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Investigating asymmetries in the bank lending channel An analysis using Austrian banks' balance sheet data

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Editorial

In the present paper, Sylvia Frühwirth-Schnatter and Sylvia Kaufmann use a balanced bank panel data set to obtain an inference on two dimensions of the asymmetric response of bank lending to interest rate changes. The cross-sectional dimension is captured by group-specific parameters whereby each bank's group membership is estimated along with the model parameters. Moreover, the asymmetric response over time is modelled with switching parameters that depend on a latent state variable. The presence of two latent indicators calls for Bayesian simulation methods. The results show that three bank groups, characterized by the groups' average asset total, differ in their lending reaction to interest rate changes. Some sensitivity analysis comparing the results for different group specifications and the models' out-of-sample forecasting performance confirms the model specification.

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Investigating asymmetries in the bank lending channel. An analysis using Austrian banks' balance sheet data.

Sylvia Frühwirth-Schnatter*and Sylvia Kaufmann†‡

June 2003

Abstract

In the present paper we use a balanced bank panel data set to obtain an inference on two dimensions of the asymmetric response of bank lending to interest rate changes. The cross-sectional dimension is captured by group-specific parameters whereby each bank's group membership is estimated along with the model parameters. Moreover, the asymmetric response over time is modelled with switching parameters that depend on a latent state variable. The presence of two latent indicators calls for Bayesian simulation methods. The results show that three bank groups, characterized by the groups' average asset total, differ in their lending reaction to interest rate changes. Some sensitivity analysis comparing the results for different group specifications and the models' out-of-sample forecasting performance confirms our model specification.

JEL classification: C11,C15,E44,E51

Key words: Bank lending, clustering, forecasting, Markov switching, Markov chain Monte Carlo, panel data.

1 Introduction

The present paper investigates whether monetary policy affects the real economy in Austria through a bank lending channel. Basically, this channel works through competition among banks for reserves and deposits to secure their lending portfolios. When restrictive monetary policy drains reserves, and thus deposits, from the banking system banks usually have to cut back on their loans to match the decrease in liquidity within the system. The extent of the cut, however, is thought to depend on the exposure of each individual bank

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to liquidity constraints. Potentially, smaller (and/or more illiquid) banks thus restrict lending more than large (and/or liquid) banks do, as their ability to resort to other forms of financing (bond issues, borrowing on the interbank market) as a substitute for deposits is limited (see Stein, 1998). In addition to this cross-sectional asymmetric response to monetary policy, we investigate here a potential asymmetric effect of monetary policy over time, e.g. over the business cycle. As liquidity constraints are potentially tighter during an economic slowdown or during periods of binding liquidity constraints, monetary policy should have a greater impact on bank lending during such periods than during periods of economic recovery or periods in which liquidity constraints are not binding. Such models of credit cycles have been developed in Azariadis and Smith (1998) and Kiyotaki and Moore (1997b, 1997a).

Various approaches have been pursued in the literature to investigate the cross-sectional asymmetric response in bank lending. Within the classical econometric context, Kashyap and Stein (1995) first aggregate individual bank balance sheet data according to relative size classes, and regress then in a second step the growth rate of loans on a measure for monetary policy. Their evidence documents a stronger reaction of small banks to monetary policy impulses. They take up a similar two-step approach in Kahsyap and Stein (2000) where they investigate the impact of balance sheet strength (measured by the ratio of liquid assets to total assets). The first step estimates a cross-section equation for each size class and each time period where the growth of loans is regressed on liquidity. A pure time-series process is then fitted to the coefficient estimate on liquidity in each size class where monetary policy is included as an explanatory variable. Indeed, they find that for the smallest size class, liquidity constraints are more binding and thus induce stronger effects of monetary policy than for large banks. Another possibility to assess the cross-sectional effect of monetary policy is to use the pooled panel-data set and to include interaction terms between bank-specific characteristics with monetary policy. We find evidence on European countries in this line of research in de Bondt (1999), where the bank lending channel appears to be strongest in Germany, Belgium and the Netherlands, followed by France and Italy. In contrast, the bank lending channel does not seem to be relevant for the United Kingdom.

Additional evidence on the bank lending channel for European countries (Favero et al., 1999, Ehrmann et al., 2003) has been rather ambiguous, however. It appears that observable bank-specific characteristics like size, liquidity or capitalisation are not adequate to explain the different lending reactions between banks. Therefore, as an alternative to the traditional approaches, we suggest to treat the relevant groups of banks as unobservable in the sense that they are part of the model estimation (Frühwirth-Schnatter and Kaufmann, 2002). Traditional cross-sectional asymmetry in bank lending behaviour should then yield a classification that is related to the size or liquidity strength of an individual bank. To this aim, the reaction to monetary policy changes is captured by group-specific parameters. Moreover, the group-specific parameters are assumed to be time-varying depending on the outcome of a latent state process in order to account for a potential asymmetric response of bank lending over time. Here, the latent specification is adopted because the overall relevant state of the economy is usually not observed with certainty. Moreover, the relation of periods when liquidity constraints are more binding to specific business cycle periods is not known a priori. So the group-specific parameters are time-varying (shifting), depending on a latent discrete state variable potentially related to a specific prevailing economic regime.

There exists only few literature that investigates asymmetric transmission of monetary policy over time within a panel data context. Asea and Blomberg (1998) infer on asymmetric pricing of lending over the business cycle using the Markov switching framework advocated by Hamilton (1989), whereby they use a variant of the EM algorithm to perform model estimation. Kaufmann (2001) investigates the time-varying lending behaviour of Austrian banks within a similar setting where cross-sectional asymmetry in the lending reaction is captured by interacting relevant bank characteristics with monetary policy. The results document a significant asymmetric effect of monetary policy over time and only weak evidence for the bank lending channel. Liquidity (rather than size) appears to be the criterion with which cross-sectional asymmetric response of lending to monetary policy is best explained in Austria. Results for a sample of the U.S. banking sector are found in Frühwirth-Schnatter and Kaufmann (2002). In particular, the inference therein yields results that are consistent with the bank lending view and, additionally, the significant asymmetric effect of monetary policy over time is consistent with predictions of credit cycles models.

As far as econometric estimation is concerned, the specification with two latent state variables renders maximum likelihood infeasible for estimation. Therefore, in the present paper, we obtain inference within a Bayesian framework using Markov chain Monte Carlo (MCMC) simulation methods as proposed in Frühwirth-Schnatter and Kaufmann (2002) (see Smith and Roberts (1993), Chib and Greenberg (1996) for an overview on MCMC methods). Three groups appear to be relevant to classify the banks by means of the strength of their lending reaction to monetary policy changes. Most of the banks fall into one group, and the banks of the other two groups are mainly smaller and more liquid. However, an absolute distinction between the groups by means of bank-specific size and/or liquidity strength is not possible. Moreover, the bank lending reaction of all groups significantly differs between the two identified regimes.

The next section presents the theoretical background of the investigation and motivates the introduction and the latent specification of the group- and the state-specific indicator variables. Section 3 introduces the econometric specification of the model (subsection 3.1) and discusses estimation (subsection 3.2) and identification issues (subsection 3.3). The characteristics of the data used for the investigation are discussed in subsection 4.1 as they reflect some typical specificities of the Austrian banking sector. The subsections 4.2 and 4.3 then present the empirical specification procedure and interpret the results in the light of the theoretical model's predictions, respectively. Section 5 contains a sensitivity analysis that compares the results to those obtained when models with two and four bank groups are estimated alternatively and when the banks are classified a priori into three groups according to their relative size. Finally, an out-of-sample forecast evaluation assesses the performance of all models and confirms the specification of the preferred one. Section 6 concludes. The choice of the prior distributions, the posterior distributions and the way how we handle/estimate outliers are described in a condensed way in appendices A to C, respectively.

2 A model for bank lending behaviour

The theoretical background of the investigation is given by an adverse-selection model for bank asset and liability management (see Stein, 1998) which is also interpretable as a micro-economic foundation of the credit channel for monetary policy transmission (Bernanke and Blinder, 1992). In particular, the model developed in Stein (1998) provides an explanation for bank-specific lending responses to monetary policy. It thus describes the credit market's supply side reaction, which is usually subsumed under the term *bank lending channel*. To motivate our analysis, we will briefly reproduce Stein's model and argue that it embeds also asymmetric lending responses over time in addition to asymmetric responses over the cross-section.

The main results can be derived by assuming two representative banks (G and B) acting on the one hand as monopolist in the credit market,[1] and, on the other hand, competing for deposits (being price-takers) in the deposit market. Both banks have two possibilities to fund new loans L. Either they raise reservable, insured deposits D or they raise external, non-reservable uninsured finance E like equity or CDs. Each bank's existing assets A are assumed to be entirely covered by previously raised finance P, $A = P$. However, the value of the old assets A differs between the banks and is not publicly observable, which leads to an asymmetric informational problem between depositors and the banks. In particular, if a bank is of type "G" (good), these assets are valued A^G, if it is of type "B" (bad), the assets are valued $A^B < A^G$. A measure for the degree of asymmetric information exposure may be given by $I = 1 - A^B/A^G$, also interpretable as the relative value (creditworthiness) of type G bank.

We analyze the model by looking at the separating equilibrium, i.e. a situation where each bank's decision about external finance E reveals its type to the market participants. The timing of the game is such that the banks decide about E after the central bank has set the amount of reserves R to be provided to the system. Having raised their uninsured finance, they choose their optimal level of deposits and loans, taking the market-clearing interest rate i as given.

To formalize, the simplified bank's balance sheet constraint takes the form

$$L + R + A = D + P + E, \text{ or } \; L \leq E + (1 - \varphi)D, \tag{1}$$

where φ represents the required reserve ratio on deposits. Moreover, write the downward-sloping loan demand as

$$L^D = a - br. \tag{2}$$

Then, the separating equilibrium has the following characteristics (see Stein, 1998, for more details). Type B bank maximizes its profit by lending at the first-best level L^B:

$$L^B = (a - bi)/2. \tag{3}$$

These loans are financed fully by raising uninsured external finance, $E^B = L^B$, in order to avoid the reserve tax φ on deposits. On the other hand, a type G bank will raise an amount of external finance $E^G < E^B$ and also provide less additional lending than a type B bank, $L^G = L^B - Z$. Thus,

$$E^G = L^B - Z - D^G(1 - \varphi). \tag{4}$$

The incentive constraint ensuring that a type B bank will not mimic the behaviour of a type G bank is that the gain obtained from issuing higher-priced equity should not exceed

[1]This reflects the intuitive fact that for borrowers it is usually costly (in terms of information) to change to another bank, which leaves the bank with some power over its customers.

the loss in terms of foregone profits when following type's G strategy. In equilibrium, the constraint holds as an equality:

$$Z^2/b + \varphi i D^G = I E^G, \tag{5}$$

where the left-hand side represents the costs incurred when either reducing lending by Z or raising new funds D^G in the deposit market.When a type G bank has chosen a level for E^G, the optimal trade-off between reduced lending Z and new deposit funds D^G implies setting Z as:[2]

$$Z = \varphi i b/2(1-\varphi). \tag{6}$$

Then, the demand for deposits of a type G bank obtains by substituting for Z and E^G in (5):

$$D^G = (Ia/2 - Ibi/(2(1-\varphi)) - i^2\varphi^2 b/(4(1-\varphi)^2))/(\varphi i + I(1-\varphi)). \tag{7}$$

Finally, given the supply of reserves in the system, the total supply of deposits is given by R/φ and the interest rate i is the solution to:

$$R/\varphi = (Ia/2 - Ibi/(2(1-\varphi)) - i^2\varphi^2 b/(4(1-\varphi)^2))/(\varphi i + I(1-\varphi)). \tag{8}$$

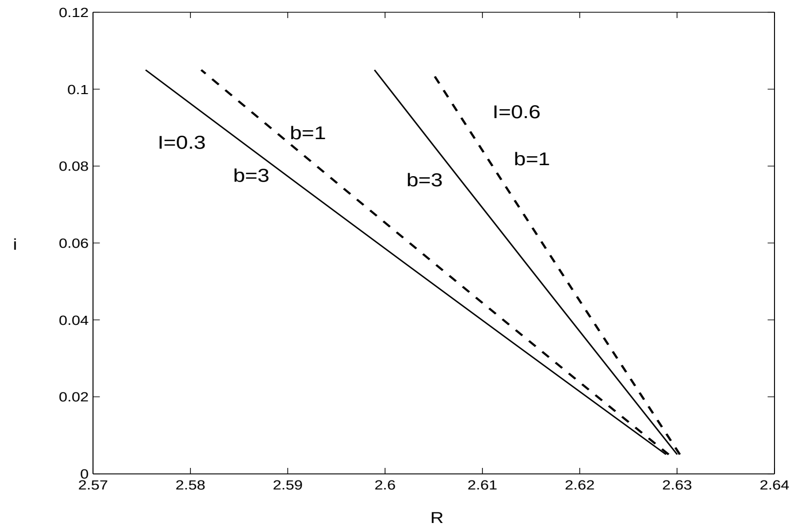
It is easily seen that the interest rate is negatively related to the amount of reserves provided by the central bank. So, indirectly, if the central bank can control the amount of reserves provided to the financial system, it can also control the interest rate.

