Kalckreuth, U. von, 2003, Monetary transmission in Germany: new perspectives on financial constraints and investment spending, in: Monetary Policy Transmission in the Euro Area, I Angeloni, A Kashyap and B Mojon (eds), Cambridge University Press.

Kashyap, A.K., J.C. Stein and D.W. Wilcox, 1993, Monetary policy and credit conditions: Evidence from the composition of external finance, The American Economic Review 83, 78-98.

Kaufmann, S., 2001, Asymmetries in bank lending behaviour. Austria during the 1990s. Oesterreichische Nationalbank, Working Paper 56.

Kaufmann, S., 2002, Is there an asymmetric effect of monetary policy over time? A Bayesian analysis using Austrian data, Empirical Economics 27, 277-297.

Kaufmann, S., 2003a, The cross-sectional and the time dimension of the bank lending channel: The Austrian case, in Monetary Policy Transmission in the Euro Area, I Angeloni, A Kashyap and B Mojon (eds), Cambridge University Press, pp 347-358.

Kaufmann, S., 2003b, The business cycle of European countries. Bayesian clustering of country-individual IP growth series, Oesterreichische Nationalbank, Working Paper 83.

Kiyotaki, N. and J. Moore, 1997a, Credit cycles, Journal of Political Economy, 105, 2, 211-248.

Kiyotaki, N. and J. Moore, 1997b, Credit chains, mimeo, London School of Economics.

Kocherlakota, N.R., 2000, Creating business cycles through credit constraints, Federal Reserve Bank of Minneapolis Quarterly Review 24, 2-10.

Krolzig, H.M., 1997, Markov-Switching Vector Autoregressions (Springer, Berlin).

Litterman, R.B., 1986, Forecasting with Bayesian vector autoregressions – Five years of experience, Journal of Business & Economic Statistics 4, 25-38.

Meng, X.-L. and W.H. Wong, 1996, Simulating ratios of normalising constants via a simple identity, Statistica Sinica 6, 831-860.

Ongena, S., and Smith, D.C., 1998, Bank Relationships: A Review, in "The performance of financial institutions, eds. P. Harker and S. Zenios, Cambridge University Press.

Petersen, M., and R. Rajan, 1994,. The Benefits of Lending Relationships: Evidence from Small Business Data, Journal of Finance 49, 1367-1400.

Petersen, M., and R. Rajan, 1995, The Effect of Credit Market Competition on Lending Relationships, Quarterly Journal of Economics 110, 406-443.

Rajan, R. and L. Zingales, 2003, Banks and Markets: The Changing Character of European Finance, NBER Working Paper No. 9595.

Scheinkman, J.A. and L. Weiss, 1986, Borrowing constraints and aggregate economic activity, Econometrica 54, 23-45.

Sensier, M., D. R. Osborn and N. Öcal, 2002, Asymmetric Interest Rate Effects for the UK Real Economy, Centre for Growth & Business Cycle Research, University of Manchester, Discussion Paper No. 010.

Stiglitz, J.E. and A. Weiss, 1981, Credit rationing in markets with imperfect information, The American Economic Review 71, 393-410.

Tierney, L., 1994, Markov chains for exploring posterior distributions (with discussion), Annals of Statistics 22, 1701-1762.

Valderrama M.T., 2001, Balance Sheet and Bank Lending Channels: some evidence from Austrian firms, Oesterreichische Nationalbank, Focus on Austria, 3-4.

Valderrama M.T., 2003a, Credit Channel and Investment Behavior in Austria: a Micro-Econometric Approach, in Monetary Policy Transmission in the Euro Area, I Angeloni, A Kashyap and B Mojon (eds), Cambridge University Press, 221-232.

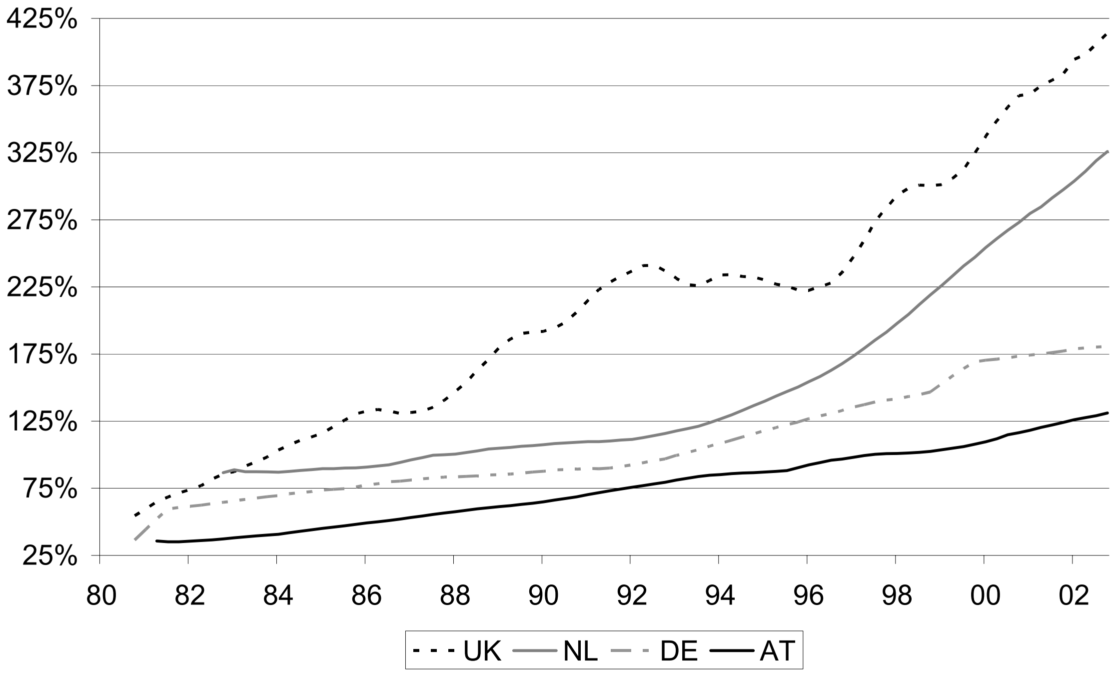
Valderrama, M.T., 2003b, Banking Structure and Investment in Austria: Some Empirical Evidence, Focus on Austria, 1.

Vermeulen, P. 2002. Business fixed investment: evidence of a financial accelerator in Europe, Oxford Bulletin of Economics and Statistics, Vol. 64, No 3, pp 213 – 231.

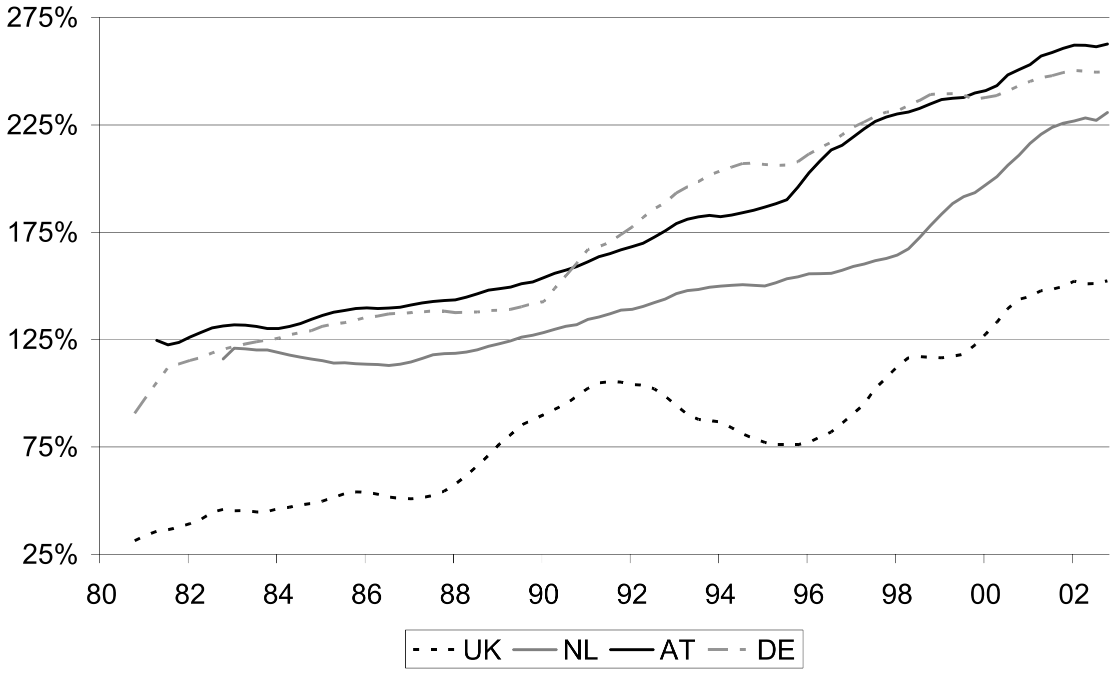
Wesche, K., 2000, Is there a Credit Channel in Austria? The Impact of Monetary Policy on Firms' Investment Decisions, Oesterreichische Nationalbank Working Papers No. 41.

A Graphs

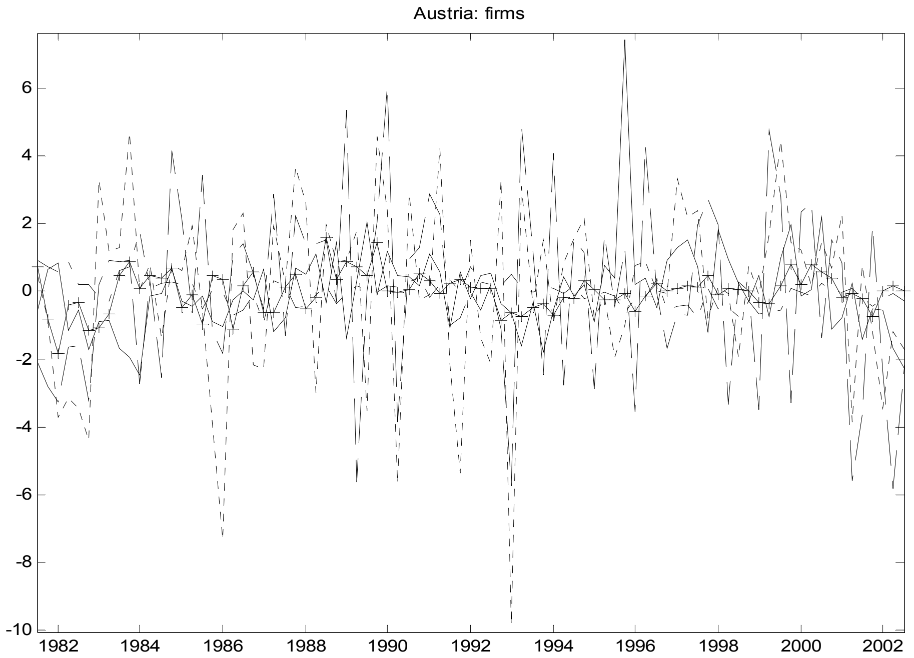
Graph 1. Ratio of loans to households to GDP



