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Bank lending in Switzerland: Capturing cross-sectional heterogeneity and asymmetry over time

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Bank lending in Switzerland: Capturing cross-sectional heterogeneity and asymmetry over time *

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Abstract

We study the bank lending channel in Switzerland over three decades using unbalanced quarterly bank-individual data spanning 1987 to 2016. In contrast to the usual empirical approach, we take an agnostic stance on which bank characteristic drives the heterogenous lending response to interest rate changes. In addition, our empirical model allows for a changing lending reaction occurring over time in a state-dependent manner. Our results are consistent with the existence of a bank lending channel, which is however muted in specific periods. Such episodes are characterized by increased economic uncertainty, which negatively impacts loan growth.

JEL classification: C11, C34, E44, E52, G21

Keywords: Bank lending channel, economic uncertainty, Markov switching model, Bayesian econometrics, unbalanced panel

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1 Introduction

In theory, changes in monetary policy transmit to the economy through multiple channels. Changes in bank loan supply represent one example, as monetary policy affects liquidity conditions in financial markets. Since the onset of the financial crisis, there has been renewed interest in the question of whether and how monetary policy affects loan growth in general and bank lending in particular (Heryán and Tzeremes 2017, Holton and d'Acri 2018). The broad credit channel posits that the general effect of monetary policy changes on both loan demand and supply is negative (Bernanke and Blinder 1988). When policy rates increase, loan demand from households and firms, including demand for mortgages, is expected to decline as borrowing costs rise (Bernanke and Gertler 1995). Likewise, under tightened liquidity conditions in financial markets, banks are expected to reduce their loan supply in response to monetary policy tightening (Kashyap and Stein 1995). In addition, Stein (1998) shows that lending reactions across banks can be heterogenous when informational frictions are present between banks and bank investors. Bank-specific characteristics such as size, liquidity or capital share determine the extent of each bank's lending reactions to monetary policy changes. Therefore, conditional on loan demand, empirical evidence for heterogenous lending reactions to monetary policy changes points towards heterogenous loan supply effects across banks.

Since the seminal work of Kashyap and Stein (1995, 2000), who found evidence of the bank lending channel in the US, a growing body of literature has examined whether the bank lending channel is also present in other countries. An early contribution for European countries based on yearly data is made by De Bondt (1999). A first comprehensive overview of euro area countries is presented in Angeloni et al. (2003), which summarizes studies based on quarterly aggregate and individual bank- and firm-level data. Additional dimensions of transmission have since been investigated, including bank capital (Van den Heuvel 2002, 2012), risk-pricing (Kishan and Opiela 2000) and risk-taking channels (Jiménez et al. 2014, Gaggl and Valderrama 2019). In the present paper, we analyze the bank lending channel in Switzerland. The channel may be relevant in Switzerland, as households and the majority of firms are also financed by the banking sector. On the other hand, the channel may be less relevant than it is in so-called market-based financial systems such as those found in the US and UK for similar reasons as those observed for Germany and Austria (Worms 2003, Kaufmann 2003). Small banks may not react more strongly to interest rate changes, as most are organized within a multi-layered system (the Raiffeisenkassen and Spar-&Leihkassen) and strong customer relationships may overcome informational frictions on the creditworthiness of debtors. Therefore, our expected results a priori remain undetermined. Likewise, previous studies on Swiss data report inconclusive results (see Steudler and Zurlinden 1998, Bichsel and Perrez 2005 and the review given in Zurlinden 2005). We contribute to the literature in analyzing an unbalanced panel of bank-individual balance sheet data for the 30-year period of 1987 to 2016. The data cover roughly 75% of the Swiss banking sector's assets, and all large banks and a sizeable fraction of small banks are observed across the observation period. The long observation period employed covers several business cycles, the housing market boom-bust period of the late 1980s and early 1990s, and the low interest rate period starting with the recent financial crisis.