In this model, the banks' specific exposure to asymmetric information implies cross-sectional differences in lending reactions to monetary policy changes. From equation (6) and (8) we can derive the following results: (i) if we assume $E^B > 0$, then a type G's lending is sensitive to the availability of reserves, $dL^G/dR > 0$; (ii) moreover, a type G' s lending reaction depends on the degree of information asymmetry, $d^2L^G/dRdI > 0$, i.e. the higher the exposure to information asymmetry, the larger the resulting lending reaction; (iii) when loan demand is relatively inelastic, the lending reaction is larger, $d^2L^G/dRdb < 0$; and finally, (iv) banks facing a higher degree of informational asymmetry contract their lending more strongly after monetary tightening when facing a relatively inelastic loan demand, $d^3L^G/dRdbdA > 0$. Figure 1 illustrates the results by depicting the relationship between interest rates and reserves for various model parameter settings. The effect of a reserve cut on interest rates is higher with a higher degree of information asymmetry I and a lower elasticity of loan demand b.

The empirical assessment of the model's predictions is complicated by the fact that, generally, a bank's particular type and also its exposure to asymmetric information is not directly observable. Therefore, bank-specific variables like the size, the liquidity share or the degree of capitalization have been used as proxies in empirical investigations. Indeed, using individual bank data Kashyap and Stein (1995 and 2000) find evidence in favour of the bank lending channel, whereby smaller banks contract their lending by a bigger extent than large banks do after a monetary tightening. Moreover, among the smaller banks in the sample, the effects of monetary policy are stronger for those who have a lower liquidity ratio. Additionally, Campello (2002) finds that internal capital markets in financial

[2]For a given level of E^G and L^B, a decrease in Z implies raising an additional amount of $D^G = Z/(1-\varphi)$. The optimal trade-off between both alternatives minimizes the cost of substitution $C = Z^2/b - \varphi i Z/(1-\varphi)$.

Figure 1: Monetary policy and interest rates. The graph is obtained when assuming a reserve ratio of 5%, $\varphi = 0.05$, and setting $a = 100$.



conglomerates alleviate credit constraints or the exposure to asymmetric information in particular for small affiliated banks. For European countries, however, empirical results so far have been more ambiguous. While de Bondt (1999), using BankScope data, finds evidence for a lending channel characterized by the size and the liquidity strength in Germany, the Netherlands and partly for Belgium, France and Italy (and no evidence for the UK), Favero et al. (1999) do not find such evidence during the period of liquidity tightening in 1992. According to their results, small European banks offset the effects of monetary policy by using excess liquidity to shield their loan portfolios. The results in Ehrmann et al. (2003), finally, document that in the largest euro area countries, the banks' size is not the key characteristic that determines their lending reaction. Rather, it is the liquidity share that matters. A similar result is found in Kaufmann (2003) for Austria in particular. In the cases where a bank-specific characteristic matters, it is the liquidity share that characterizes the lending channel. All in all, however, the inconsistent evidence obtained from the results might also reflect the possibility that size, liquidity or capitalization are not the adequate variables to proxy the exposure of European banks to asymmetric information, assuming they are exposed at all. Therefore, in the empirical investigation below, we treat bank-specific exposure to asymmetric information as unobservable and define a bank-specific indicator which classifies each bank according to its lending reaction. In particular, this group-specific indicator is not defined a priori; rather, it is estimated along with the model parameters. In the last section of the paper, we report on the improvements in terms of inference and forecasting performance we achieve when using the latent-group specification rather than pre-classifying the banks according to their relative size.

In addition to the cross-sectional differences in bank lending reaction, the model is also able to explain changing lending reactions over time. One might well imagine that the loan demand elasticity faced by banks might change over time according to the state of the economy. During periods of good economic performance and/or in periods where liquidity is not restricted, it might be easier for borrowers to get substitute finance for bank loans (e.g. through retained earnings or securities issues) while this might be more difficult in periods of subdued economic performance or when liquidity constraints are tight in the banking system. The first situation would correspond to the Walrasian equilibrium regime obtained in Azariadis and Smith (1998) in which incentive constraints (necessary to cope with adverse selection on the borrowers' side) are compatible with the full-information allocation of credit. The authors show that adverse selection creates an indeterminacy of equilibrium and in particular many equilibria that show recurrent transitions between the Walrasian credit allocation regime and a regime of credit rationing that is accompanied by cyclical contractions and declining interest rates. This motivates our intention to include a potentially asymmetric effect of monetary policy over time according to the economic state or the tightness of liquidity constraints in the banking system. As the changing economic state is typically not observed with certainty, we will model it by introducing (additionally) a latent state indicator capturing the time-varying nature of monetary policy effects.

3 The model and its estimation

3.1 Model formulation

The econometric investigation of the model's prediction is based on an extended version of a reduced form equation also used in previous empirical literature (see Kashyap and Stein, 1995 and de Bondt, 1999). New lending of bank i, $i = 1, \ldots, N$, is proxied by the (quarterly) growth rate in total loans, $\{y_{it}\}, t = 1, \ldots, T$, and is assumed to react bank-specifically and differently over time to interest rate changes:

$$
\begin{aligned}
y_{it} \quad = \quad & \alpha_0 + \sum_{j=1}^{3} \alpha_j D_{jt} + \alpha_4 \mathrm{dy}_t + \alpha_5 \mathrm{dp}_t + \sum_{j=1}^{p} \alpha_{5+j} y_{i,t-j} + \\
& \sum_{j=1}^{q} \beta_{S_i,j}^{G} \mathrm{dir}_{t-j} + \sum_{j=1}^{q} \beta_{S_i,j}^{R} (I_t - 1) \mathrm{dir}_{t-j} + \varepsilon_{it}. \qquad (9)
\end{aligned}
$$

The variables dy_t and dp_t stand for the GDP growth rate and the inflation rate (in percentage terms, computed as 100 times the difference of the logarithmic level), respectively. These two variables are included to control for the overall demand situation in the economy and for the growth rate in the nominal loan level, respectively. dir_t represents the first difference of the 3-month Austrian interest rate, which is our measure for monetary policy.[3] We only include lagged values of the interest rate change to comply with the standard identification made in related literature investigating monetary policy effects where it is assumed that policy moves affect real variables only with a lag while policy itself may react contemporaneously with developments in real variables. Moreover, rather than taking a policy shock (that would have to be identified first) as a measure for monetary policy, we assume that inflation expectations do not react instantaneously and that,

[3] Over the observation period, the Austrian schilling was pegged to the German mark and thus German monetary policy, reflected in German interest rates, was relevant for Austria. Nevertheless, we use the Austrian interest rate because the correlation between both rates is very high, in particular above 0.9 for the differenced rates.

therefore, monetary policy is reflected in short-term interest rate moves. Finally, $D_{j,t}$, $j = 1, 2, 3$, is a set of quarterly dummy variables that capture the seasonality in our data.

The model additionally includes two latent variables, S_i and I_t. S_i, $i = 1, \ldots, N$, is the group indicator for bank i and takes on one out of K distinct values, $\{1, \ldots, K\}$. As such, it is not observable a priori and the group indicator of bank i will be estimated along with the model parameters. The K different bank groups are characterized by their different response in bank lending reaction to interest rate changes. This is captured by the vector $\beta^G_{S_i} = (\beta^G_{S_i,1}, \ldots, \beta^G_{S_i,q})$, which takes on one out of K values, depending on the group bank i is classified in, $\beta^G_{S_i} = \beta^G_k$ iff $S_i = k$. The K different vectors thus capture the cross-sectional dimension of the asymmetry in the bank lending reaction. This specification relates to the switching regression or latent class model, where the banks form K different groups having different, but fixed mean reactions. An extension not applied in the present paper would be to assume random effects for each group.

The second latent state variable, I_t, captures the state of the economy in period t. We will assume two states, one in which $I_t = 1$ and one in which $I_t = 0$. If we assume interest rate changes to have a negative effect on bank lending, then these effects will be larger (in absolute terms) when $I_t = 0$ than when $I_t = 1$. Thus, the interest rate effect is $\beta^G_{S_i}$ iff $I_t = 1$ and $\beta^G_{S_i} - \beta^R_{S_i}$ iff $I_t = 0$. For S_i we do not assume to know a priori I_t. Rather, it is part of the model estimation. Note that switching state effect is modelled as being group-specific.

To complete the model specification, we formulate a probabilistic model for each of the latent state variables, which will turn out to be the prior distributions of the Bayesian estimation we pursue in the following. A priori, we assume that the probability of each bank to belong to group k is equal to the relative size η_k of group k:

$$Pr(S_i = k) = \eta_k. \tag{10}$$

For the regime indicator, we assume a priori that the probability of being in state 1 or 0 in t depends on which state was prevailing in $t - 1$:

$$\begin{aligned} Pr(I_t = 1 | I_{t-1} = 1) &= \xi_{11}, \\ Pr(I_t = 0 | I_{t-1} = 0) &= \xi_{00}. \end{aligned} \tag{11}$$

From this, obviously, $Pr(I_t = 0|I_{t-1} = 1) = \xi_{10} = 1 - \xi_{11}$ and $Pr(I_t = 1|I_{t-1} = 0) = \xi_{01} = 1 - \xi_{00}$. This is the Markov switching prior that has been commonly applied in this context (Hamilton, 1989). The group sizes in $\eta = (\eta_1, \ldots, \eta_k)$, which also sum to 1, and the transition matrix $\xi = (\xi_{00}, \xi_{01}, \xi_{10}, \xi_{11})$ are assumed to be unknown and are part of the model estimation.

Finally, we need to specify the error term ε_{it} in (9). One possibility is to assume iid normal errors with homogeneous variance: $\varepsilon_{it} \sim N(0, \sigma^2)$. Here, as an alternative, we consider conditional error variance heterogeneity:

$$\varepsilon_{it} | \lambda_i \sim N(0, \sigma_i^2), \quad \sigma_i^2 = \lambda_i^{-1} \sigma^2,$$

where the weight λ_i increases or decreases the "overall" variance σ^2 for each bank. By assuming a gamma prior on λ_i,

$$\lambda_i \sim G(\nu/2, \nu/2), \tag{12}$$

marginally, the error term ε_{it} in (9) follows a t_ν-distribution.

An interesting aspect of the model is that the one-step ahead predictive distribution $f(y_{it}|y^{t-1},\cdot)$ of y_{it}, where the unknown group indicator S_i and the indicator $I^{t-1} = (I_0, I_1, \ldots, I_{t-1})$ are integrated out, is a mixture of t_ν-distributions with an increasing number of components.

3.2 Bayesian estimation using MCMC

First, we introduce some convenient notation to facilitate the exposition of the estimation method. Note that the effect of the constant, the dummies, the GDP growth rate and the inflation rate as well as the lagged endogenous variables in model (9) are *fixed* in the sense that a change in these variables affects y_{it} in the same way for all banks. All these variables are gathered in the vector X^1_{it}, $X^1_{it} = (1, D_{1t}, D_{2t}, D_{3t}, \mathrm{dy}_t, \mathrm{dp}_t, y_{i,t-1}, \ldots, y_{i,t-p})$. The variable dir_t and its lagged values represent the *group-specific* effects, i.e. a change in the interest rate is thought to affect y_{it} differently across banks depending on which group bank i falls into. They also represent the *state-specific* effects, whereby the impact of interest rate changes depends on the regime prevailing in t. Define $X^2_{it} = (\mathrm{dir}_{t-1} \ldots \mathrm{dir}_{t-q})$, then model (9) can compactly be written:

$$y_{it} = X^1_{it}\alpha + X^2_{it}\left(\beta^G_{S_i} + \beta^R_{S_i}(I_t - 1)\right) + \varepsilon_{it}, \tag{13}$$

where $\alpha = (\alpha_0, \ldots, \alpha_{5+p})$, $\beta^G_{S_i} = (\beta^G_{S_i,1}, \ldots, \beta^G_{S_i,q})$ and $\beta^R_{S_i} = (\beta^R_{S_i,1}, \ldots, \beta^R_{S_i,q})$ gather the parameters of the fixed, group- and state-specific effects, respectively.