Graph 2. Ratio of loans to non-financial corporations to GDP

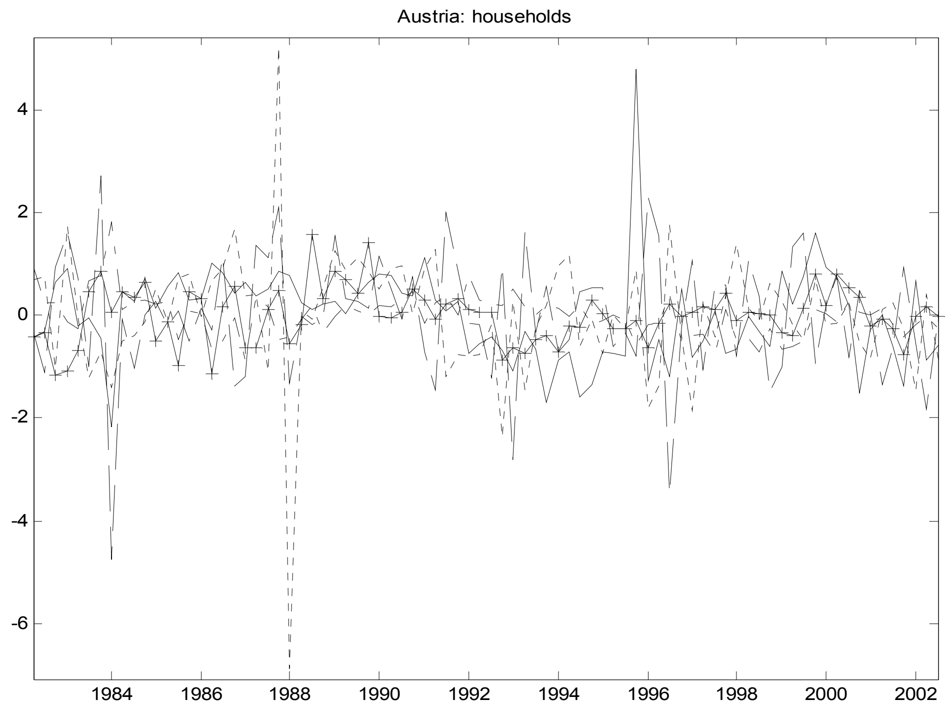


Graph 3. Austria. Loans to non-financial corporations



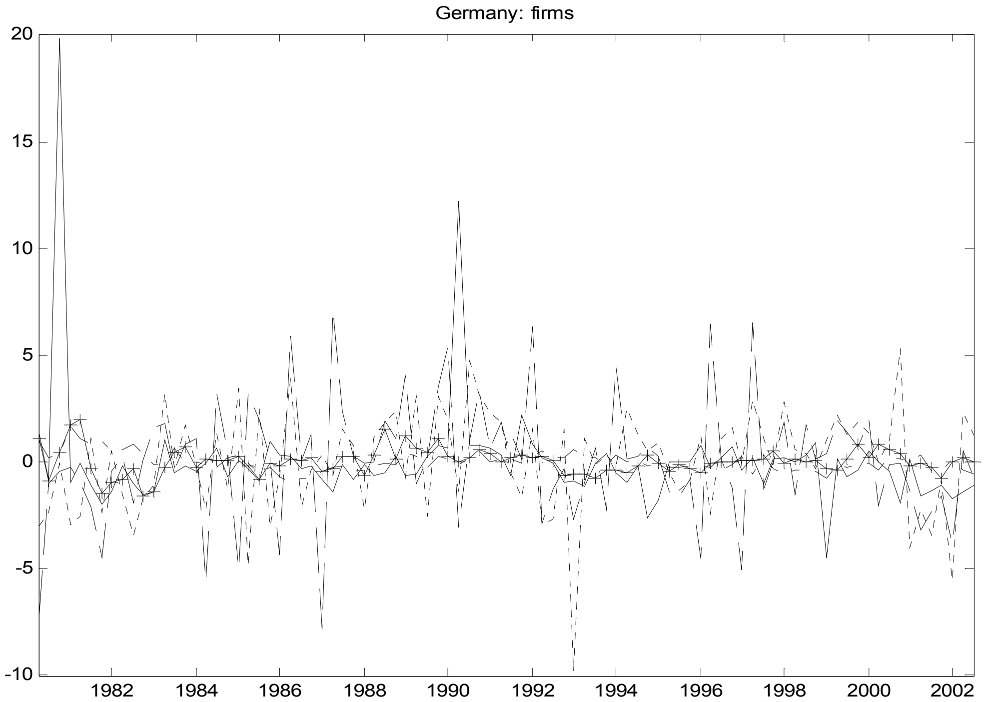
Investment (dashed), Imports (dotted), CPI (dash-dotted), Loans to firms (solid), Interest rate (solid +). Dummy variables: Loans (1995Q4) and CPI (1984Q1, VAT increase).

Graph 4. Austria. Loans to households



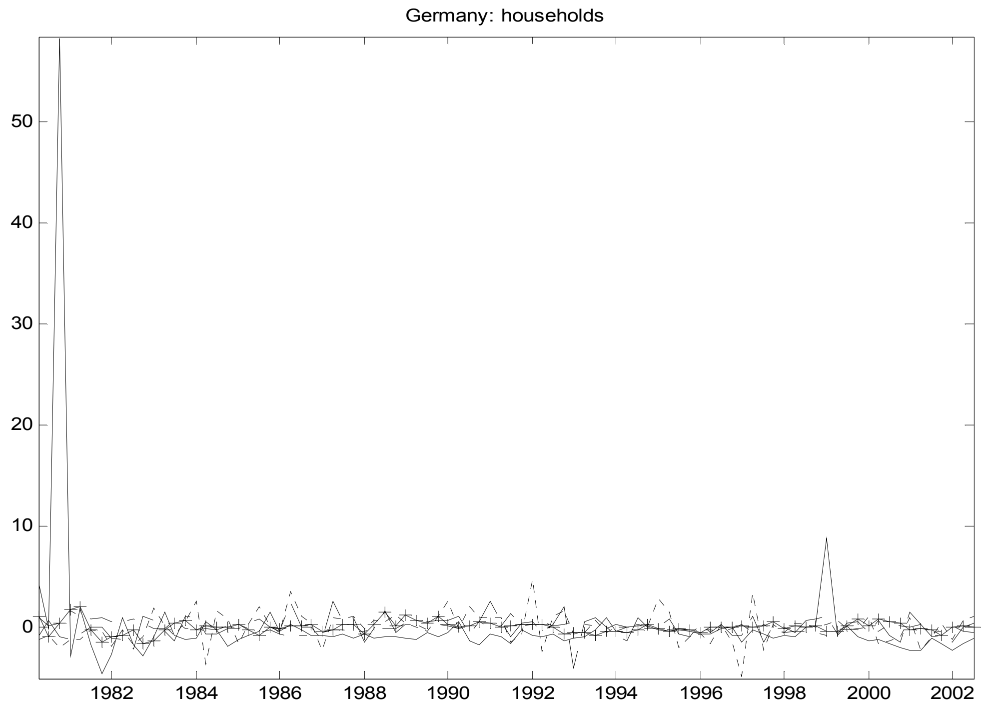
Households' Consumption (dashed), Net disposable income (dotted), CPI (dash-dotted), Loans to households (solid), Interest rate (solid +). Dummy variables: Loans (1995Q4), CPI (1984Q1, VAT increase), consumption (1983Q4, 1984Q1, anticipated and actual effect of VAT increase), net disposable income (1987Q4, 1988Q1).

Graph 5. Germany. Loans to non-financial corporations



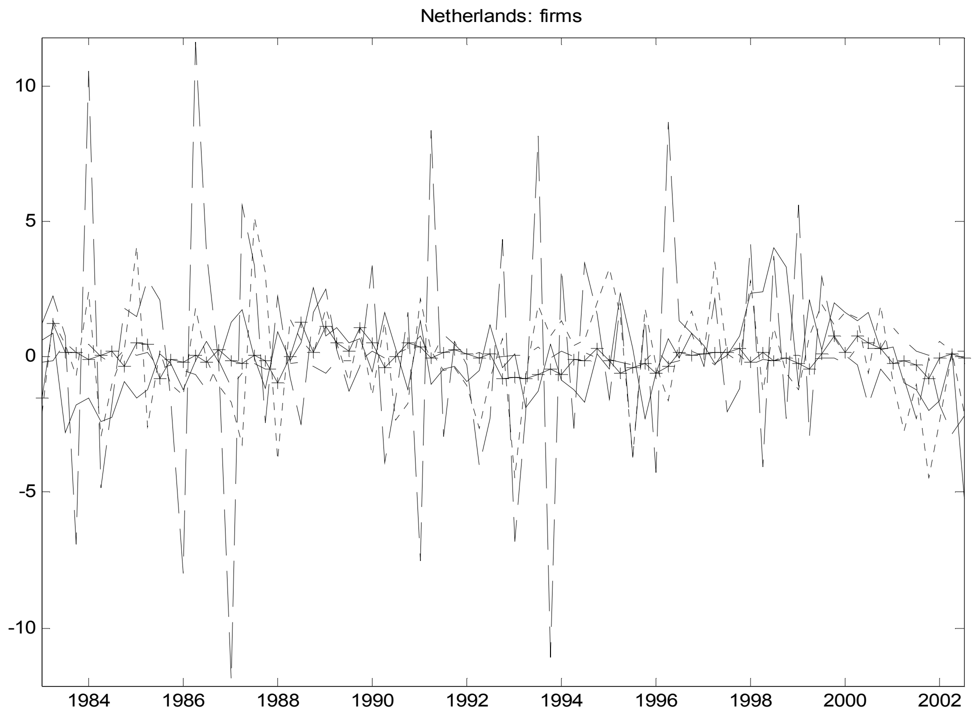
Investment (dashed), Imports (dotted), CPI (dash-dotted), Loans to firms (solid), Interest rate (solid +). Dummy variables: Loans (1980Q4, 1990Q2, 1999Q1).

Graph 6. Germany. Loans to households



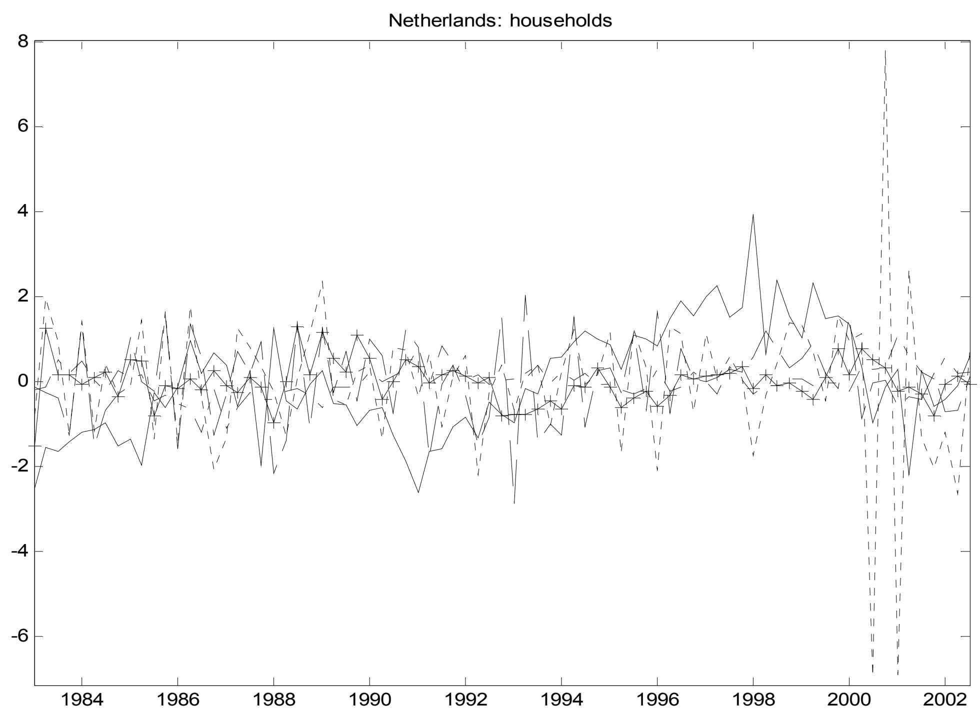
Households' Consumption (dashed), Net disposable income (dotted), CPI (dash-dotted), Loans to households (solid), Interest rate (solid +). Dummy variables: Loans (1980Q4, 1999Q1).