Our empirical approach has two key features. First, in contrast to most papers in the vast literature on bank lending channel, we remain agnostic about which characteristic determines heterogenous bank lending responses and assume that cross-section heterogeneity is unobserved. As in Frühwirth-Schnatter and Kaufmann (2006), the relevant grouping of bank-individual lending dynamics is part of our model estimation. Second, due to our use of a long observation period, we allow for period-specific, i.e. state-dependent, lending reactions among bank groups. Here too we remain agnostic with respect to state determination and estimate periods characterized by different bank lending reactions. We view this approach as advantageous particularly for analyzing a large (120 banks on average) unbalanced bank panel dataset covering a long time period, for which it may be difficult to identify prior estimation bank characteristics determining heterogenous bank lending responses and periods in which banks' responses change.

Our baseline model allows for two bank groups and two states. We find empirical evidence for both heterogenous and state-dependent bank lending reactions to changes in the short-term interest rate. These findings are consistent with a bank lending channel. In fact, we find a significantly stronger reaction for banks that have a lower share of liquid assets and a lower book equity ratio and that are, to a larger extent, deposit-financed and more exposed to the domestic loan market. However, the channel does not prevail continuously over the observation period. Indeed, our results point to asymmetric effects of interest rate changes over time. The overall effect of interest rate changes on loan growth and on the bank lending channel in particular appears muted in specific periods of increased economic uncertainty. During these periods, economic uncertainty directly affects loan growth and partly overrides interest rate effects. The results are robust along a number of dimensions. First, the conclusions are robust to sample period adjustments (e.g. excluding the recent period of low interest rates) and included control variables. Second, our results are not driven by small banks or banks for which the Swiss loan market is only of marginal relevance. In addition, allowing for three instead of two bank groups does not provide additional key insights.

As financial markets have become increasingly global, recent studies have examined the potential impacts of increasing international financial linkages on the bank lending channel. Based on data for eleven CEE transition countries, Denderski and Paczos (2017) find that foreign-owned banks respond less to monetary policy of a host country than domestic-owned banks and that foreign parent bank characteristics are irrelevant to the bank lending channel. Cao and Dinger (2018) and Lindner et al. (2018) focus on banks' access to international funding. The former authors show that the bank lending channel is weaker when banks can insulate their costs of funding from domestic monetary policy. The latter authors find weak evidence for spillovers from US monetary policy to German and Austrian banks' domestic real sector lending. The effect is stronger for banks with a larger funding share in US dollars. When analyzing Swiss data, explicit consideration of international linkages is likely irrelevant, as the Swiss loan market is dominated by Swiss banks and most banks are financed almost exclusively in Swiss francs.

The hypothesis of the asymmetric effects of monetary policy was first formulated in Neftçi (1984), Cover (1992) and Karras (1996). Subsequent research analyzed the issue by subjecting policy effects to changes driven by a latent Markov switching process (Hamilton 1990). In investigations of mainly aggregate data, evidence for asymmetric effects of monetary policy has been documented, among others, for the US (Ravn and Sola 2004) and for some European countries (Peersman and Smets 2002, Kaufmann 2002, see also the survey by Florio 2004). So far, the analysis of asymmetric effects of monetary policy using disaggregated data as we do in the present work has been less frequent. As in Frühwirth-Schnatter and Kaufmann (2006), we allow for asymmetric effects of monetary policy by specifying time-varying effects driven by a latent Markov switching process. We in turn find that regimes of different monetary policy effects can partly be related to level changes in economic uncertainty.

In a recent study, Alessandri and Bottero (2020) show that economic uncertainty impacts bank lending in Italy. The authors find that heightened economic uncertainty weakens the bank lending channel. We contribute to their findings by showing that this effect might be time-varying. In Switzerland, economic uncertainty also weakens the bank lending channel, but only in times of very high or very low economic uncertainty. This finding is in line with Albrizio et al. (2019), who finds that US monetary policy shocks have a lesser impact on cross-border bank lending in periods of higher global uncertainty. Our results are also consistent with the empirical evidence for weaker effects of US monetary policy during recessions (Mumtaz and Surico 2015, Tenreyro and Thwaites 2016) and in times of increased uncertainty (Aastveit et al. 2017, Castelnuovo and Pellegrino 2018).