Given the data, the estimation of the model yields an inference on all model parameters, i.e. on the regression parameters α, $\beta^G_1, \ldots, \beta^G_K$, $\beta^R_1, \ldots, \beta^R_K$, on the variance σ^2, and on the group probabilities η of the group indicator S_i and the transition matrix ξ of the state indicator I_t as well. All these parameters are summarized in $\theta = (\alpha, \beta^G_1, \ldots, \beta^G_K, \beta^R_1, \ldots, \beta^R_K, \sigma^2, \eta, \xi)$. We also have to draw an inference on the latent state variable I_t, the latent group indicators S_i and the latent weights λ_i, and therefore, we will treat these variables as random as well. This leads to the *augmented* parameter vector $\psi = (\theta, S^N, \lambda^N, I^T)$, with the sequences $S^N = (S_1, \ldots, S_N)$, $\lambda^N = (\lambda_1, \ldots, \lambda_N)$, and $I^T = (I_0, I_1, \ldots, I_T)$. Finally, the information in the data will be denoted in the following way: $y_i = (y_{i1}, \ldots, y_{iT})$ gathers all observations of bank i. y_i^{t-1} and y_i^t denote observations of bank i up to time $t-1$ and t, respectively. Last, $y^N = (y_1, \ldots, y_N)$ denotes all observations of all banks.

Due to the presence of the two latent state variables S^N and I^T, the problem is not amenable to maximum likelihood as the marginal likelihood $L(y^N|\theta)$ is not available. Therefore, we apply a Bayesian approach and use MCMC simulation methods to estimate model (13).[4] From Bayes' theorem we obtain the posterior distribution $\pi(\psi|y^N)$ of ψ given all information in the data y^N:

$$\pi(\psi|y^N) \propto \prod_{i=1}^{N}\prod_{t=p+1}^{T} f_N(y_{it}|S_i, \lambda_i, I_t, \alpha, \beta^G_1, \ldots, \beta^G_K, \beta^R_1, \ldots, \beta^R_K, \sigma^2, y_i^{t-1})\pi(\psi), \tag{14}$$

[4]In principle, another possibility would be to approximate the likelihood function using the truncation filter described in Kim and Nelson (1999).

where $f_N(y_{it}|\cdot)$ is the density of the normal distribution with the moments easily derived from (13):

$$E(y_{it}|S_i, \lambda_i, I_t, \alpha, \beta_1^G, \ldots, \beta_K^G, \beta_1^R, \ldots, \beta_K^R, \sigma^2, y_i^{t-1}) = X_{it}^1 \alpha + X_{it}^2 \left(\beta_{S_i}^G + \beta_{S_i}^R (I_t - 1) \right),$$
$$V(y_{it}|S_i, \lambda_i, I_t, \alpha, \beta_1^G, \ldots, \beta_K^G, \beta_1^R, \ldots, \beta_K^R, \sigma^2, y_i^{t-1}) = \sigma^2/\lambda_i.$$

The prior $\pi(\psi)$ is given by:

$$\pi(\psi) = \pi(I^T|\xi)\pi(S^N|\eta)\pi(\lambda^N|\nu)\pi(\theta). \tag{15}$$

The prior distributions of S^N, I^T and λ^N are derived from (10), (11), and (12):

$$\begin{aligned}
\pi(S^N|\eta) &\propto \prod_{k=1}^{K} \eta_k^{\#(S_i=k)} \\
\pi(I^T|\xi) &\propto (\xi_{00})^{\#(I_t=0,I_{t-1}=0)}(1-\xi_{00})^{\#(I_t=1,I_{t-1}=0)} \times \\
&\quad (\xi_{11})^{\#(I_t=1,I_{t-1}=1)}(1-\xi_{11})^{\#(I_t=0,I_{t-1}=1)}. \\
\pi(\lambda^N|\nu) &= \prod_{i=1}^{N} \pi(\lambda_i|\nu).
\end{aligned}$$

The prior $\pi(\theta)$ of θ is user-specific and its specification is commented in appendix A.

Basically, Bayesian estimation by MCMC means sampling from the posterior distribution $\pi(\psi|y^N)$. To this aim we split ψ into seven different blocks in order to sample the parameters of each block from their posterior distribution conditional on the currently sampled values of the other parameters:

1. sample S^N from the conditional distribution $\pi(S^N|\theta, I^T, \lambda^N, y^N)$;
2. sample the group probabilities η from the conditional distribution $\pi(\eta|S^N)$;
3. sample the transition matrix ξ from the conditional distribution $\pi(\xi|I^T)$;
4. sample all model parameters $\alpha, \beta_1^G, \ldots, \beta_K^G, \beta_1^R, \ldots, \beta_K^R$ jointly from the conditional distribution $\pi(\alpha, \beta_1^G, \ldots, \beta_K^G, \beta_1^R, \ldots, \beta_K^R|\sigma^2, S^N, \lambda^N, I^T, y^N)$;
5. sample σ^2 from the conditional distribution $\pi(\sigma^2|\alpha, \beta_1^G, \ldots, \beta_K^G, \beta_1^R, \ldots, \beta_K^R, S^N, \lambda^N, I^T, y^N)$;
6. sample I^T from the conditional distribution $\pi(I^T|\theta, S^N, \lambda^N, y^N)$;
7. sample λ^N from the conditional distribution $\pi(\lambda^N|\theta, S^N, I^T, y^N)$

MCMC sampling proves to be quite attractive here, as any of the required conditional densities arises from standard distribution families that are easy to sample from. For more details, the reader is referred to Appendix B.

3.3 Identification

As it stands, the model in (13) is not identified with respect to the group- and state-specific parameters. Note that the likelihood $f(y^N|\theta)$ is invariant to relabelling the group indicator S_i:

$$\begin{aligned} &f(y^N|\beta_1^G,\ldots,\beta_K^G,\beta_1^R,\ldots,\beta_K^R,\eta_1,\ldots,\eta_K,\alpha,\xi,\sigma^2) = \\ &f(y^N|\beta_{\rho(1)}^G,\ldots,\beta_{\rho(K)}^G,\beta_{\rho(1)}^R,\ldots,\beta_{\rho(K)}^R,\eta_{\rho(1)},\ldots,\eta_{\rho(K)},\alpha,\xi,\sigma^2). \end{aligned} \tag{16}$$

where $\rho(1),\ldots,\rho(K)$ is an arbitrary permutation of $\{1,\ldots,K\}$, i.e. the right-hand side corresponds to the labelling $\tilde{S}_i = \rho(S_i)$.[5] Likewise, the likelihood $f(y^N|\theta)$ is symmetric for certain components due to the arbitrariness of labelling I_t:

$$\begin{aligned} &f(y^N|\beta_1^G,\ldots,\beta_K^G,\beta_1^R,\ldots,\beta_K^R,\eta_1,\ldots,\eta_K,\alpha,\xi_{00},\xi_{11},\sigma^2) = \\ &f(y^N|\beta_1^G-\beta_1^R,\ldots,\beta_K^G-\beta_K^R,-\beta_1^R,\ldots,-\beta_K^R,\eta_1,\ldots,\eta_K,\alpha,\xi_{11},\xi_{00},\sigma^2), \end{aligned} \tag{17}$$

where the right hand side corresponds to the labelling $\tilde{I}_t = 1 - I_t$.

If relevant differences between the two states and the K groups are actually present, then the likelihood exhibits $2K!$ equivalent modes. Invariance, symmetry and multi-modality of the likelihood causes invariance, symmetry and multi-modality of the marginal posterior $\pi(\theta|y^N)$. Identification of the model is then achieved by identifying one of the $2K!$ modal regions of the posterior. As usual, order constraints on group- and state-specific parameters serve as identification constraints.

For the group-specific parameters in model (13), it is, however, not clear a priori which elements of $\beta_{S_i}^G$ discriminate between the groups, as it might well be that some parameters differ between groups but some others do not. Likewise, which elements turn out to be significant in $\beta_{S_i}^R$ is not known a priori either. The relevant restrictions to discriminate between the groups and the states are then obtainable by exploring the unconstrained posterior distribution, i.e. the simulations out of the posterior distributions, through univariate and/or bivariate marginal distributions (see figure 2 below). It turns out that this post-processing reveals whether there are indeed different states and groups (see figure 5), whereby the shape of the posterior distribution reveals additionally the efficient number of groups to model the data (see also Frühwirth-Schnatter and Kaufmann, 2002).

To obtain simulations out of the unconstrained posterior distribution, however, it is necessary to force the sampler to effectively visit each modal region of the posterior distribution by completing it with a random sign switch for $\beta_{S_i}^R$ as in (17) and a random permutation of the labelling as in (16) as well. Without this random permutation, invariance and symmetry of the marginal posterior $\pi(\theta|y^N)$ is often not reproduced in the simulated values, because the sampler might get stuck at one modal region with switches to other modal regions occurring only occasionally. This would make it difficult to compare and evaluate MCMC draws from different runs, to assess convergence and to interpret the posterior density. Therefore, the random permutation sampler introduced in Frühwirth-Schnatter (2001) is extended to estimate the present model (see also Frühwirth-Schnatter and Kaufmann, 2002).

[5] As an example, think of a group specification fulfilling the restriction $\beta_{1,2} < \beta_{2,2} < \beta_{3,2}$ as it will be the case in the empirical investigation. Then, reordering the groups according to $\beta_{1,2} > \beta_{2,2} > \beta_{3,2}$, i.e. choosing $\rho = (3,2,1)$, does not change the likelihood.

4 Results

4.1 The data

To estimate model (9) for the Austrian banking system, we use quarterly individual bank balance sheet data covering the period 1990Q1 through 1998Q4. They stem from the monthly bank statements reported to the Austrian central bank (OeNB) by each individual bank. The initial sample covers all banks present at the end of the observation period. The computer system of the OeNB compiles the database in such a way that the balance sheets of banks involved in a merger during the observation period are consolidated and reported under the absorbing banks from the period when the merger took place onwards. The absorbed banks are dropped from the sample during the compilation. Therefore, some of the remaining banks' balance sheet series, in particular the loans series or the asset total, display breaks in periods when mergers took place. The original bank sample includes 934 banks, of which 182 were involved in mergers in the course of which 268 banks were overtaken. Most mergers are small-scale mergers, where small local banks joined together to improve effectiveness and cost efficiency (Mooslechner, 1989 and 1995), while regional and large-scale mergers are the exception during the observation period. To keep as much information as possible in the data, we will treat the outlying values in the loans growth rate series due to these mergers as missing values and replace them by an estimate given all information in the data (see appendix C). The original sample has also missing values at the beginning of the observation period. These refer to 130 banks that were newly founded during the 1990s. As the estimation is done for a balanced sample, these banks are excluded from the dataset.

Additionally, statistical outliers were identified as observations for each bank's loan growth rate series lying outside the interval of +/-5 times the interquartile range around the median. As for the outliers due to mergers, we treat them as missing values. Finally, a preliminary investigation revealed some banks having very volatile loan series not displaying the usual pattern of most commercial banks. It turned out that these banks pertain mainly to two groups, specialized leasing and foreign banks. The first group specializes in leasing contracts (mainly car financing) and therefore their lending is mainly related to the launch of new car series or changes in fiscal regimes. Specialized foreign banks' business activity on the other hand, might depend more heavily on the international financial situation or on the financial situation faced by their Head Office abroad rather than on Austrian monetary policy. Therefore, these (37) banks are removed from the sample as we think that the information content in these banks' series to infer about monetary policy effects on bank lending is very limited.

A total of 767 banks remain in the sample for the analysis, covering nearly 65% of the banking sector at the beginning and and 87% at the end of the 1990s. Table 1 presents some summary statistics on the balanced sample for the first quarter of 1996. 29 banks account for 78% of the banking sector's asset total, while the 29 smallest banks have just a negligible share. Even the 50% relative smallest banks account for only 3% of the banking sector. Note also that the span of the balance sheet total is much larger for big than for small banks. Interestingly, the table also reveals that on average, large banks are more illiquid than small banks, whereby the span of the liquidity share is again larger for big banks than for small banks (see the second panel of the table). The bottom panel of the table, finally, reveals that the distribution of loans reflects approximately the asset

Table 1: Summary statistics of the balanced data set (in million euro), 1996Q1. The 95% interval is measured by the bottom and the top 2.5th percentile, respectively.