Graph 7. Netherlands. Loans to non-financial corporations



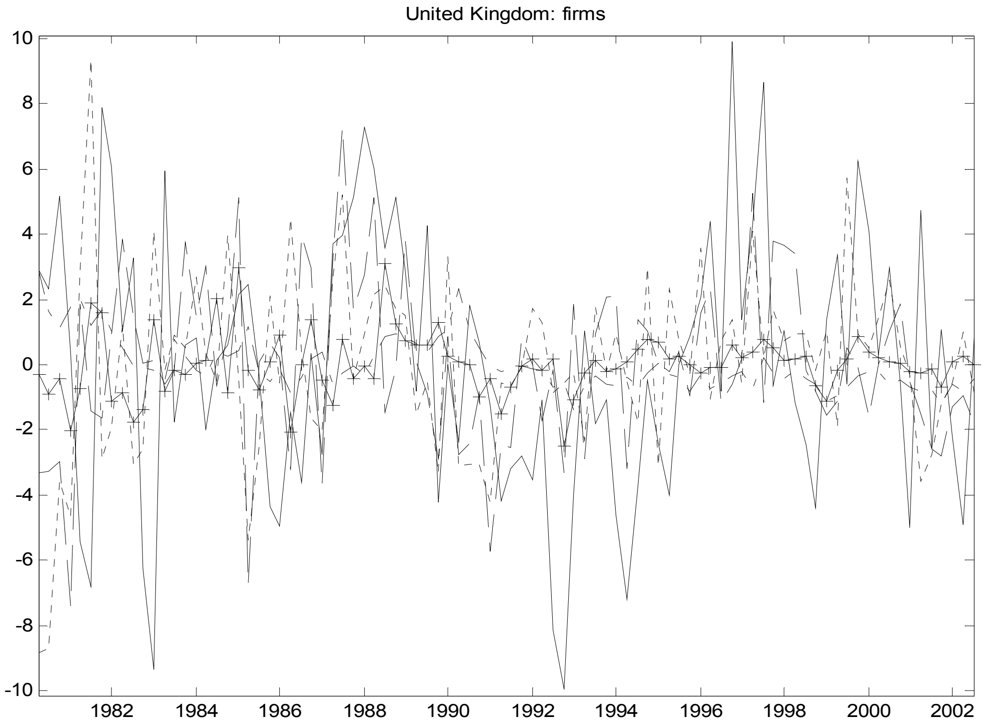
Investment (dashed), Imports (dotted), CPI (dash-dotted), Loans to firms (solid), Interest rate (solid +). Dummy variables: Loans (1995Q4) and CPI (1984Q1, VAT increase).

Graph 8. Netherlands. Loans to households



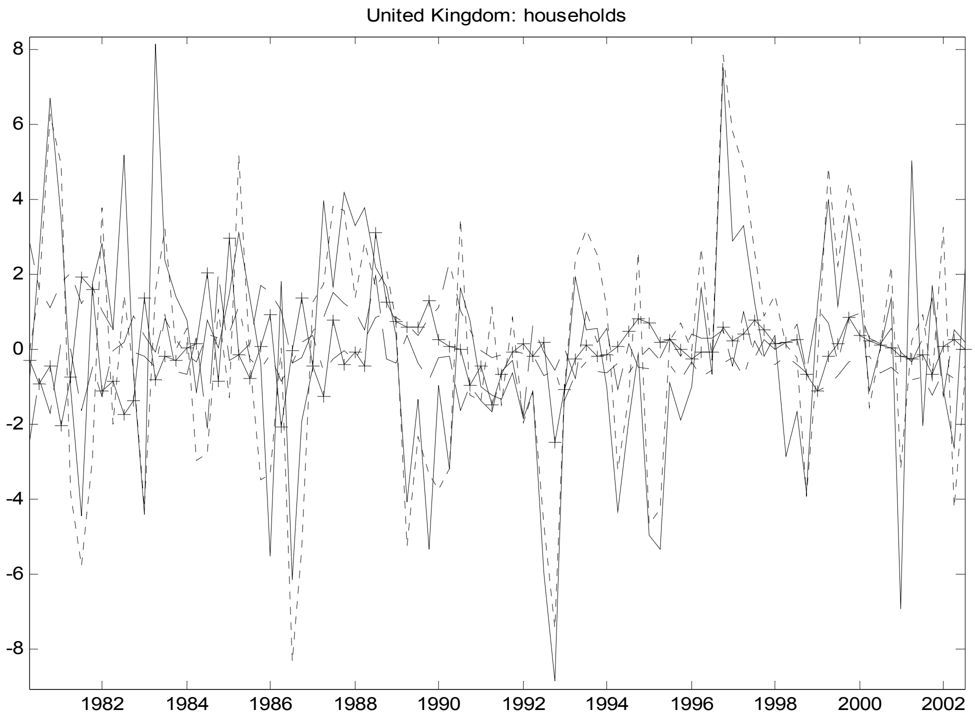
Households' Consumption (dashed), Net disposable income (dotted), CPI (dash-dotted), Loans to households (solid), Interest rate (solid +). Dummy variables: Net disposable income (2000Q3, 2000Q4, 2001Q1).

Graph 9. United Kingdom. Loans to non-financial corporations



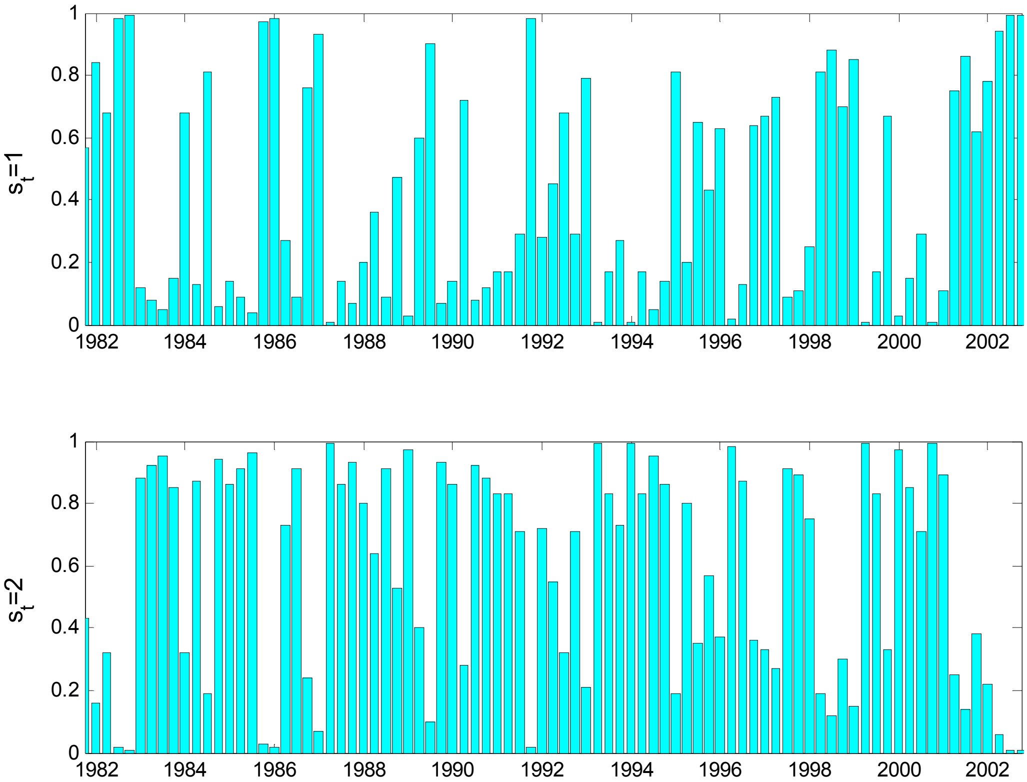
Investment (dashed), Imports (dotted), CPI (dash-dotted), Loans to firms (solid), Interest rate (solid +). Dummy variables: Loans (1995Q4) and CPI (1984Q1, VAT increase).

Graph 10. United Kingdom. Loans to households

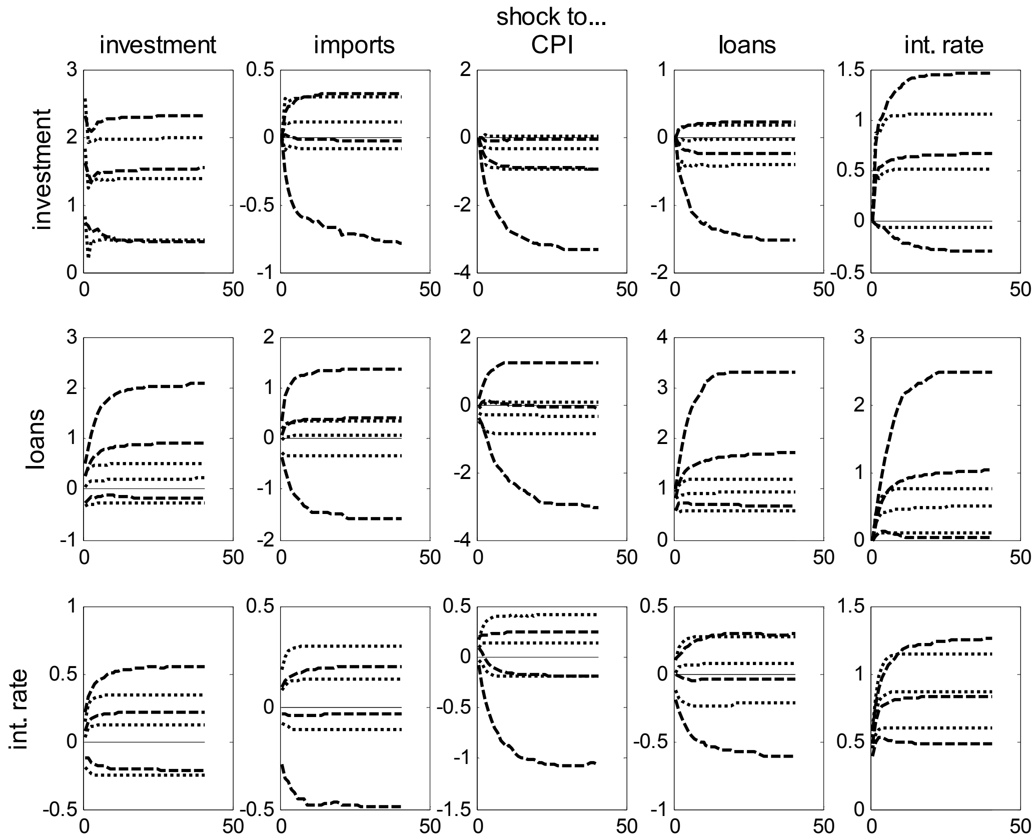


Households' Consumption (dashed), Net disposable income (dotted), CPI (dash-dotted), Loans to households (solid), Interest rate (solid +).