The remainder of the paper is organized as follows. Section 2 provides an overview of the Swiss banking system and describes the data and data cleaning process used. Section 3 presents the model and estimation method employed. Section 4 presents our empirical results and robustness analysis. Finally, Section 5 concludes.

2 Data

This section provides stylized facts about the Swiss banking system, presents the data and discusses data cleaning method used.

2.1 Stylized facts on the Swiss banking system

By the end of 2016, the Swiss banking system included 261 banks with total assets denominated in CHF amounting to roughly 1.9 trillion.[1] It includes very heterogenous banks with respect to their business model and hence balance sheet structure as well as

[1]The size of the banking system amounted to CHF 3.4 trillion when considering positions in all currencies.

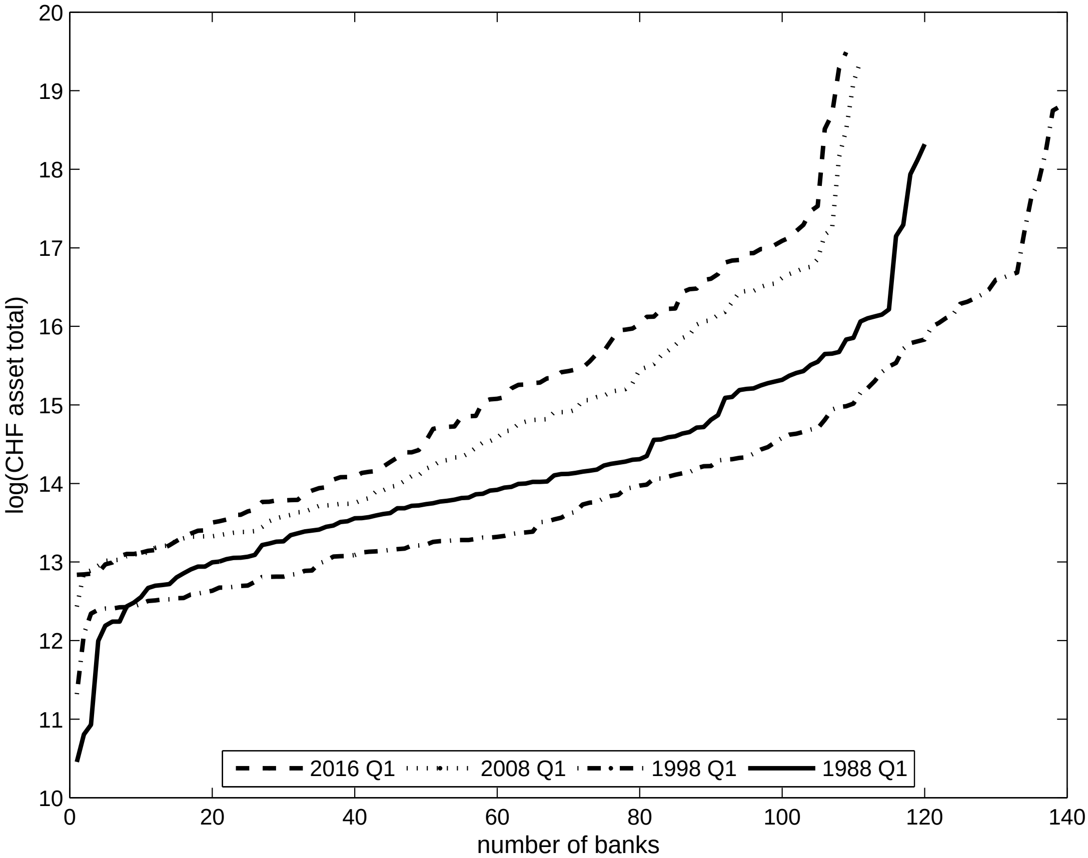
their size, which represents an advantage when investigating the bank lending channel. The banking system is also very concentrated, as the two largest banks accounted for roughly half of the system's asset total in 2016. The two largest banks offer a broad range of services in not only being internationally active, universal banks but also large players on the domestic credit market. Together, in 2016, they reached a share of approximately 28% in the domestic loan market although doing two-thirds of their business abroad and holding a large share of financial assets on their balance sheets. Banks mainly engaged into domestic business account for two-thirds of the domestic loan market. These include retail banks with a share of domestic loans to the asset total of over 50%. For 2016, we found approximately 100 domestically focused banks, of which 24 were mostly state-owned cantonal banks and 62 were regional and savings banks, including the cooperative of Raiffeisen banks. The remaining banks - a heterogenous group of banks specializing in various business models such as asset management, brokerage, and trade financing - play only a minor role in the domestic loan market.