	Total	absolute size		relative size	
		above 1,601 asset total	below 11 asset total	above 97.5th percentile	below 50.0th percentile
Number of banks	767	29	29	21	385
Total assets	304,437	238,108	206	220,467	10,291
Asset market share		0.78	0.00	0.72	0.03
Average size	397	8,211	7	10,498	27
95% interval	9/2,613	1,841/46,084	1/11	2,613/46,084	7/51
Average liquidity share[1]	20.54	12.54	22.86	12.86	22.87
95% interval	6.41/38.72	1.80/31.34	11.18/34.19	1.80/29.06	11.97/38.06
Total loans[2] (market share)	144374	0.75	0.00	0.67	0.04
Average loan share	53.57	54.99	49.80	50.68	51.09
95% interval	25.69/77.94	24.95/86.34	23.54/76.60	25.33/86.34	25.52/77.64

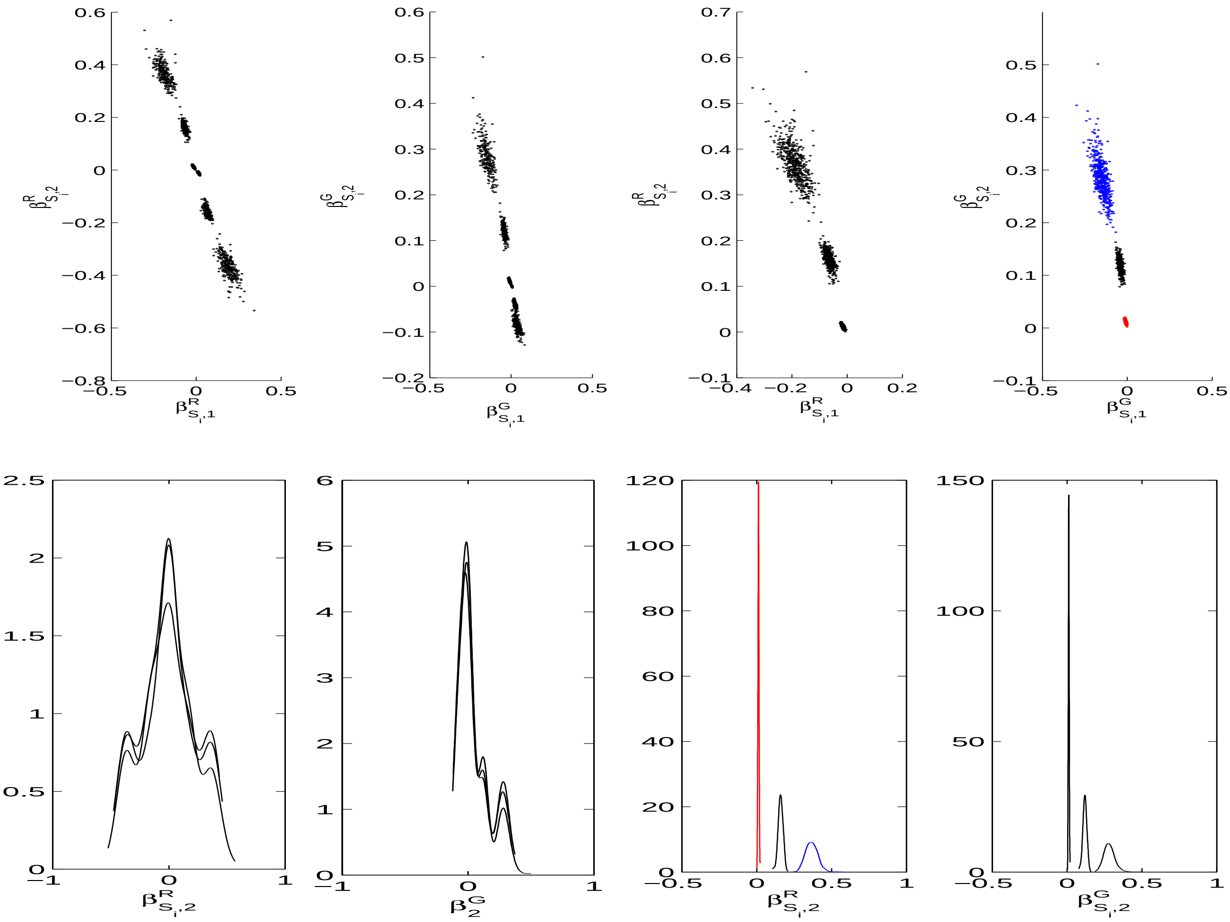
[1] Cash, short-term interbank deposits and government securities divided by the asset total.

[2] Loans to non-financial corporations and households.

distribution of the banking sector. The credit market share of large banks amounts to 75% while small banks' market share is only minor. Interestingly, the mean loan share is higher for large banks, but not very much higher than for small banks.

These features reflect some characteristics of the Austrian banking sector, which is mainly populated by small banks (around 90% of the banks) that are embedded within two- or three-tier systems and do business primarily on a local scale. This alleviates their exposure to liquidity constraints during periods of restrictive monetary policy due to the possibility of refinancing at the central institutions, which themselves represent some of the largest banks in Austria. What follows is that the size of a bank might not be decisive for its lending reaction to monetary policy moves. A feature that is linked with the predominance of small banks doing business locally is the emergence of a "house bank"" system - with firms or households relying on a single bank to effect most of their financial and financing transactions - that reduces potential informational asymmetries. These close customer relationships also apply to large banks as they, too, offer the whole spectrum of financial services to their customers. A "traditional" bank lending channel might therefore be unobservable, as banks are willing to retain/service their most captive customers even during periods of tight monetary policy, given the superior, relatively higher-rewarding (in terms of profits) customer-specific information accumulated over time. Braumann (2002) documents such a "financial decelerator" for Austria. He finds in particular that interest rate margins are widening when credit growth is high and narrowing in a downturn. This is consistent with the strategy of intertemporal smoothing (Allen and Gale, 2000) aiming at long-term rather than short-term profits, whereby reserves are accumulated during good times and liquidated during bad times.

Figure 2: $K = 3$, Scatter plots of the state- and group-specific simulated parameter values (top) and marginal distribution of $\beta^R_{S_i,2}$ and $\beta^G_{S_i,2}$ (bottom). Panel (a) and (b) are simulated values of the random permutation sampler, panel (c) and (d) are the reordered simulated values according to the restrictions (18) and (19). $\beta^R_{S_i,1}, \beta^G_{S_i,1}$ and $\beta^R_{S_i,2}, \beta^G_{S_i,2}$ relate to the coefficient on the first and second lag of the interest rate change, respectively.



(a) (b) (c) (d)

4.2 Specification and identification

Various specifications of equation (9) were estimated in a first round combining the values for $q = 1, \ldots, 4$ and $p = 1, \ldots, 5$ and setting $K = 3$. It turned out that the last two lags of the interest rate changes as well as autoregressive lags of order higher than 5 were not significant. Thus, our final specification sets $q = 2$ and $p = 5$. The number of groups, $K = 3$, was confirmed by a sensitivity analysis comparing the results obtained for alternatively assuming a lower ($K = 2$) and a higher ($K = 4$) number of groups (see section 5.2).

We obtain the posterior inference by iterating over the sampler 18,000 times, deleting the first 8,000 to remove dependence on initial values. The random permutation sampler is used to explore the unconstrained posterior distribution, as a priori no information is available to discriminate between the different groups and because we do not know with which state-dependent parameter we can identify the state indicator, either.

The output of the random permutation sampler for the state- and group-specific parameters is depicted in figure 2, panel (a) and (b). In the upper two graphs, the effect of the first lag of the interest rate change is plotted against the effect of the second lag of it. The lower two graphs reproduce the marginal posterior of $\beta^R_{S_i,2}$ and $\beta^G_{S_i,2}$, respectively. As expected, the random sign switching and group permutation yield marginal posteriors that are symmetric around zero for $\beta^R_{S_i}$ and that are nearly identical across the groups for $\beta^R_{S_i}$ and $\beta^G_{S_i}$.

Panel (a) confirms that the state-specific effect is significant and identifiable by means of either $\beta^R_{\cdot,1}$ or $\beta^R_{\cdot,2}$ (both are mirrored around zero). In a first step, we therefore choose to identify the state by means of $\beta^R_{\cdot,2}$, which means that we permute (or reorder) accordingly the simulated state- and group-specific parameter vectors if the restriction $\beta^R_{\bar{k},2} > 0$ is violated, where $\bar{k}$ is the group corresponding to $\max(\text{abs}(\beta^R_{\cdot,2}))$:[6]

$$
\begin{array}{ll}
\text{if } \beta^R_{\bar{k},2} < 0 & \left\{ \begin{array}{lcl} \beta^G_{k\cdot} & := & \beta^G_{k\cdot} - \beta^R_{k\cdot},\ k = 1, \ldots, K, \\ \beta^R_{k\cdot} & := & -\beta^R_{k\cdot}, \\ \xi_{ij} & := & \xi_{1-i,1-j},\ i, j = 0, 1 \\ I_t & := & 1 - I_t,\ t = 0, \ldots, T \end{array} \right. \\
\text{if } \beta^R_{\bar{k},2} \geq 0 & \text{no permutation.}
\end{array}
\tag{18}
$$

The result of this first reordering step is reproduced by the same scatter plots in the top graphs of panel (c) and (d), figure 2. Now, the three groups of banks are identifiable (see panel (d)) by means of $\beta^G_{S_i,2}$:

$$\beta^G_{1,2} < \beta^G_{2,2} < \beta^G_{3,2}. \tag{19}$$

Note that, alternatively, we might also identify the groups by means of $\beta^R_{S_i}$. As before, if the simulated parameter values of the retained iterations violate the restriction, the group-specific parameter vectors, the simulated group probabilities and the group indicator as well are reordered accordingly.[7] The bottom graphs of panel (c) and (d) display the marginal posterior distribution we obtain for the identified state- and group-specific parameters $\beta^R_{S_i,2}$ and $\beta^G_{S_i,2}$, respectively. Similar graphs are obtained for $\beta^R_{S_i,1}$ and $\beta^G_{S_i,1}$, but are not displayed here in order to save space.

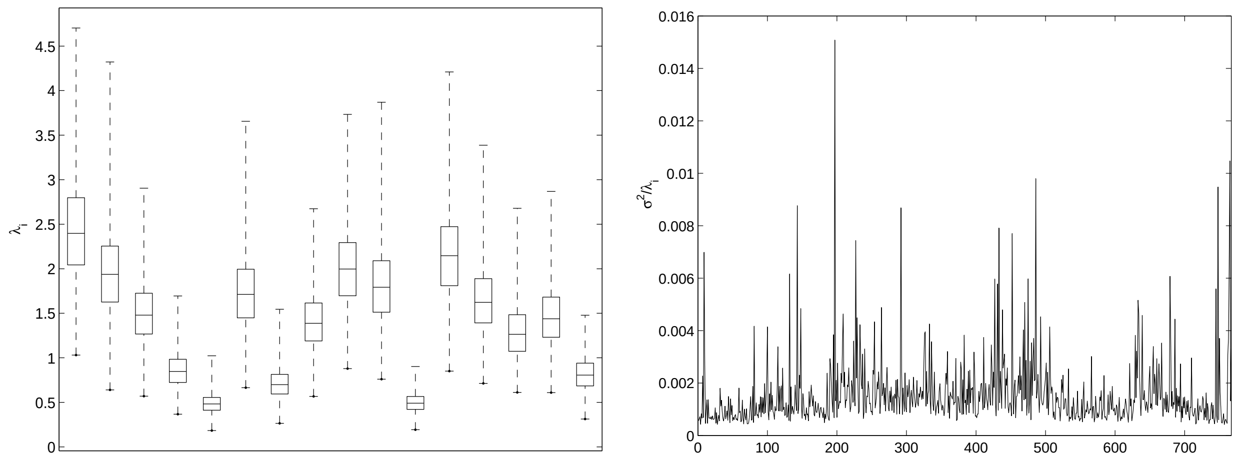
To finally obtain the inference on the posterior distribution of the group- and state-specific parameters we simply average over the ordered simulated values to obtain the mean and estimate the confidence interval by computing the shortest interval covering 95% of the simulated values (see table 2). Likewise, the posterior inference on the total effect of interest rate changes is obtained by averaging over the sum of the respective parameters for the mean and computing the shortest 95% interval for the confidence interval. The next section discusses the inference and gives an interpretation of the results.