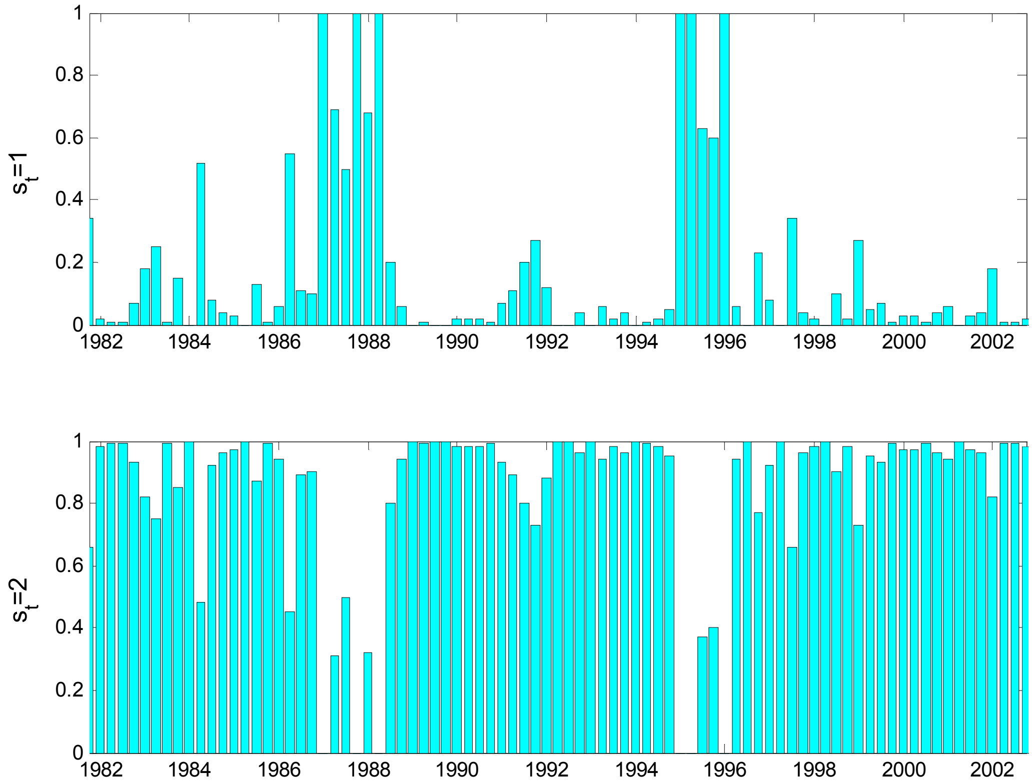
Graph 11. Austria. Loans to firms, posterior state probabilities.



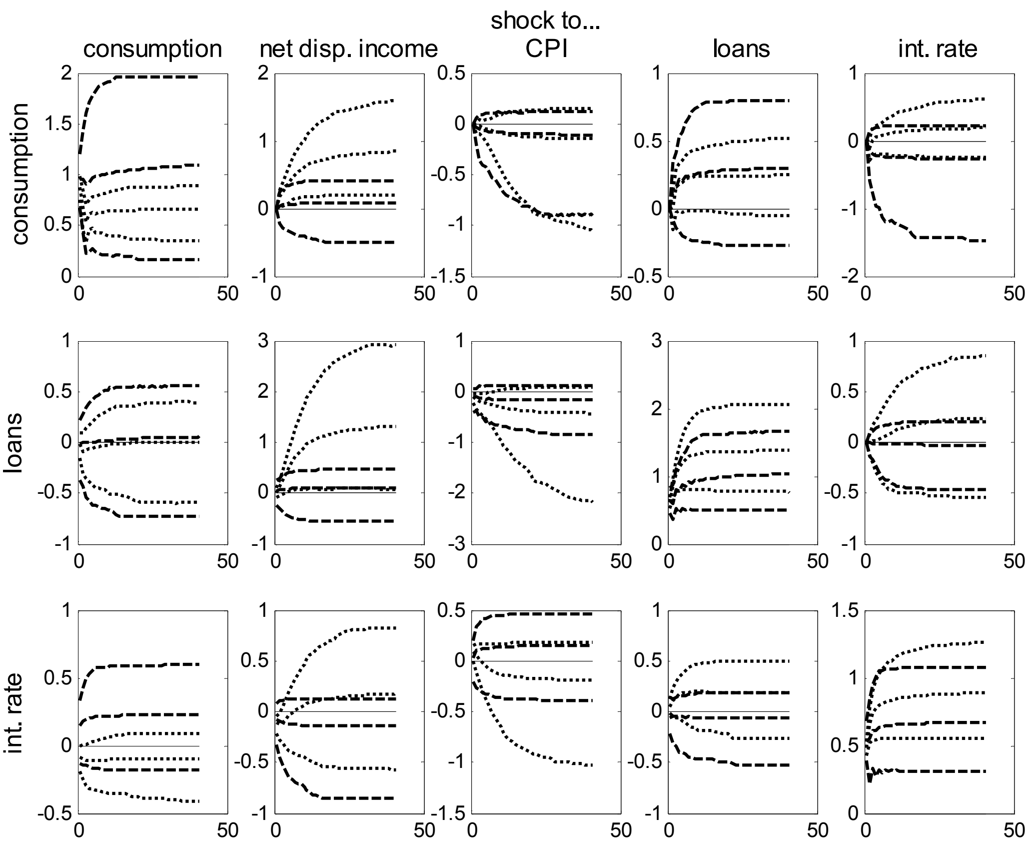
Graph 12. Austria. Loans to firms, IRF, regime 1 (dashed) and regime 2 (dotted).



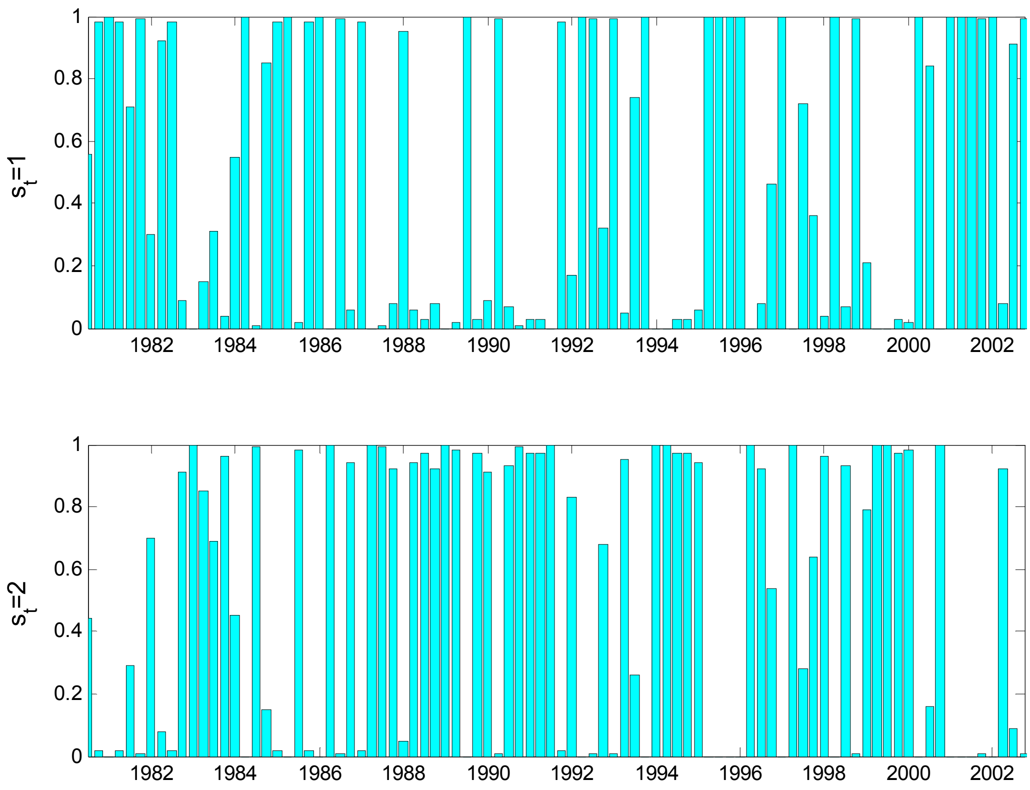
Graph 13. Austria. Loans to households, posterior state probabilities.



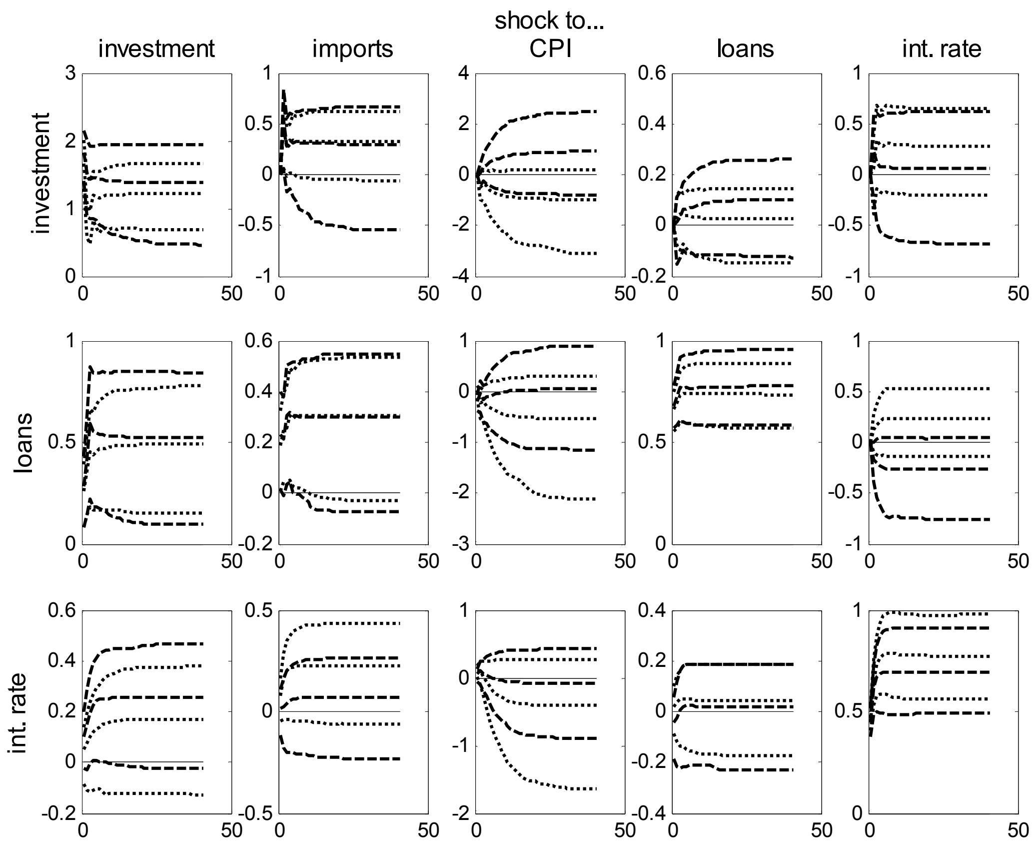
Graph 14. Austria. Loans to households, IRF, regime 1 (dashed) and regime 2 (dotted).