The Swiss banking system has experienced significant structural changes over the last three decades. In the aftermath of the real estate crisis of the early 1990s, a consolidation phase led to several mergers and acquisitions, cutting the number of banks by roughly one-quarter from approximately 450 to approximately 330 a decade later. In particular, the number of regional banks fell from roughly 200 institutions in the late 1980s to less than 100 in the early 2000s as several larger banks overtook smaller regional banks. Such consolidation also affected the largest commercial banks, which decreased in number from five institutions in the early 1990s to two by the end of 2016.

As the number of banks has significantly decreased over the past three decades, the size of the banking sector in terms of balance sheet positions denominated in CHF grew steadily from roughly CHF 0.6 trillion to CHF 1.9 trillion in 2016.[2] For illustration, Figure 1 shows the empirical size distribution of the banks included in our sample for four selected quarters. Overall, the shape of the size distribution remains nearly unchanged over time. The upward-left shift reflects growth and long-term consolidation in the banking sector. Compared to 1988 Q1, a larger number of small banks transitorily populates our sample in 1998 Q1. This is due to an extension of mandatory reporting (see also Subsection 2.2).

[2]For comparison, Swiss nominal GDP totalled CHF 660.4 billion in 2016.

Figure 1 – Empirical size distribution in four different quarters



Nevertheless, despite working with an unbalanced panel, the number of banks per quarter remains relatively constant at roughly 120 over the observation period, as loans granted by many small banks in the 1990s fell below the threshold of mandatory reporting to the Swiss National Bank (SNB); see Subsection 2.2 for more details.

2.2 Data properties and data cleaning

Our data set includes quarterly information on bank-individual balance sheet data based on banks' mandatory reporting to the SNB. As we are interested in the transmission of Swiss monetary policy, we focus on balance sheet positions denominated in CHF provided a currency differentiation is available in the data. The sample period runs from the first quarter of 1987 to the fourth quarter of 2016. Our main variable of interest is bank lending in all currencies to domestic firms and households. However, this represents a good proxy for loans denominated in CHF as on aggregate, total domestic loans are almost congruent with loans denominated in CHF: for example, 97% of domestic loans were denominated in CHF and roughly 99% of outstanding CHF-denominated loans were domestic loans at the end of 2016. Domestic loans mainly include mortgage loans, representing a share of approximately 85% at the end of 2016. The mortgage share is high for both bank lending to households (96%) and to firms (65%). A differentiation of bank lending to households and firms would thus not provide significant additional insights. We calculate the quarter-on-quarter loan growth rate, which averages 1.2% over the sample period.

While we want to keep as many banks as possible in the sample, we require for each retained bank a continuously observed sample period of at least eight quarters. We view this as necessary to formulating a model in which banks cluster into groups based on bank-individual time series dynamics and display within group changes in bank lending reaction over time. Based on this criterion, 645 of 890 banks were removed from the sample. Most of these banks for most of the observed periods did not report to the SNB because they were very small or did not reach the minimum threshold requiring mandatory reporting.