A look at figure 3 closes this section. Panel (a) displays boxplots of selected λ_i's, the unit-specific variance weight. The box delimits the lower and the upper quartile value with the median in the midst and the dashed lines show the extent of the rest of the simulated values. We can observe that, indeed, the λ_i's differ and that small values are estimated with more precision than larger ones. The unit-specific mean variances are depicted in panel (b) of figure 3.

[6] The model specification assumes that the state indicator switches at the same time for all groups. After estimation with the random permutation sampler, the identification is based on the simulated parameter value that is most distinctively mirrored around zero.

[7] If e.g. $\beta^G_{1,2} > \beta^G_{2,2} > \beta^G_{3,2}$, the appropriate reordering for the parameter vectors and for the group indicator would be $\rho = (3, 2, 1)$.

Figure 3: $K = 3$, boxplot of selected λ_i's, panel (a), and mean posterior unit-specific variance, σ^2/λ_i, panel (b).



(a) (b)

4.3 Interpretation

The inference on the marginal posterior distribution of the state- and group-specific parameters is presented in table 2, which summarizes mean and confidence interval of the parameters of interest. The three identified groups emerge clearly from the table. The first group contains most of the banks (711) and also the large ones (see the average size of the group). The second and third group contain mainly small and very small banks, respectively. Note also that the average liquidity share of the second and third groups are about 25% and 72% higher than for the first group's banks. When $I_t = 0$, the regime that prevailed during most of the observation period (see figure 4), the total effect of interest rate changes on bank lending is strongest for the banks of the third group. A 100 basis point-increase would reduce lending of these banks by 4.6%. The effect on lending diminishes with increasing average size, which is consistent with the model's prediction in section 2, if we take average size as the characteristic that reflects the groups' exposure to asymmetric information. Moreover, changing market conditions effect stronger changes in lending reactions for banks with a higher asymmetric information exposure. Indeed, group one's lending reaction turns from slightly positive to insignificant when I_t switches from 0 to 1, while the third group's banks reaction turns from significantly negative to significantly quite positive and banks of group two lie in between.

Table 2: $K = 3$: Mean estimates (with confidence interval) of the group-specific parameters. The confidence interval is estimated by the shortest 95% interval of the simulated parameters.

coefficient	$I_t = 1$			$I_t = 0$					
	$\beta^G_{1\cdot}$	$\beta^G_{2\cdot}$	$\beta^G_{3\cdot}$	$\beta^G_{1\cdot} - \beta^R_{1\cdot}$	$\beta^G_{2\cdot} - \beta^R_{2\cdot}$	$\beta^G_{3\cdot} - \beta^R_{3\cdot}$	$\beta^R_{1\cdot}$	$\beta^R_{2\cdot}$	$\beta^R_{3\cdot}$
dir_{t-1}	-0.008	-0.041	-0.149	0.006	0.026	0.041	-0.015	-0.067	-0.190
	(-0.015 -0.002)	(-0.062 -0.020)	(-0.211 -0.091)	(0.004 0.008)	(0.013 0.039)	(0.010 0.072)	(-0.022 -0.007)	(-0.095 -0.037)	(-0.261 -0.123)
dir_{t-2}	0.012	0.119	0.281	-0.000	-0.041	-0.087	0.012	0.160	0.368
	(0.006 0.017)	(0.091 0.145)	(0.218 0.353)	(-0.002 0.002)	(-0.052 -0.030)	(-0.114 -0.059)	(0.005 0.018)	(0.125 0.192)	(0.289 0.444)
total effect	0.003	0.078	0.132	0.006	-0.015	-0.046			
	(-0.002 0.009)	(0.052 0.102)	(0.073 0.193)	(0.004 0.007)	(-0.025 -0.005)	(-0.070 -0.022)			
number of banks	711	44	12						
average asset total	413.04	116.69	469.28						
(mill. euro)			47.74*						
average liquidity	20.02	25.11	34.44						
(in % of asset total)									
ξ_{00}	0.66								
	(0.46 0.85)								
ξ_{11}	0.32								
	(0.06 0.58)								

* without the largest bank. This bank is one large (regional) savings bank.

[h]

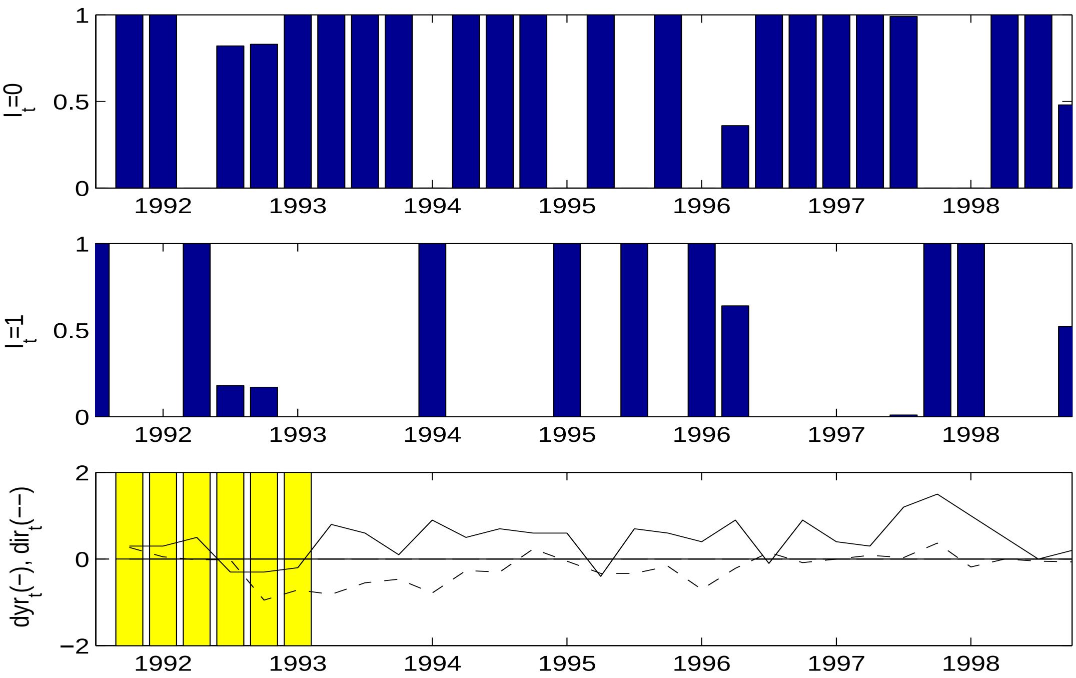
Broadly speaking, the results obtained are consistent with the predictions of the bank lending model presented in section 2 and as such also consistent with previous literature assessing the bank lending channel in the USA (Kashyap and Stein, 1995) and European data (de Bondt, 1999). The distinguishing feature of our results (besides the fact that they report evidence for Austria) is that the banks are not classified a priori according to a bank-specific characteristic but that the relevant grouping is estimated and emerges according to the bank-specific lending reaction to interest rate changes. The evidence documents that discrimination between the groups might be based on the group's average size and/or liquidity share, but it is nevertheless the case that banks of the same size/liquidity share might fall into different groups. At the individual level, the size/liquidity share of a bank, therefore, do not ultimately determine to which group it belongs. Indeed, the bank lending reaction is the same across groups, if we estimate the model by assuming a priori the classification of banks according to their size (see section 5.2 below). This is again consistent with results on the bank lending channel for other European countries (see Ehrmann et al., 2003, and the citations therein) reporting that lending differentials between banks can usually not be explained by the size of a bank.

Nevertheless, only about 7% (56 out of 767) of the banks, which in fact cover only 3.5% of the banking market in terms of the asset total (2% without the largest bank in the third group), form the second and the third group, and this renders the evidence for a bank lending channel rather weak. It is the first group that effectively represents the lending behaviour of Austrian banks. The Austrian economic performance combined with the specificity of the banking sector might be the major factors to explain the very weak lending reaction (0.6% effect of a 100 bps increase) to interest rate changes. During the 1990s, the Austrian economy experienced a relatively strong growth accompanied by continually declining interest rates in the process of convergence to European monetary union (see figure 4, bottom panel). The recessionary period lasting from the last quarter of 1991 through the first quarter of 1993 (marked by the shaded areas in the bottom panel of the figure)[8] turned out to be quite mild in comparison to what other major European countries experienced. Falling interest rates throughout the period, on the other hand, show that apparently there were no inflationary threats that would put pressures on monetary policy and liquidity in the banking system. This is one factor that might explain that bank lending has apparently not been driven by interest rate changes during the observation period.

However, even if monetary policy had been more restrictive, it is doubtful whether interest rate effects would have been much larger than estimated. The specificities of the banking sector described in section 4.1 are typical for a bank-based financial system in which close customer relationships develop when firms and households rely on a house bank to effect financial and financing transactions. These relationships alleviate the asymmetric information problem (on the borrowers' as well as on the depositors' side) that small banks are more exposed to according to the bank lending view. Long-lasting customer relationship lead to accumulated, detailed mutual information, which in turn leads to a flight-to-quality/captivity effect described in Dell'Ariccia and Marquez (2000). If banks are able to accumulate relatively higher rewarding, private information on customers, the banks' lending reaction to changes in the monetary stance will consist in a loan portfolio shift from less opaque and less bank-dependent customers (i.e. customers that

[8]As no official business cycle turning points are available for Austria, the dating is taken from Kaufmann (2001).

Figure 4: $K = 3$, Posterior state probabilities estimated by averaging over the simulated paths I^T. The bottom panel depicts quarterly GDP growth rates (solid line) and interest rate changes (broken line). The shaded area refers to the recession period.



can credibly communicate their creditworthiness to other lenders) towards more opaque and more bank-dependent customers. We find some first evidence for this behaviour in our results in periods when $I_t = 1$ (figure 4). These periods occur occasionally, during 1992, 1995/1996 and 1997/98, during which the banks of all groups react significantly negatively to interest rate changes after one quarter and significantly positively after half a year. Although the results say nothing about compositional changes, they might however reflect what is observable at the loans' total level when banks consolidate their loan portfolios in a first reaction and then offer again new lending to the retained customer. Moreover, this reaction pattern is consistent with the expansionary lending practices pursued by most banks to gain market shares in the private sector after financial market liberalization had been completed by the mid-1990s and fiscal adjustment was continually retiring bank debt and issuing more bonds (see also Braumann, 2003). Note finally, that again in accordance with the model presented in section 2, the lending reactions are stronger for the group of smaller banks (the second and the third) than for the group of larger banks (the first one).

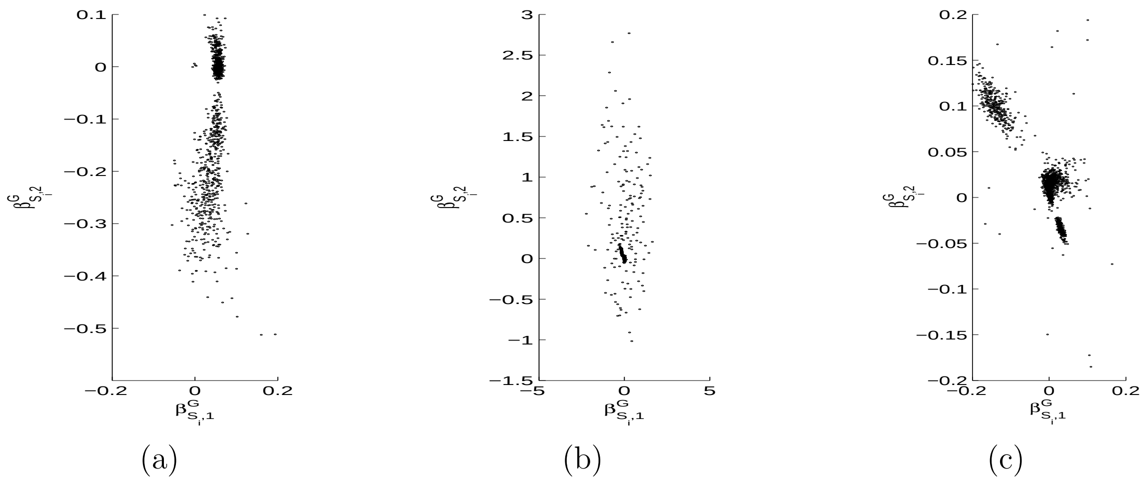
5 Comparative analysis

5.1 Changing the number of groups

As we have seen in the previous section, a graphical inspection of the MCMC output (see figure 2, panel (d)) reveals 3 groups very distinctively. Estimating alternative specifications with $K = 2$ and $K = 4$ confirms our model selection. Figure 5, panel (a) displays the scatter plot of the simulated group-specific parameters when setting $K = 2$. Although two groups can be identified quite distinctively, the very widely spread cluster in the lower part of the picture reveals some potential additional group.