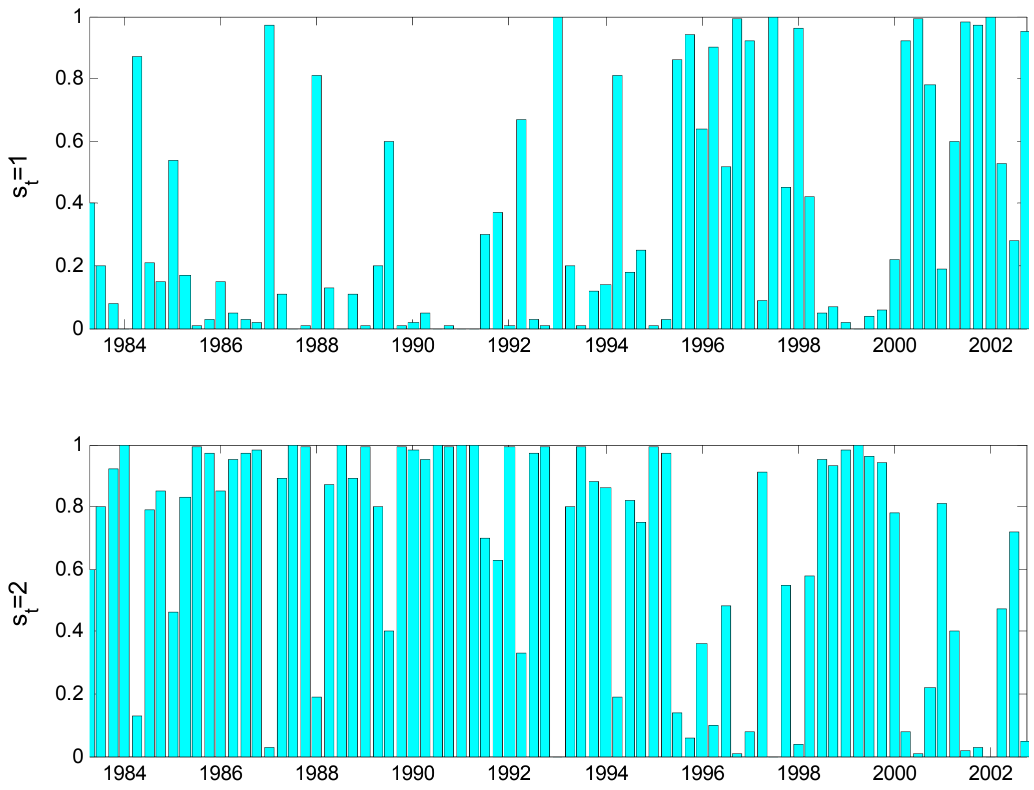
Graph 15. Germany. Loans to firms, posterior state probabilities.



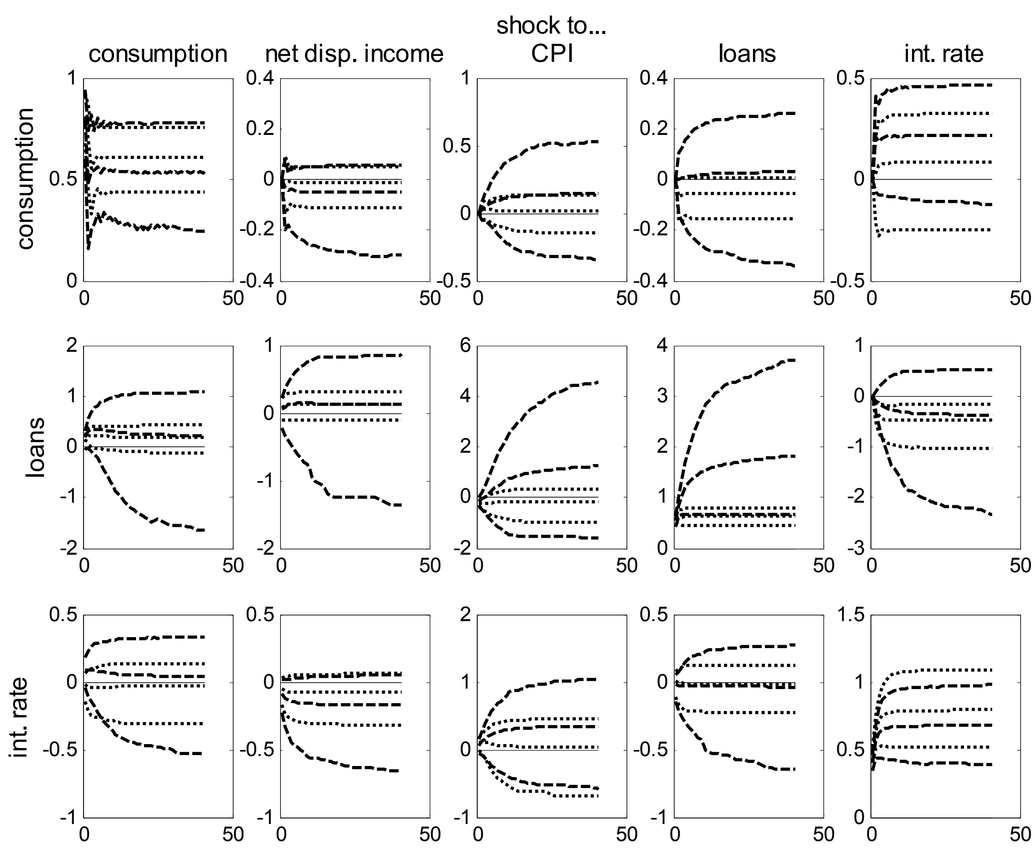
Graph 16. Germany. Loans to firms, IRF, regime 1 (dashed) and regime 2 (dotted).



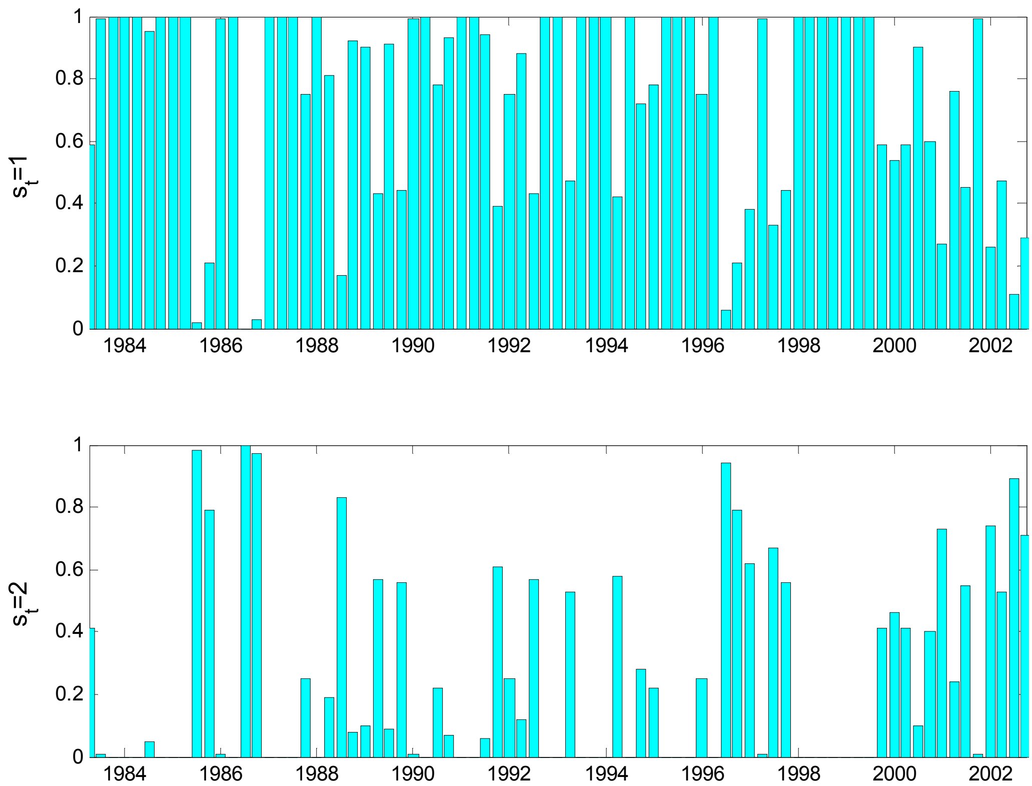
Graph 17. Germany. Loans to households, posterior state probabilities.



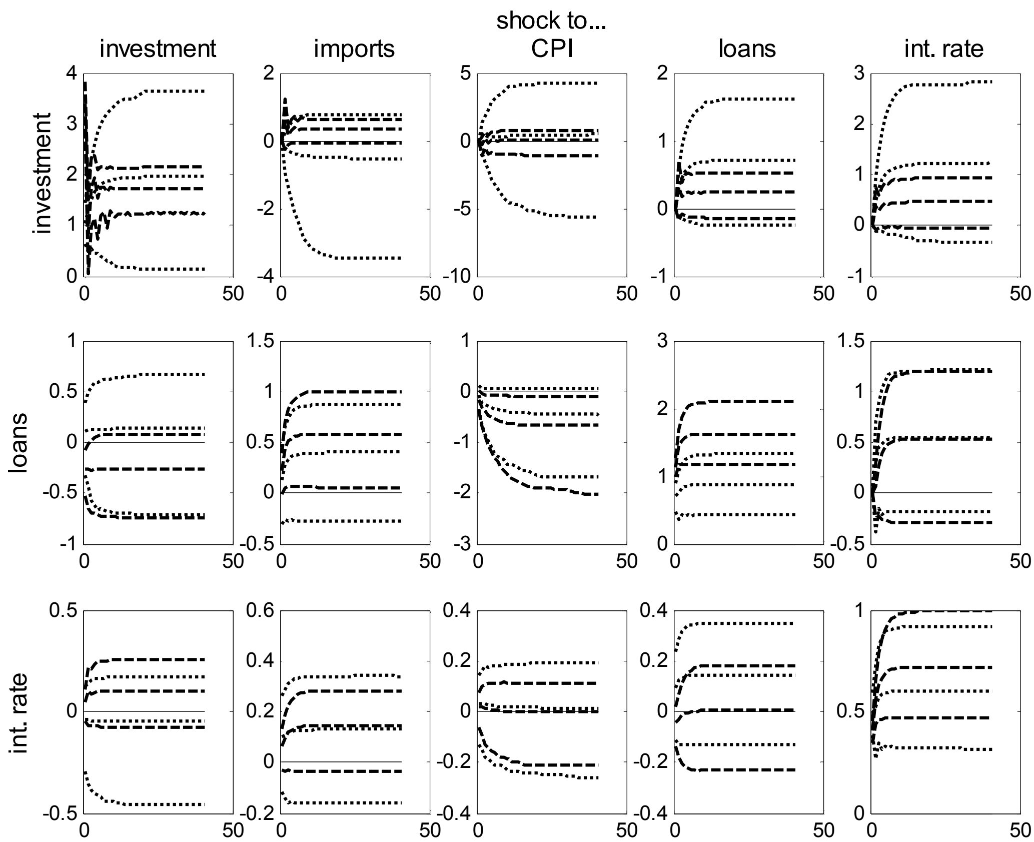
Graph 18. Germany. Loans to households, IRF, regime 1 (dashed) and regime 2 (dotted).