When the number of groups is raised to $K = 4$, on the other hand, it turns out that the scatter plot of the group-specific parameters does not reveal a distinct grouping (see panel (b) of figure 5), in particular a center cluster is recognizable, while a whole range of widely spread values appears to be simulated out of the prior distribution. This means that while iterating over the sampling steps, one of the groups is recurrently redundant such that no bank is classified into it. Magnifying the center cluster (see panel (c)) indeed reveals that in fact only three groups can appropriately be discriminated in the data.

Figure 5: Scatter plots of the group-specific simulated parameter values for $K = 2$, panel (a), and for $K = 4$, panel (b) and (c). In panel (c), the axes are adjusted to magnify the centered cluster in panel (b). $\beta^G_{S_i,1}$ and $\beta^G_{S_i,2}$ relate to the first and second lag of the interest rate change, respectively.



5.2 Classifying banks a priori into 3 groups

In related literature on the bank lending channel (Kashyap and Stein (1995, 2000)), the traditional approach has been to first classify the banks into groups according to their relative size and then estimate the lending equation (9) for each group separately either at the aggregate or at the disaggregate level. We might compare the results discussed in section 4 with the ones obtained when taking the traditional approach. In our setup, this amounts to fixing S_i for each bank and excluding the first two steps of the sampler described in subsection 3.2 for the estimation. The three size classes are defined using the empirical size distribution of the bank sample. Accordingly, a small (large) bank is one that belongs to the bottom 15th (top 10th) percentile. To exemplify, the relevant limits for the 4th quarter of 1998 are depicted in figure 6. As the classification is performed for each quarter, some banks (those at the limits) switch class several times during the observation period. These are classified according to the class in which they fall most of the time.

Figure 6: Empirical size distribution of the banks sample as of 1998, 4th quarter.

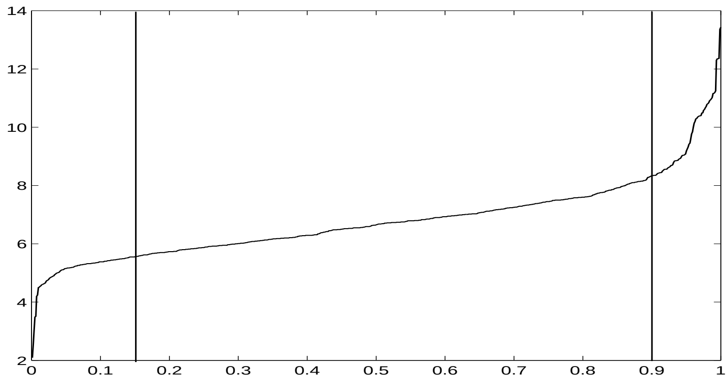


Table 3: $K = 3$ with a priori classification of banks by means of their relative size: Mean estimates of the group-specific parameters. The confidence interval is estimated by the shortest 95% interval. When the groups are fixed a priori, there is no evidence of time switching effects.

coeff.	$\beta^G_{1\cdot}$	$\beta^G_{2\cdot}$	$\beta^G_{3\cdot}$
dir_{t-1}	0.006	0.005	0.002
	(-0.073 0.100)	(-0.037 0.049)	(-0.104 0.107)
number of banks	113	572	79
average size	13.11	71.71	3312.91
average liquidity	25.00	20.49	14.52

Table 3 contains the estimates of the group-specific parameters under the fixed classification. Interestingly, it turns out that no switching effects are present and, moreover, even the first lag of interest rate changes is insignificant in this specification. If we take the mean estimate, the reaction of lending to interest rate changes is also not significantly different between the groups. These results are in line with the ones documented in Kaufmann (2003) where the size effect in the bank lending reaction is not significant when estimated within a pooled panel including interaction terms between interest rate changes and bank characteristics.

5.3 Out-of-sample forecasting performance

We use additional quarterly data for the years 1999 to 2001 to evaluate the models' forecasting performance over a one-period (one quarter) to a twelve-period (three years) ahead horizon. We compare our preferred model $K = 3$ with the ones discussed in the previous subsections, in particular the $K = 2$, $K = 3$ and the a-priori fixed groups specification. For all banks i, $i = 1, \dots, N$, and all forecasting horizons h, $h = 1, \dots, 12$, evaluation is based on the stochastic properties of the forecasting errors $\varepsilon_{i,T+h|T}$, defined by $\varepsilon_{i,T+h|T} = y_{i,T+h|T} - y_{i,T+h}$, where $y_{i,T+h}$ is the actual observation and $y_{i,T+h|T}$ is a random forecast drawn from the joint Bayesian forecasting density $\pi(y_{1,T+1}, \dots, y_{1,T+H}, \dots, y_{N,T+1}, \dots, y_{N,T+H}|y^N)$.

A straightforward way to draw M forecasts $y_{i,T+h|T}^{(m)}, m = 1, \ldots, M$, from this density is to use the following recursion:

$$\begin{aligned} y_{i,T+h|T}^{(m)} &= \alpha_0^{(m)} + \sum_{j=1}^{3} \alpha_j^{(m)} D_{j,T+h} + \alpha_4^{(m)} \mathrm{dy}_{T+h} + \alpha_5^{(m)} \mathrm{dp}_{T+h} + \sum_{j=1}^{p} \alpha_{5+j}^{(m)} y_{i,T+h-j|T}^{(m)} + \\ & \sum_{j=1}^{q} \beta_{i,T+h,j}^{(m)} \mathrm{dir}_{T+h-j} + \varepsilon_{i,T+h}^{(m)}, \end{aligned} \tag{20}$$

where $\beta_{i,T+h}^{(m)} = \beta_s^{G,(m)} + \beta_s^{R,(m)}(I_{T+h}^{(m)} - 1)$ with $s = S_i^{(m)}$, and m refers to the mth MCMC parameter draw.

We assume perfect knowledge of the future values of the exogenous variables dy_{T+h}, dp_{T+h}, and dir_{T+h} by basing the forecast on the actual observations, whereas $y_{i,T+h}, \varepsilon_{i,T+h}$ and I_{T+h} are forecasted endogenously. $y_{i,T+h-j|T}^{(m)}$ is equal to the observed value for $j \geq h$, and equal to the actual forecast, otherwise. The actual observations contain no information about future values of the error process, therefore $\varepsilon_{i,T+h}^{(m)} \sim N(0, \sigma^{2,(m)}/\lambda_i^{(m)})$. The future state process I_{T+h} is forecasted endogenously based on the draw $I_{T+h-1}^{(m)}$, where, for $h = 1$, $I_T^{(m)}$ is equal to the mth MCMC draw for I_T. If $I_{T+h-1}^{(m)}$ is equal to 0, then $I_{T+h}^{(m)}$ is sampled from $(\xi_{00}^{(m)}, \xi_{01}^{(m)})$ of the transition matrix $\xi^{(m)}$, otherwise $I_{T+h}^{(m)}$ is sampled from $(\xi_{10}^{(m)}, \xi_{11}^{(m)})$.

To evaluate the models we consider the following aggregate measures:

$$\mathrm{B}_{wh} = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{M} \sum_{m=1}^{M} w_i \varepsilon_{i,T+h|T}^{(m)}, \quad \mathrm{MSE}_{wh} = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{M} \sum_{m=1}^{M} \left(w_i \varepsilon_{i,T+h|T}^{(m)} \right)^2. \tag{21}$$

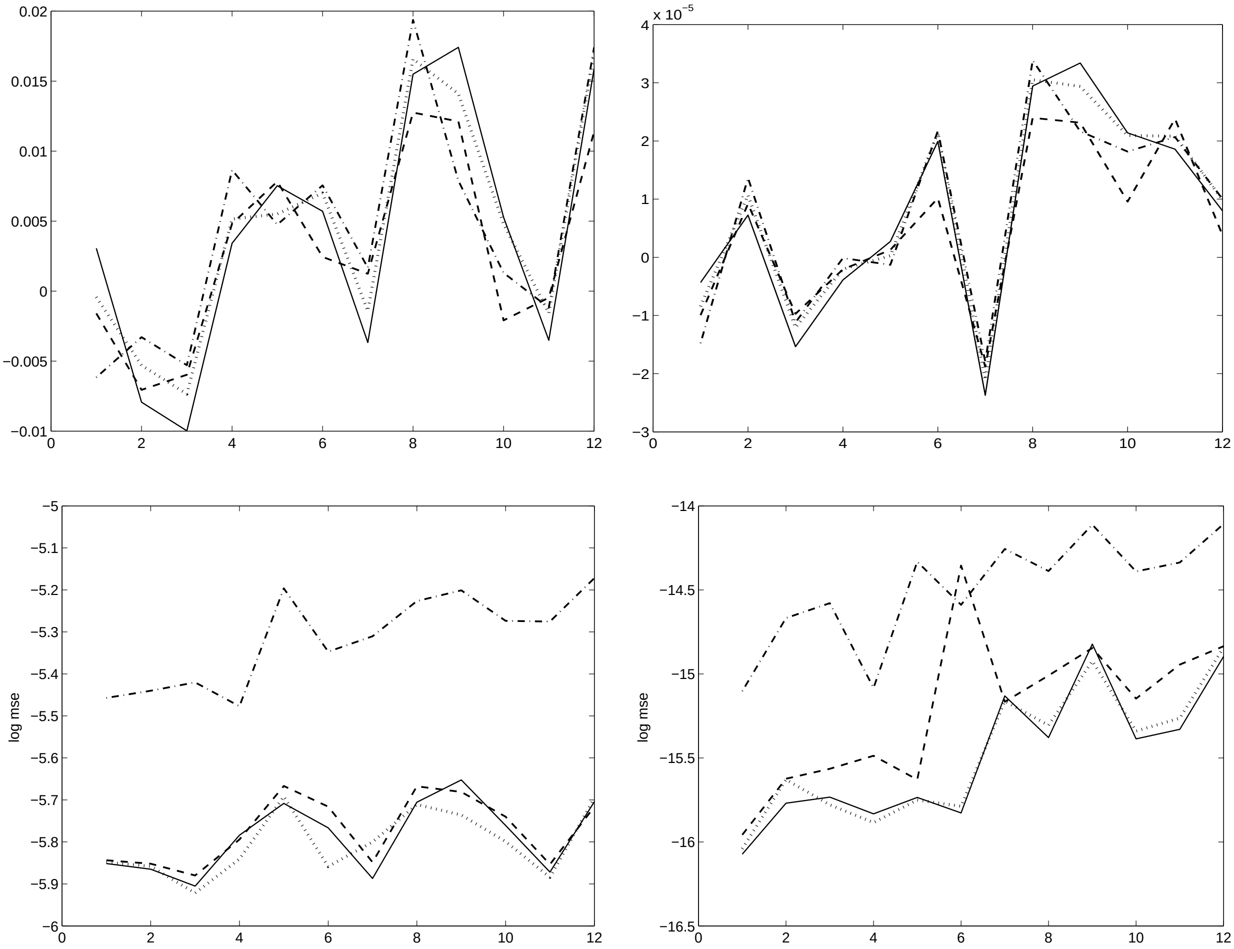
The subscript w refers to a different weighting scheme of the forecast errors. Usually, the measures are based on equally weighted forecast errors, $w_i = 1$. We additionally consider a weighting scheme that takes into account the variability of the time series whereby $w_i = \sqrt{\lambda_i}$, and one that takes into account the relative size of the individual bank, $w_i = \mathrm{size}_i / (\sum_{j=1}^{N} \mathrm{size}_j)$, giving more weight to the forecast errors of large banks.

Figure 7 summarizes the general results graphically, whereby the left-hand side uses unweighted forecast errors and the right-hand side forecast errors weighted by relative bank size.[9] The models do not differ much in their bias at all forecast horizons, irrespective of the weighting scheme. In terms of mean squared errors, however, $K = 3$ with endogenous grouping outperforms clearly the a-priori grouping specification and the $K = 2$ specification. On the other hand, augmenting the number of groups to $K = 4$, does not improve significantly the forecasting performance over the $K = 3$ specification.

Table 4 compares the average performance over all forecast horizons. In terms of mean and mean absolute bias, $K = 2$ performs best regardless of the weighting scheme. In terms of mean squared errors, however, $K = 3$ performs far better than a-priori grouping. On average, the mean squared forecast error of a-priori grouping is 177% higher when the forecast errors are weighted by relative bank size. Also, $K = 3$ performs better than $K = 2$ in general, in particular when forecast errors are weighted by relative bank size the mean squared forecast error is 46% higher on average for $K = 2$. Again, increasing K to $K = 4$ does not improve the forecasting performance significantly.

[9]The results using $\sqrt{\lambda_i}$ as weigths are similar to those using $w_i = 1$. They are therefore not displayed here but available upon request.

Figure 7: Mean bias, top panel, and (logarithmic) mean squared forecast errors, bottom panel, at forecast horizon of one quarter to 12 quarters. Panel (a) is computed with unweighted forecast errors and in panel (b) the forecast errors are weighted by relative bank size. A-priori grouping (dash-dotted), $K = 2$ (dashed), $K = 3$ (solid), $K = 4$ (dotted).



(a) (b)

Table 4: Forecast evaluation, averaged over all forecast horizons $h = 1, \ldots, 12$.

	a-priori grouping	$K = 2$	$K = 3$	$K = 4$
mean bias $1/12 \sum_{h=1}^{12} \mathrm{B}_{wh}$				
unweighted errors, $w_i = 1$, $(\times 10^{-2})$	0.44	0.30	0.41	0.45
weighted with $w_i = \lambda_i^{-1/2}$, $(\times 10^{-2})$	0.48	0.31	0.42	0.47
weighted with bank size[1], $(\times 10^{-5})$	0.79	0.54	0.78	0.84
mean absolute bias $1/12 \sum_{h=1}^{12} \lvert \mathrm{B}_{wh} \rvert$				
unweighted errors, $(\times 10^{-2})$	0.70	0.58	0.82	0.72
weighted with $\lambda^{-1/2}$, $(\times 10^{-2})$	0.76	0.60	0.84	0.75
weighted with bank size, $(\times 10^{-4})$	0.15	0.12	0.16	0.16
mean squared error				
unweighted errors, $(\times 10^{-2})$	0.49	0.31	0.31	0.31
	(0.61)[2]	(0.02)		(-0.01)
weighted with $\lambda_i^{-1/2}$, $(\times 10^{-2})$	0.50	0.27	0.27	0.26
	(0.89)	(0.01)		(-0.02)
weighted with bank size, $(\times 10^{-6})$	0.53	0.27	0.20	0.20
	(1.77)	(0.46)		(0.02)

[1] $w_i = \mathrm{size}_i / (\sum_{j=1}^{N} \mathrm{size}_j)$

[2] $1/12 \sum_{h=1}^{H} (\mathrm{MSE}_{wh}/\mathrm{MSE}_{wh} \text{ (for model } K = 3)) - 1$

Overall, the results, besides documenting the improvement of endogenous grouping relatively to a-priori grouping, confirm the model specification of section 3.3.

6 Conclusion

In the present paper, we investigate a panel of quarterly individual bank balance sheet data to find evidence on the bank lending channel in Austria. The data cover the period of the first quarter of 1990 through the last quarter of 1998. The end of the sample is chosen to coincide with the start of the European monetary union. The model we estimate allows for a group- and a state-specific lending reaction to interest rate changes, with both the group- and the state indicator being part of the model estimation. This is implemented by data augmentation and calls for the use of Bayesian simulation methods to obtain the posterior inference on the model parameters and the two latent indicators as well.

The theoretical background of the investigation is given by an adverse-selection model for bank asset and liability management, where information asymmetry exists with respect to the bank's asset value. Given the unobservable asset value, the empirical assessment of the model's prediction has usually relied on bank-specific characteristics like size, liquidity and capitalization to proxy the banks' informational exposure. Based on this approach, the evidence obtained so far for the US has been consistent with the model's prediction, while in contrast evidence for European countries has been weakly consistent with the predictions of the bank lending channel. Apparently, the usual bank-specific characteristics are not appropriate to discriminate between groups of banks with different lending reactions. Therefore, we suggest a model where the appropriate grouping of banks is estimated rather than fixed a priori based on relative size or liquidity strength.

It turns out that the results of the preferred model specification (with three bank groups) can broadly be related to the theoretical model's prediction; in particular, the group with the smallest average bank size displays the strongest lending reaction to interest rate changes. Nevertheless, the evidence for a bank lending channel is quite weak as most of the banks fall into one group that displays only a minor reaction to interest rates during the observation period. This can be explained by the structure of the Austrian banking system, which is typical for a bank-based financial system. Most of the banks (around 90%) are very small, and operate on a local or regional basis. They developed close customer relationships as, traditionally, firms and households have relied on one bank to effect their financial transactions. This helps in overcoming the asymmetric informational problem on the borrowers' as well as on the depositors' side normally present when banks' customers have easier access to substitute finance possibilities (as it is the case in market-based financial systems). Moreover, the small Austrian banks are organized in a multi-tier system, which gives them the possibility of refinancing at the central institution and alleviates liquidity constraints in periods of tight monetary policy.

Finally, the improvement of endogenous grouping versus a-priori grouping in relative size classes is documented in a sensitivity analysis. There is no evidence of lending differences between groups when banks are classified a priori according to their relative size and the out-of-sample forecast performance lies significantly below the one of our preferred model specification.

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A Choice of the prior distributions

Assuming independence between the various parameter blocks of θ, the prior distribution is given by:

$$\pi(\theta) = \pi(\eta)\pi(\xi)\pi(\alpha, \beta_1^G, \dots, \beta_K^G, \beta_1^R, \dots, \beta_K^R)\pi(\sigma^2).$$

For the relative group sizes η we assume a Dirichlet prior distribution

$$\pi(\eta) \propto D(e_{1,0}, \dots, e_{K,0}).$$

The two conditional transition distributions $\xi_{1\cdot}$ and $\xi_{0\cdot}$ are independent *a priori* and each follows a Dirichlet distribution $D(f_{i0,0}, f_{i1,0}), i = 0, 1$:

$$\pi(\xi_{i0}, \xi_{i1}) \propto \xi_{i0}^{f_{i0,0}-1}\xi_{i1}^{f_{i1,0}-1}.$$

For the fixed parameters α we use a normal prior $N(c_0, C_0)$. Concerning the pairs of group-specific regression parameters, (β_k^G, β_k^R), $k = 1, \dots, K$, we assume that they are independent *a priori* and use a normal prior distribution which is invariant to group-permutations:

$$N(m_0, M_0), \tag{22}$$

where

$$m_0 = \begin{pmatrix} b_0 \\ 0 \end{pmatrix}, \quad M_0 = \begin{pmatrix} B_0 & B_0 \\ B_0 & 2B_0 \end{pmatrix}.$$

The specific feature of the prior comes from the parameterization of the state-specific effect in model (9). Remember that one state relates to $I_t = 0$ with parameter $\beta_k^G - \beta_k^R$ and the other state relates to $I_t = 1$ with parameter β_k^G. To apply the permutation sampler, the prior distribution of the state-specific parameters needs to be symmetric and invariant with respect to state permutation. Therefore, the prior distribution on the pair of coefficients $(\beta_k^G - \beta_k^R, \beta_k^G)$ is assumed to be normal,

$$\begin{pmatrix} \beta_k^G - \beta_k^R \\ \beta_k^G \end{pmatrix} \sim N\left(\begin{pmatrix} b_0 \\ b_0 \end{pmatrix}, \begin{pmatrix} B_0 & 0 \\ 0 & B_0 \end{pmatrix}\right).$$

It is then easy to derive that the prior specification on $(\beta_k^G - \beta_k^R, \beta_k^G)$ implies the one given in (22) for (β_k^G, β_k^R). Finally, for the variance parameter σ^2 we assume an inverted gamma prior, $\sigma^2 \sim IG(\nu_{\varepsilon,0}, G_{\varepsilon,0})$.

For practical implementation, we use rather diffuse priors by assuming the following hyperparameters: $e_{k,0} = 4$, $k = 1, \dots, K$; $f_{11,0} = f_{00,0} = 2$ and $f_{10,0} = f_{01,0} = 1$; $c_0 = 0$, $C_0 = I$; $b_0 = 0$, $B_0 = \kappa I$, where I is an appropriately dimensioned identity matrix and $\kappa = 2/3$. The hyperparameters for the variance are set to $\nu_{\varepsilon,0} = G_{\varepsilon,0} = 1$ and for the prior on λ_i we set $\nu = 8$.

B MCMC sampling

To sample from the joint posterior distribution $\pi(\psi|y^N)$, we alternatively sample out of the conditional distributions of the appropriately blocked parameter vector, given the current value of the parameters. Here, we will briefly reproduce the relevant conditional posterior distributions.

1. *Sampling the group indicator from* $\pi(S^N|\theta, I^T, \lambda^N, y^N)$. As $S_1, \dots, S_N$ are conditionally independent given θ, I^T, λ^N, y^N, the group indicator S_i is sampled from the discrete distribution $\pi(S_i = k|y_i, \lambda_i, \theta, I^T)$, $k = 1, \dots, K$:

$$\pi(S_i = k|y_i, \lambda_i, \theta, I^T) \propto \prod_{t=p+1}^{T} f(y_{it}|\beta_k^G, \alpha, \beta_k^R, \sigma^2, I_t, \lambda_i, y_i^{t-1}) \cdot \eta_k,$$

   where $f(y_{i,t}|\beta_k^G, \alpha, \beta_k^R, \sigma^2, I_t, \lambda_i, y_i^{t-1})$ is the density of a normal distribution with mean $\hat{y}_{it}$,

$$\hat{y}_{it} = X_{it}^1 \alpha + X_{it}^2 \left(\beta_k^G + \beta_k^R (I_t - 1)\right) \tag{23}$$

   and variance σ^2/λ_i.

2. *Sampling the group probabilities from* $\pi(\eta|S^N)$. The conditional distribution is a Dirichlet distribution $D(e_{1,N}, \dots, e_{K,N})$, where

$$e_{k,N} = e_{k,0} + \#(S_i = k), \quad k = 1, \dots, K.$$

3. *Sampling the transition matrix from* $\pi(\xi|I^T)$. The two conditional transition distributions $\xi_{1\cdot}$ and $\xi_{0\cdot}$, are independent *a posteriori* and each follows a Dirichlet distribution $D(f_{i0,T}, f_{i1,T}), i = 0, 1$, where:

$$f_{ij,T} = f_{ij,0} + \#(I_t = j, I_{t-1} = i), \quad i = 0, 1, j = 0, 1.$$

4. *Sampling of all regression parameters* $\alpha^\star = (\alpha, \beta_1^G, \dots, \beta_K^G, \beta_1^R, \dots, \beta_K^R)$ *jointly from* $\pi(\alpha^\star|\sigma^2, S^N, \lambda^N, I^T, y^N)$. Conditional on S^N and I^T model (13) is a classical regression model:

$$y_{it} = Z_{it}\alpha^\star + \varepsilon_{it}, \quad \varepsilon_{it} \sim \mathrm{N}(0, \sigma^2/\lambda_i),$$

   with parameter $\alpha^\star = (\alpha, \beta_1^G, \dots, \beta_K^G, \beta_1^R, \dots, \beta_K^R)$ and

$$Z_{it} = \begin{pmatrix} X_{it}^1 & X_{it}^2 D_i^{(1)} & \cdots & X_{it}^2 D_i^{(K)} & X_{it}^2 D_i^{(1)}(I_t - 1) & \cdots & X_{it}^2 D_i^{(K)}(I_t - 1) \end{pmatrix},$$

   where $D_i^{(k)} = 1$ iff $S_i = k$, for $k = 1, \dots, K$. The posterior of $\alpha^\star$ is given by $\pi(\alpha^\star|\sigma^2, S^N, \lambda^N, I^T, y^N) \sim \mathrm{N}(a_N, A_N)$, where

$$A_N = (\sum_{i=1}^{N} \lambda_i \sum_{t=p+1}^{T} Z_{it}' Z_{it}/\sigma^2 + A_0^{-1})^{-1}, \tag{24}$$

$$a_N = A_N(\sum_{i=1}^{N} \lambda_i \sum_{t=p+1}^{T} Z_{it}' y_{it}/\sigma^2 + A_0^{-1} a_0).$$

   The parameters of the prior, a_0 and A_0, are constructed from the normal priors of the fixed, the group- and state-specific parameters as well.