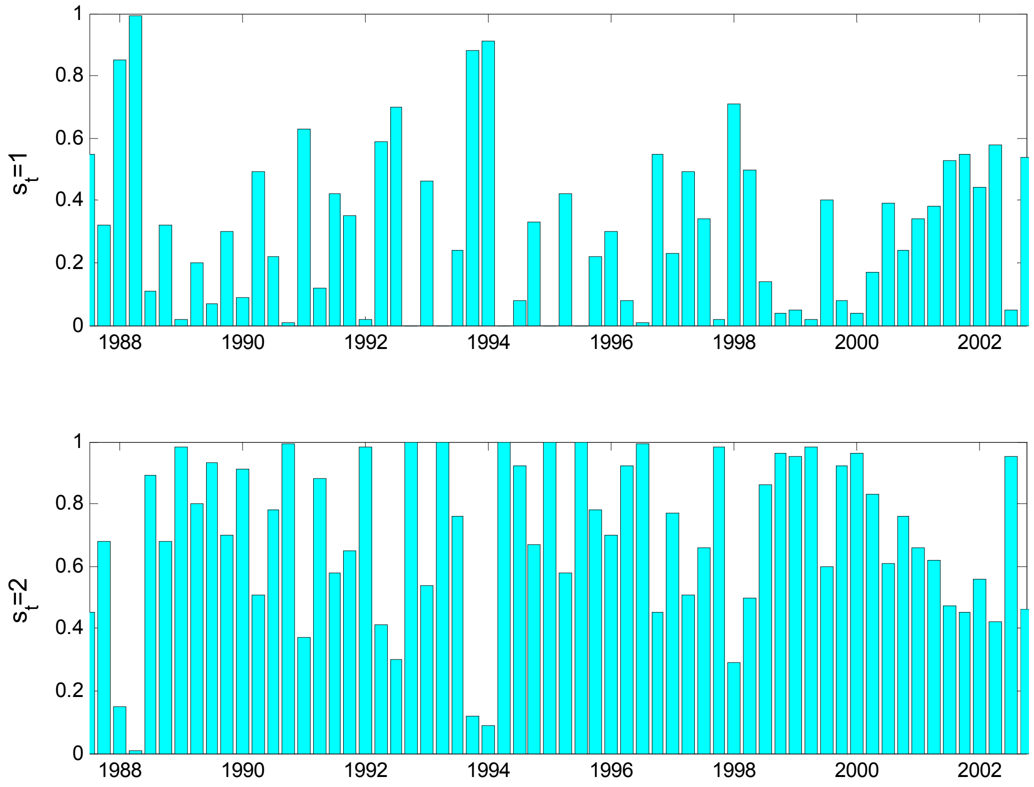
Graph 19. Netherlands. Loans to firms, posterior state probabilities.



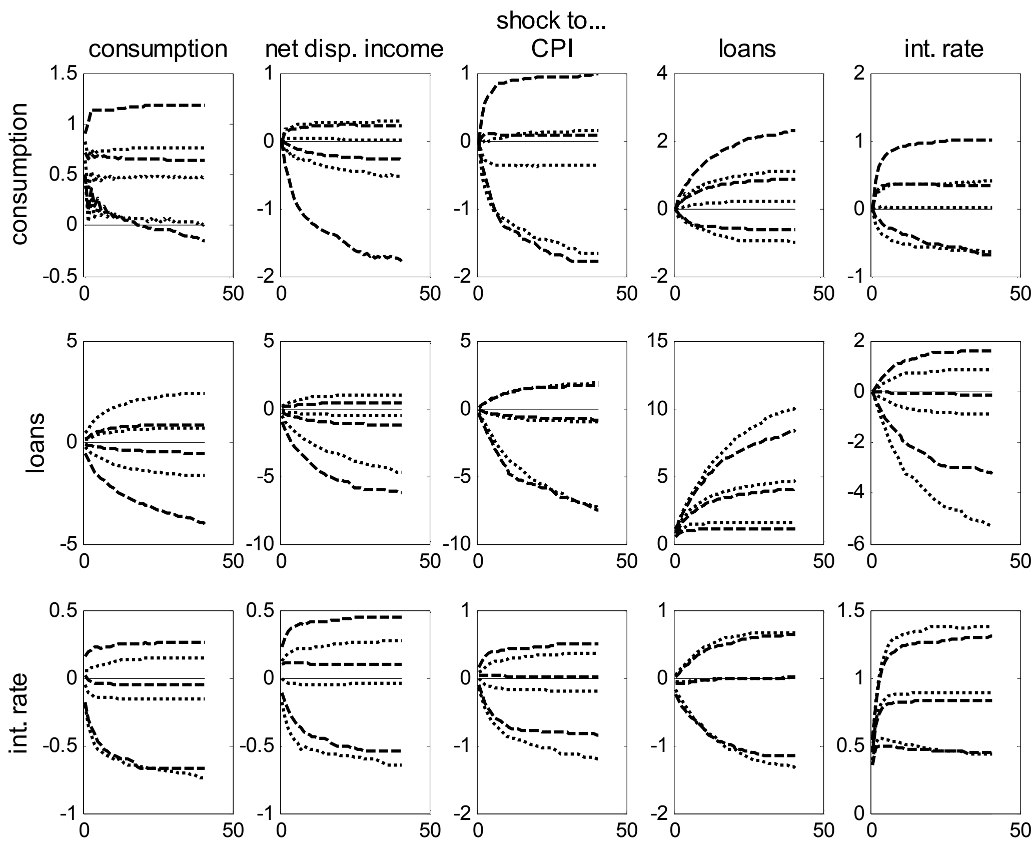
Graph 20. Netherlands. Loans to firms, IRF, regime 1 (dashed) and regime 2 (dotted).



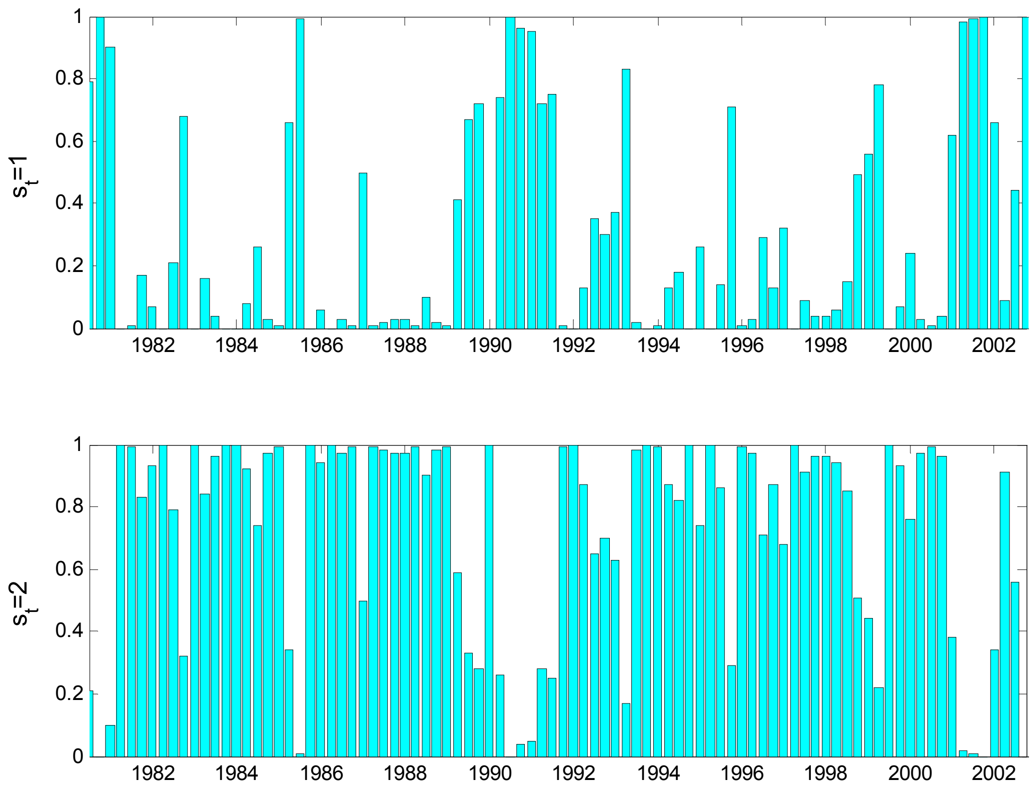
Graph 21. Netherlands. Loans to households, posterior state probabilities.



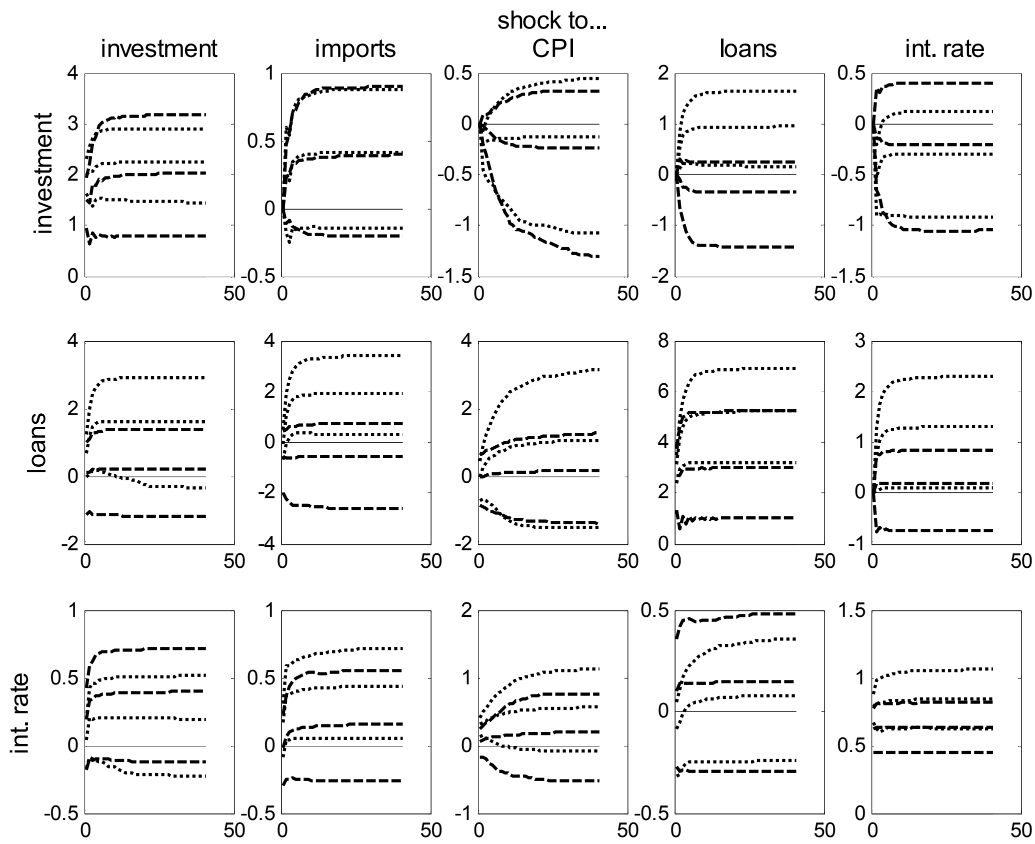
Graph 22. Netherlands. Loans to households, IRF, regime 1 (dashed) and regime 2 (dotted).