5. *Sampling the variance from* $\pi(\sigma^2|\alpha, \beta_1^G, \dots, \beta_K^G, \beta_1^R, \dots, \beta_K^R, S^N, \lambda^N, I^T, y^N)$. The posterior is given by the following inverted gamma distribution:

$$\begin{aligned}
\sigma^2|\alpha, \beta_1^G, \dots, \beta_K^G, \beta_1^R, \dots, \beta_K^R, S^N, \lambda^N, I^T, y^N) &\sim IG(\nu_{\varepsilon,N}, G_{\varepsilon,N}), \\
\nu_{\varepsilon,N} &= \nu_{\varepsilon,0} + N(T-p)/2, \\
G_{\varepsilon,N} &= G_{\varepsilon,0} + 1/2(\sum_{i=1}^{N} \lambda_i \sum_{t=p+1}^{T} (y_{it} - \hat{y}_{it})^2),
\end{aligned}$$

   where p is the lag of y_{it}, and $\hat{y}_{it}$ is defined in (23).

6. *Sampling the state indicator from* $\pi(I^T|\theta, S^N, \lambda^N, y^N)$. This step is carried out in a multimove manner as in Chib (1996). First we run a (forward) filter to compute $\pi(I_t|\theta, S^N, \lambda^N, y^{N,t})$ starting for $t=1$ from the prior distribution $\pi(I_0)$:

$$\pi(I_t|\theta, S^N, \lambda^N, y^{N,t}) \propto \prod_{i=1}^{N} f(y_{it}|y_i^{t-1}, \lambda_i, \theta, S_i, I_t) \pi(I_t|\theta, S^N, \lambda^N, y^{N,t-1}) \tag{25}$$

   where $y^{N,t-1}$ contains all bank observations up to $t-1$ and $f(y_{it}|y_i^{t-1}, \lambda_i, \theta, S_i, I_t)$ is the density of a normal distribution with mean $\hat{y}_{it}$ and variance σ^2/λ_i. $\pi(I_t|\theta, S^N, \lambda^N, y^{N,t-1})$ is given by extrapolation:

$$\pi(I_t|\theta, S^N, \lambda^N, y^{N,t-1}) = \sum_{I_{t-1}=0}^{1} \pi(I_{t-1}|\theta, S^N, \lambda^N, y^{N,t-1}) \xi_{I_{t-1}, I_t}.$$

   Given the filter probabilities the backward sampler starts from $t=T$ with sampling I_T from $\pi(I_T|\theta, S^N, \lambda^N, y^{N,T})$. For $t = T-1, \dots, 0$ we sample from I_t from the discrete density $\pi(I_t|I_{t+1}, \dots, I_T, \theta, S^N, \lambda^N, y^{N,T})$, given by:

$$\pi(I_t|I_{t+1}, \dots, I_T, \theta, S^N, \lambda^N, y^{N,T}) = \pi(I_t|I_{t+1}, \theta, S^N, \lambda^N, y^{N,t}) \propto \pi(I_t|\theta, S^N, \lambda^N, y^{N,t}) \xi_{I_t, I_{t+1}}$$

7. *Sampling the weights from* $\pi(\lambda^N|\theta, I^T, S^N, y^N)$. As $\lambda_1, \dots, \lambda_N$ are conditionally independent given θ, I^T, S^N, y^N, the weight λ_i is sampled from $\pi(\lambda_i|y_i, \theta, S_i, I^T)$, which is equal to the Gamma density $G(\nu_{N,i}/2, g_{N,i}/2)$ where:

$$\nu_{N,i} = \nu + (T-p), \quad g_{N,i} = \nu + \frac{1}{\sigma^2} \sum_{t=p+1}^{N} (y_{it} - \hat{y}_{it})^2.$$

   $\hat{y}_{it}$ has been defined in (23).

To improve the sampler with respect to invariance and symmetry of estimates of the joint posterior distribution we append a random sign switch as in (17) and a random permutation of the labeling as in (16). This means that first, with a probability of 0.5, the labelling of the latent state variable I_t is permuted, i.e. state 1 becomes 0 and vice versa. This amounts to a random sign switch for β_k^R:

$$\begin{aligned}
&I_t := 1 - I_t, \quad t = 0, \dots, T, \quad \xi_{ij} := \xi_{1-i,1-j}, i, j = 0, 1, \\
&\beta_k^G := \beta_k^G - \beta_k^R, \quad \beta_k^R := -\beta_k^R, \quad k = 1, \dots, K,
\end{aligned} \tag{26}$$

while all other components of ψ are unaffected by relabelling the states and remain unchanged. Second, we perform a random relabelling for the group indicator S_i. Thereby, we select one out of the possible $K!$ different permutations, $\rho = (\rho(1), \dots, \rho(K))$ with probability $1/K!$, and reorder the group-specific parameters accordingly:

$$\begin{aligned} &S_i := \rho(S_i), \quad i = 1, \dots, N, \\ &\beta_k^G := \beta_{\rho(k)}^G, \quad \beta_k^R := \beta_{\rho(k)}^R, \quad \eta_k := \eta_{\rho(k)}, \quad k = 1, \dots, K. \end{aligned} \tag{27}$$

C How to deal with merger and statistical outliers

If a merger occurred for bank i at time t or an outlying value is present, we treat y_{it} as missing and estimate y_{it} along with ψ from the data using MCMC methods. It is possible to consider more than one missing value for each bank. Let $\tilde{y}_i$ summarize all missing values for time series i, let $y_i^\star$ denote the remaining observations.

For each bank with missing values we use the median of the non-missing values as starting values. All steps of the MCMC sampling scheme described in appendix B are carried out conditional on a given value for all missing observations. The scheme is then concluded by an additional step sampling the missing values $\tilde{y}_i$ jointly for all banks from the conditional posterior $\pi(\tilde{y}_1, \dots, \tilde{y}_N | \psi, y_1^\star, \dots, y_N^\star)$.

The presence of lagged values of y_{it} as explanatory variables for future observations leads to a somewhat tedious algebra to compute the posterior distribution of the missing values given the remaining observations and the parameter ψ. A second problem with the presence of lagged values (lag of p periods) arises with missing value at the very beginning of the time series ($t = 1, \dots, p$). These missing observations appear only as right hand variables in our model and MCMC estimation of these variables turned out to be sometimes instable. These numerical problems however could be avoided by using a slightly informative prior. We assume apriori independence of all missing values with the mean given by the median of the non-missing values and a diagonal covariance matrix that depends of the inter quartile range of the non-missing values:

$$\begin{aligned} \pi(\tilde{y}_1, \dots, \tilde{y}_N) &= \prod_{i=1}^{N} \pi(\tilde{y}_i), \\ \pi(\tilde{y}_i) &\sim N(m_{0i}, C_{0i}), \end{aligned}$$

where m_{0i} is the median of the non-missing values $y_i^\star$ and C_{0i} depends on the inter quartile range IQR_i of the non-missing values through: $C_{0i} = (5/1.34 \cdot \mathrm{IQR}_i)^2$.

The posterior distribution of the missing values. Obviously, for any time series the missing values $\tilde{y}_i$ are independent from the missing values of the other time series given ψ. Therefore we sample each $\tilde{y}_i$ separately from $\pi(\tilde{y}_i | \psi, y_i^\star)$. Within a certain time series the missing values are independent, only if the time between the missing values is longer than the lag p. This, however, is not the case for all time series within our panel. Therefore we derive the joint posterior of all missing values $\tilde{y}_i$ for each time series.

To this aim we rewrite model (13) as

$$y_{it} = \Phi_{it} \begin{pmatrix} y_{i,t-p} \\ \vdots \\ y_{i,t-1} \end{pmatrix} + c_{it} + \varepsilon_{it}, \quad t = p+1, \dots, T \tag{28}$$

where

$$\Phi_{it} = \left(\begin{array}{ccc} \beta_{it}^{[p]} & \cdots & \beta_{it}^{[1]} \end{array} \right)$$

with $\beta_{it}^{[l]}$ being the parameter belonging to lag l, and

$$c_{it} = X_{it}^{\star}\beta_{it}^{\star},$$

with $X_{it}^{\star}$ consisting of those columns of $[X_{it}^1,\ X_{it}^2,\ X_{it}^2(I_t-1)]$ which do not contain lagged values of the dependent variable. $\beta_{it}^{\star}$ consists of the corresponding parameters. Equation (28) is equivalent to the following model:

$$0 = B_i y_i + c_i + \varepsilon_i, \tag{29}$$

where $y_i = (y_{i1}, \ldots, y_{iT})'$, $B_i \in \Re_{(T-p)\times T}$:

$$B_i = \left(\begin{array}{cccccc} \Phi_{i,p+1} & -1 & 0 & \cdots & & 0 \\ 0 & \Phi_{i,p+2} & -1 & \cdots & & 0 \\ 0 & 0 & \Phi_{i,p+3} & \cdots & & 0 \\ & & & \ddots & & \\ & & & \Phi_{i,T-1} & -1 & 0 \\ & & & & \Phi_{iT} & -1 \end{array} \right),$$

$c_i = (c_{i,p+1}, \ldots, c_{iT})'$ and $\varepsilon_i = (\varepsilon_{i,p+1} \ldots \varepsilon_{iT})'$. From equation (29) we obtain an explicit model for $\tilde{y}_i$:

$$-\left[B_i^{\star} y_i^{\star} + c_i^{\star}\right] = \tilde{B}_i \tilde{y}_i + \varepsilon_i. \tag{30}$$

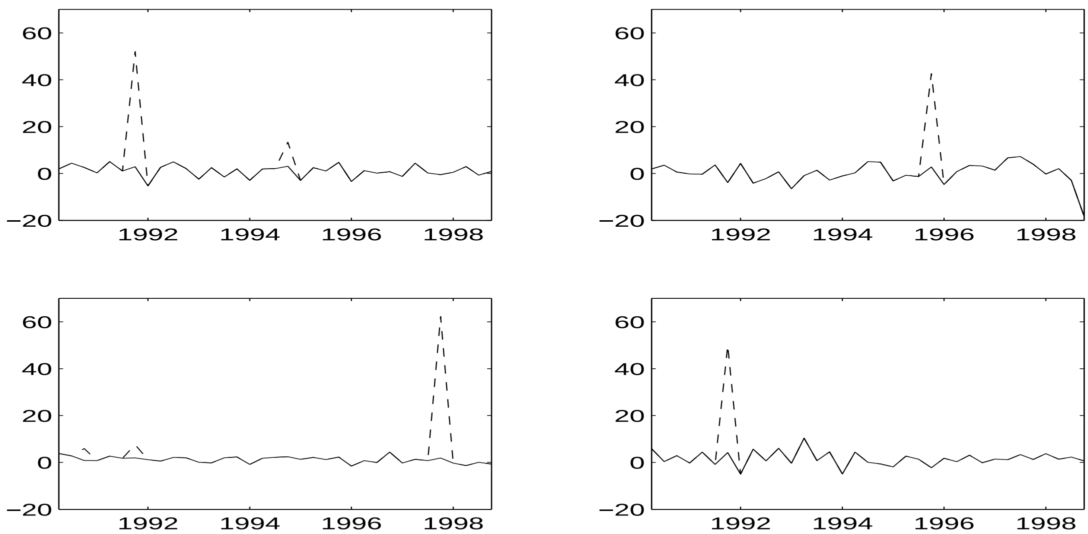
$\tilde{B}_i$, $B_i^{\star}$ and $c_i^{\star}$ are constructed in a two-step procedure: first, $\tilde{B}_i$ contains all columns of B_i which correspond to the missing values, whereas $B_i^{\star}$ contains the remaining columns. In the first step $c_i^{\star}$ is equal to c_i. Then we delete all rows of $\tilde{B}_i$ which are zero rows and therefore do not provide any information about $\tilde{y}_i$ and delete the corresponding rows from $B_i^{\star}$ and $c_i^{\star}$. Then the posterior $\pi(\tilde{y}_i|\psi, y_i^{\star})$ is given by:

$$\begin{aligned} &\pi(\tilde{y}_i) \sim N(m_i, C_i), \\ &C_i = \left(\tilde{B}_i' \tilde{B}_i / \sigma_i^2 + C_{0i}^{-1}\right)^{-1} \\ &m_i = C_i \left(-\tilde{B}_i'(B_i^{\star} y_i^{\star} + c_i^{\star})/\sigma_i^2 + C_{0i}^{-1} m_{0i}\right), \end{aligned}$$

where $\sigma_i^2 = \sigma^2/\lambda_i$.

For illustration, figure 8 reproduces some time series in which estimated missing values are substituted for the outlier.

Figure 8: Substitution of outliers with estimated missing values



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1) vergriffen (out of print)
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