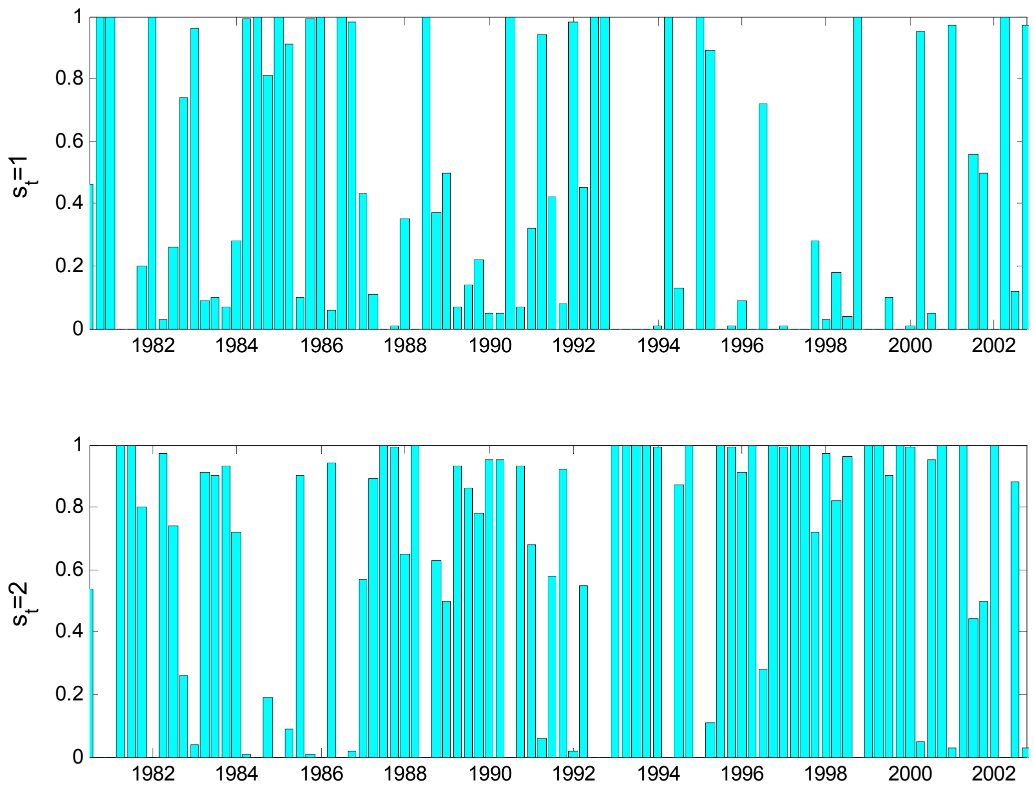
Graph 23. United Kingdom. Loans to firms, posterior state probabilities.



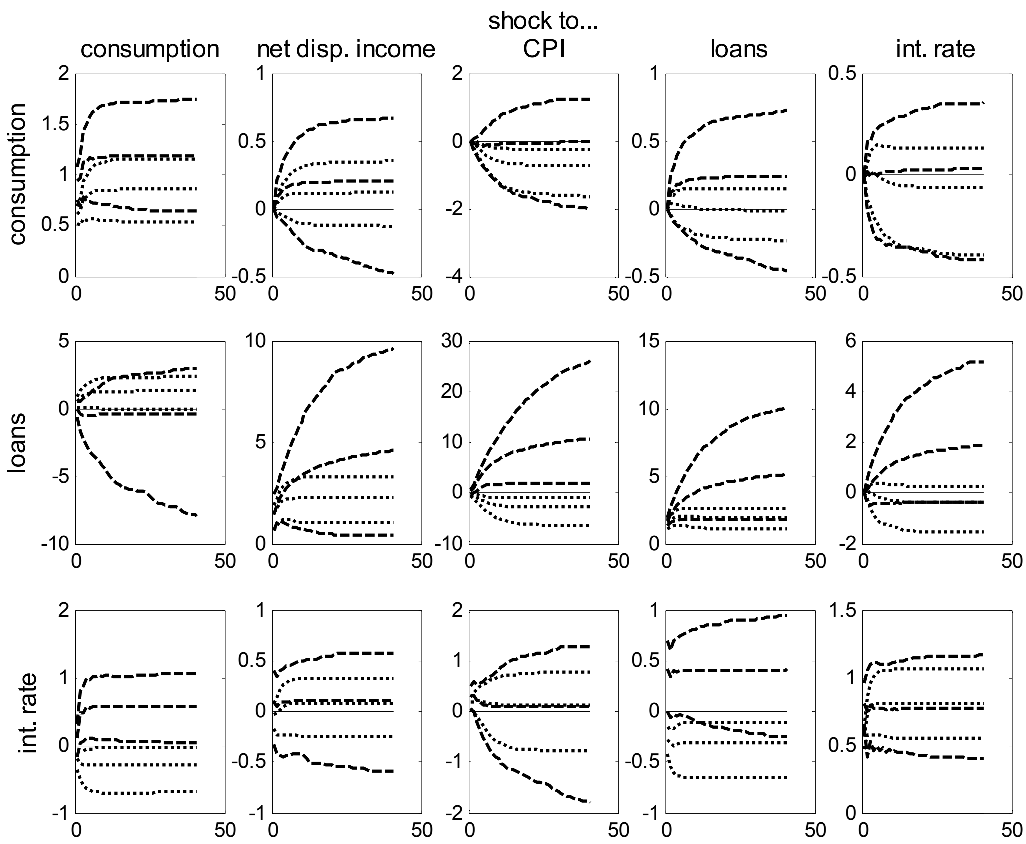
Graph 24. United Kingdom. Loans to firms, IRF, regime 1 (dashed) and regime 2 (dotted).



Graph 25. United Kingdom. Loans to households, posterior state probabilities.



Graph 26. United Kingdom. Loans to households, IRF, regime 1 (dashed) and regime 2 (dotted).



B Sampling scheme

The present appendix derives explicitly the moments of the conditional posterior distributions of the model parameters and the state variable. To simplify notation, the MS-VAR in equation (1) is assumed to be of order one. The extension to higher order lags is straightforward. Equation (1) thus writes

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

To derive the posterior distribution of the model of the model parameters, it is convenient to rewrite the model as:

$$y_t = y^*_{t-1}\beta(s_t) + \varepsilon_t\,, \tag{2'}$$

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

Simulate $\beta = (\beta(1),...,\beta(K))$ *from* $\pi(\beta \mid y^T, s^T, \Sigma)$. Given s^T, the posterior distribution is normally distributed $N(b, B^{-1})$, with $B = Y'WY + B_0$ and $b = B^{-1}(Y'Wy + B_0 b_0)$. The matrices Y and W are the predictor and the weighting matrices of model (2'), respectively:

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

where $D_t^k = 1$, iff $s_t = k$ 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.

Simulate $\Sigma = (\Sigma(1),...,\Sigma(K))$ *from independent Wishart distributions,* $\Sigma^{-1}(k) \sim W(\nu_k, S_k)$, where $\nu_k = \nu_0 + N_k$ and $S_k = S_0 + \sum_{s_t = k} \varepsilon_t{}'\varepsilon_t$ with $N_k = \#\{s_t = k\}$.

Simulate the state variable from the joint posterior distribution $\pi(s^T \mid y^T, \theta)$ with the multi-move sampler described in detail in Chib (1996). It involves two steps. In the first, forward-filtering one, we compute the filter distributions $\pi(s_t \mid y^t, \theta)$, $t = 1,\ldots,T$. They can be factored as:

$$\pi(s_t \mid y^t, \theta) \propto f(y_t \mid y^{t-1}, s_t, \beta, \Sigma)\pi(s_t \mid y^{t-1}, \theta)\,,$$

where the observation density $f(y_t \mid y^{t-1}, s_t, \beta, \Sigma)$ is the multivariate normal distribution given in (4). The second term is given by extrapolation:

$$\pi(s_t \mid y^{t-1}, \theta) = \sum_{s_{t-1}=1}^{K} \pi(s_{t-1} \mid y^{t-1}, \theta)\eta_{s_{t-1},s_t} .$$

where the starting distribution $\pi(s_0)$, which we set to the unconditional distribution ρ of s_t, is given by the ergodic probabilities of the Markov process.

Then, the backward sampling step starts sampling s_T from $\pi(s_T \mid y^T \theta)$ and runs backwards to sample from $\pi(s_t \mid y^T, s_{t+1}, \ldots, s_T, \theta)$ for $t = T-1, \ldots, 1$ which is given by

$$\pi(s_t \mid y^T, s_{t+1}, \ldots, s_T, \theta) = \pi(s_t \mid y^T, s_{t+1}, \theta) \propto \pi(s_t \mid y^t, \theta)\eta_{s_t, s_{t+1}} .$$

Given s^T, the transition probabilities are simulated from independent Dirichlet distributions, $\pi(\eta \mid s^T) = \prod_{k=1}^{K} D(e_1 + N_{k1}, \ldots, e_K + N_{kK})$, where $N_{kj} = \#\{s_t = j \mid s_{t-1} = k\}$.

We start the sampler by simulating the VAR parameters and we therefore 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.

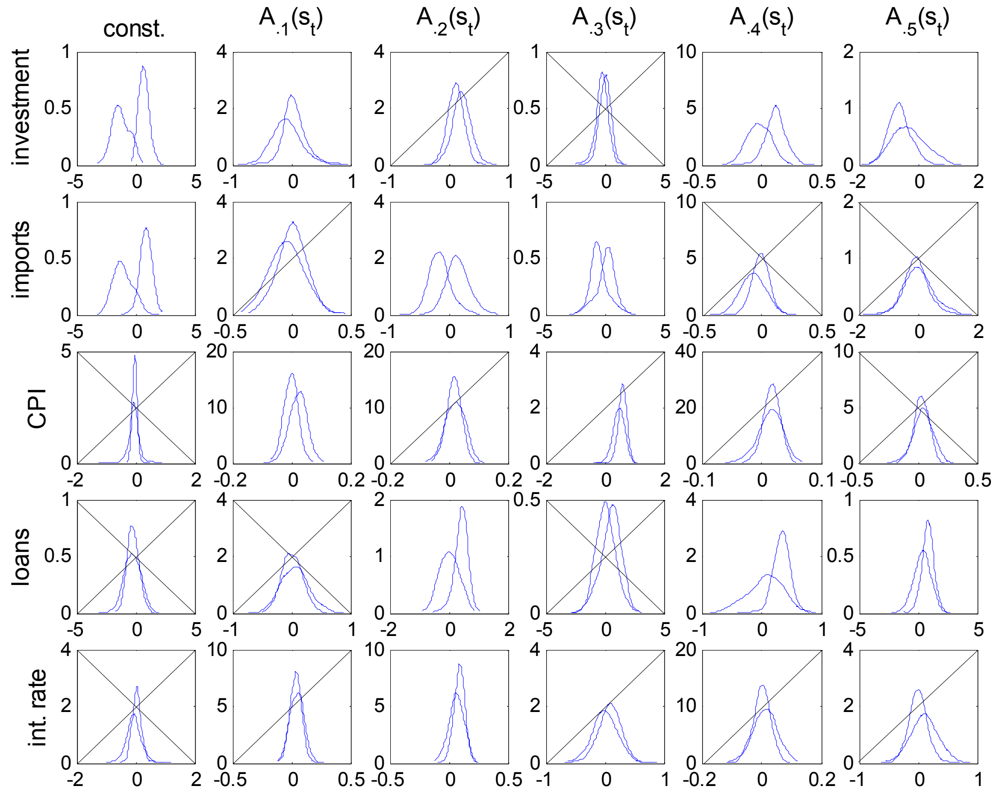
C Parsimonious model specification and marginal likelihood.

To give an example of our model specification procedure, we reproduce in graph 27 the posterior distribution of the (first-lag) VAR-parameters for the UK system of loans to non-financial corporations. The state-identification is based on the constant in the investment equation, i.e. all simulated state-dependent parameters and the state variable are reordered accordingly to fulfill the restriction $\beta_1(1) < \beta_1(2)$.

To obtain the parsimonious specification, in a first round, we restrict the insignificant parameters on the second lag to zero. Then, we restrict the parameters that are not switching (single crossed) to be equal across regimes. And finally, insignificant parameters on the first lag are restricted to zero (double crossed). In graph 27, we reproduce the marginal distributions that we obtain after restricting the insignificant parameters on the second lag to zero (see the final specification in appendix D).

To test the parsimonious switching specification against the benchmark unrestricted and the linear alternative, we compare the marginal likelihoods of the respective models, i.e. we compute Bayes factors. The optimal bridge sampler described in Frühwirth-Schnatter (1999) is readily applied with the obtained simulated values and the retained posterior moments of the model parameters. To estimate the marginal likelihood, first

Graph 27: Posterior distributions of the firms' loans system for the UK.



note that the model likelihood can be obtained by rearranging the following identity: $1=\frac{\int \alpha(\theta)\pi(\theta \mid y^T)q(\theta)d(\theta)}{\int \alpha(\theta)q(\theta)\pi(\theta \mid y^T)d(\theta)}=\frac{\int \alpha(\theta)\pi^*(\theta \mid y^T)q(\theta)d(\theta)}{L(y^T)\int \alpha(\theta)q(\theta)\pi(\theta \mid y^T)d(\theta)}$,

where $\pi^*(\theta \mid y^T)$ is the unnormalized posterior of the model parameters, $\pi(\theta \mid y^T) \propto \pi^*(\theta \mid y^T)$, the arbitrary function $\alpha(\theta)$ is set such that $\int \alpha(\theta)\pi(\theta \mid y^T)q(\theta)d(\theta)>0$, and $q(\theta)$ is a distribution approximating in a reasonable manner the posterior distribution $\pi(\theta \mid y^T)$. If E_f denotes the expectation with respect to the density *f*, we can express $L(y^T)$ as:

$$L(y^T)=\frac{\int \alpha(\theta)\pi^*(\theta \mid y^T)q(\theta)d(\theta)}{\int \alpha(\theta)q(\theta)\pi(\theta \mid y^T)d(\theta)}=\frac{E_q\left(\alpha(\theta)\pi^*(\theta \mid y^T)\right)}{E_\pi\left(\alpha(\theta)q(\theta)\right)},.$$

Suppose we have a sample of size *M* out of $\pi(\theta \mid y^T)$, $\theta^{(1)},\ldots,\theta^{(M)}$, and of size *L* out of $q(\theta)$, $\tilde{\theta}^{(1)},\ldots,\tilde{\theta}^{(L)}$, then we may estimate the model likelihood by averaging:

$$\hat{L}(y^T) = \frac{\hat{E}_q}{\hat{E}_\pi} = \frac{L^{-1}\sum_{l=1}^{L}\alpha(\tilde{\theta}^{(l)})\pi^*(\tilde{\theta}^{(l)} \mid y^T)}{M^{-1}\sum_{m=1}^{M}\alpha(\theta^{(m)})q(\theta^{(m)})}.$$

Frühwirth-Schnatter (1999) demonstrates that the most accurate result is obtained by using the optimal bridge function (Meng and Wong, 1996) for $\alpha(\theta)$, and using the mixture of posterior distributions to simulate *L* values out of $q(\theta)$:

$$q(\theta) = U^{-1}\sum_{u=1}^{U}\pi(\beta \mid y^T, s^{T^{(u)}}, \Sigma^{(u)})\pi(\Sigma \mid y^T, s^{T^{(u)}}, \beta^{(u)})\pi(\eta \mid s^{T^{(u)}}).$$

The *U* elements that form the mixture are chosen randomly from the simulations of the MCMC output, whereas the *M* values out of $\pi(\theta \mid y^T)$ entering $\hat{L}(y^T)$ may directly be chosen (randomly) from the simulated parameter values of the MCMC output.

D Parsimonious model specifications

The results discussed in section 5 were obtained by estimating the following parsimonious specifications. The notation $a(s_t)$ means that the coefficient is switching, a means that the coefficient is restricted to be equal across regimes and 0 denotes coefficients restricted to zero. The regime identification is based on the coefficients in bold. denote In each system, we identify the regimes by means of the coefficient highlighted in bold face.. The variables in the system for loans to non-financial corporations are ordered investment first, then imports, inflation, loans to non-financial corporations and the 3-month interest rate last. In the system for loans to households, households' consumption is ordered first, followed by net disposable income, inflation and the 3-month interest rate.

Austria Loans to non-financial corporations:

$$y_t = \begin{bmatrix} \upsilon(s_t) \\ \upsilon(s_t) \\ 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} a_1(s_t) & 0 & a_1 & a_1 & a_1 \\ 0 & a_1(s_t) & a_1 & a_1(s_t) & a_1 \\ 0 & 0 & a_1(s_t) & 0 & \boldsymbol{a_1(s_t)} \\ a_1 & a_1(s_t) & a_1(s_t) & a_1(s_t) & a_1 \\ a_1 & 0 & a_1(s_t) & a_1(s_t) & a_1 \end{bmatrix} y_{t-1} + \begin{bmatrix} a_2(s_t) & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} y_{t-2} + \varepsilon_t$$

Loans to households:

$$y_t = \begin{bmatrix} \upsilon(s_t) \\ 0 \\ \upsilon(s_t) \\ \upsilon(s_t) \\ \upsilon(s_t) \end{bmatrix} + \begin{bmatrix} a_1(s_t) & a_1(s_t) & 0 & a_1(s_t) & a_1(s_t) \\ 0 & a_1(s_t) & a_1(s_t) & 0 & \boldsymbol{a_1(s_t)} \\ a_1(s_t) & a_1 & a_1(s_t) & a_1(s_t) & a_1 \\ a_1(s_t) & a_1(s_t) & 0 & a_1(s_t) & a_1 \\ 0 & a_1(s_t) & a_1(s_t) & a_1(s_t) & a_1(s_t) \end{bmatrix} y_{t-1} + \begin{bmatrix} a_2(s_t) & 0 & 0 & a_2(s_t) & a_2(s_t) \\ a_2 & a_2(s_t) & 0 & 0 & 0 \\ 0 & 0 & a_2(s_t) & 0 & 0 \\ 0 & 0 & 0 & a_2(s_t) & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} y_{t-2} +$$

Germany Loans to non-financial corporations:

$$y_t = \begin{bmatrix} \boldsymbol{\upsilon(s_t)} \\ \upsilon(s_t) \\ 0 \\ \upsilon(s_t) \\ 0 \end{bmatrix} + \begin{bmatrix} a_1(s_t) & a_1 & a_1(s_t) & a_1 & a_1(s_t) \\ 0 & a_1(s_t) & a_1(s_t) & a_1(s_t) & a_1 \\ 0 & a_1(s_t) & a_1 & a_1(s_t) & 0 \\ a_1(s_t) & 0 & a_1(s_t) & a_1 & a_1(s_t) \\ 0 & a_1(s_t) & a_1(s_t) & a_1(s_t) & a_1 \end{bmatrix} y_{t-1} + \begin{bmatrix} a_2(s_t) & 0 & a_2(s_t) & 0 & a_2(s_t) \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & a_2 & 0 & 0 \\ a_2(s_t) & 0 & a_2(s_t) & a_2 & 0 \\ 0 & 0 & a_2(s_t) & a_2(s_t) & 0 \end{bmatrix} y_{t-2} + \varepsilon_t$$

Loans to households:

$$y_t = \begin{bmatrix} \boldsymbol{\upsilon(s_t)} \\ \upsilon(s_t) \\ 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} a_1(s_t) & a_1 & 0 & a_1(s_t) & a_1(s_t) \\ 0 & a_1 & a_1(s_t) & a_1(s_t) & a_1(s_t) \\ 0 & a & a_1 & a_1(s_t) & a_1 \\ a & 0 & a_1(s_t) & a_1(s_t) & a_1(s_t) \\ a & 0 & a_1(s_t) & a_1(s_t) & a_1 \end{bmatrix} y_{t-1} + \begin{bmatrix} a_2(s_t) & 0 & 0 & 0 & 0 \\ 0 & a_2 & a_2(s_t) & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & a_2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} y_{t-2} + \varepsilon_t$$

The Netherlands Loans to non-financial corporations:

$$y_t = \begin{bmatrix} \upsilon(s_t) \\ 0 \\ 0 \\ 0 \\ \upsilon(s_t) \end{bmatrix} + \begin{bmatrix} \boldsymbol{a_1(s_t)} & a_1(s_t) & a_1(s_t) & a_1 & a_1 \\ 0 & a_1(s_t) & 0 & 0 & a_1 \\ a_1(s_t) & 0 & a_1(s_t) & 0 & a_1 \\ 0 & a_1 & a_1 & a_1(s_t) & a_1(s_t) \\ a_1(s_t) & 0 & 0 & a_1(s_t) & a_1(s_t) \end{bmatrix} y_{t-1} + \begin{bmatrix} a_2(s_t) & 0 & a_2(s_t) & 0 & 0 \\ 0 & a_2(s_t) & 0 & 0 & 0 \\ 0 & 0 & a_2(s_t) & 0 & 0 \\ 0 & 0 & 0 & 0 & a_2(s_t) \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} y_{t-2} + \varepsilon_t$$

Loans to households:

$$y_t = \begin{bmatrix} \boldsymbol{\upsilon(s_t)} \\ \upsilon(s_t) \\ 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} a_1(s_t) & a_1(s_t) & a_1(s_t) & a_1(s_t) & a_1(s_t) \\ a_1(s_t) & a_1 & a_1(s_t) & a_1(s_t) & a_1(s_t) \\ 0 & 0 & a_1(s_t) & a_1 & a_1 \\ 0 & a_1(s_t) & a_1(s_t) & a_1 & a_1(s_t) \\ a_1 & a_1 & a_1(s_t) & a_1(s_t) & a_1 \end{bmatrix} y_{t-1} + \begin{bmatrix} 0 & 0 & a_2(s_t) & 0 & 0 \\ 0 & 0 & a_2(s_t) & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & a_2(s_t) & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} y_{t-2} + \varepsilon_t$$

United Kingdom Loans to non-financial corporations:

$$y_t = \begin{bmatrix} \boldsymbol{\upsilon(s_t)} \\ \upsilon(s_t) \\ 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} a_1(s_t) & a_1 & 0 & a_1(s_t) & a_1(s_t) \\ a_1 & a_1(s_t) & a_1(s_t) & 0 & 0 \\ a_1(s_t) & a_1 & a_1 & a_1 & 0 \\ 0 & a_1(s_t) & 0 & a_1(s_t) & a_1(s_t) \\ a_1 & a_1(s_t) & a_1 & a_1 & a_1 \end{bmatrix} y_{t-1} + \begin{bmatrix} a_2(s_t) & 0 & 0 & a_2(s_t) & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & a_2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} y_{t-2} + \varepsilon_t$$

Loans to households:

$$y_t = \begin{bmatrix} \upsilon(s_t) \\ \upsilon(s_t) \\ 0 \\ \upsilon(s_t) \\ \upsilon(s_t) \end{bmatrix} + \begin{bmatrix} a_1 & 0 & a_1(s_t) & a_1(s_t) & a_1(s_t) \\ a_1(s_t) & a_1 & \boldsymbol{a_1(s_t)} & a_1 & a_1(s_t) \\ 0 & a_1 & a_1 & a_1(s_t) & a_1 \\ a_1(s_t) & 0 & a_1(s_t) & a_1(s_t) & a_1(s_t) \\ a_1(s_t) & a_1(s_t) & a_1(s_t) & a_1(s_t) & a_1(s_t) \end{bmatrix} y_{t-1} + \begin{bmatrix} a_2 & 0 & a_2(s_t) & 0 & a_2(s_t) \\ 0 & 0 & a_2(s_t) & 0 & a_2(s_t) \\ 0 & 0 & a_2 & 0 & 0 \\ 0 & 0 & a_2(s_t) & a_2(s_t) & a_2(s_t) \\ 0 & a_2(s_t) & a_2(s_t) & 0 & 0 \end{bmatrix} y_{t-2} + \varepsilon_t$$