The data on the remaining banks are unbalanced for several reasons. While we observe loan data for 40 of 245 banks for the whole observation period, 80 banks[3] disappear due to mergers, acquisitions or dissolution; 67 banks started business at some point. Moreover, reporting obligations changed several times such that 58 banks report only intermittently.

In addition to these missing observations, we identify and address outliers, i.e. unusual or outlying growth rates. From records on mergers and acquisitions, we check by visual inspection whether and in which precise quarter these were reflected in the outlying growth rates of overtaking banks.[4] It turns out that indeed most mergers show as unusual lending growth rates in the month-related quarter of the merger. We thus shift the outlier dummy when mergers show up in the data with some lead or lag. Finally, growth rates lying roughly five standard deviations away from the median[5] are identified as statistical outliers. For illustration, Figure 2 displays three artificially generated time series of loan growth rates, with bars indicating missing (magenta) or outlying values identified statistically

[3] One of these banks reappears later in the sample period, without reporting loans over a longer time period.

[4] Note that we had to manually merge data for a few banks because their main legal entities did not match with lending activities. Lending activity was sometimes reported by the subsidiary and not the parent company.

[5] We approximate the standard deviation by the interquartile range of observed values divided by 1.34.

(red) or by mergers and acquisitions (yellow).[6]

There are two ways of treating occasionally missing data and outlying values. We can remove them all, which would reduce the number of observations and, more importantly, lead to discontinuous bank-specific time series. As argued above, we are interested in considering as many continuous time series as possible in estimating bank groups and analyzing within group asymmetric bank lending reactions over time. Therefore, we substitute occasionally missing and outlying observations with a model-based estimate as proposed in Frühwirth-Schnatter and Kaufmann (2006). For example, Panel 2a shows two outliers identified by, respectively, mergers and the statistical criterion. While the first merger and acquisition obviously leads to an outlying value, the second one barely reflects in the time series. In such a case we replace the first merger and both statistical outliers with a model-based estimate while the observed value of the second merger is not replaced and taken at face value.

To limit the risk of inducing a statistical artifact by replacing too many consecutive observations with an estimate, we require that at most eight consecutive observations be missing or outlying to be replaced with a model-based estimate. If more than eight observations are missing or outlying in a row, we remove them all from the estimation sample.[7] For example, for the time series displayed in Panel 2c, we only used observations for the beginning and end of the sample for estimation, without replacing the relatively long series of missing values (indicated by the magenta bars) with model-based estimates.[8] Obviously, for each bank the number of missing or outlying values that we replace with a model-based estimate should not exceed the number of observed values. Panel 2d shows an example, for which we identify too many outliers relative to remaining observed values. Based on this criterion, we removed four small banks.[9]

After carefully inspecting and cleaning the data, we work with 241 banks with an average sample length of 56 observations. Overall, the number of model-based estimated

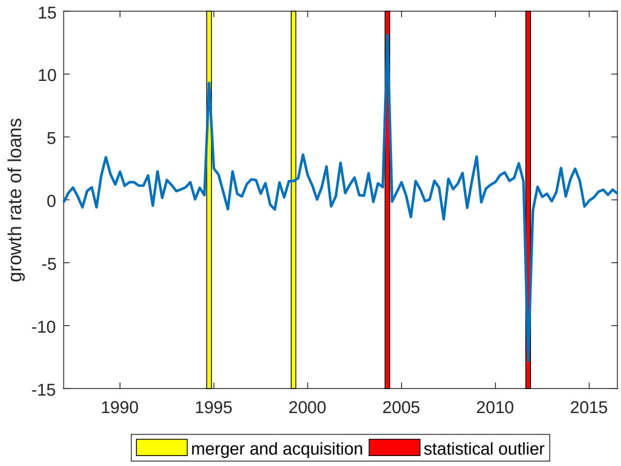
[6]Due to confidentiality issues, we do not plot data on individual banks.

[7]Moreover, for each of the eleven banks, we remove the last, very large negative observation despite it not being identified as a statistical outlier (see Panel 2b). We believe that very large negative growth rates were reported ahead of mergers or dissolution.

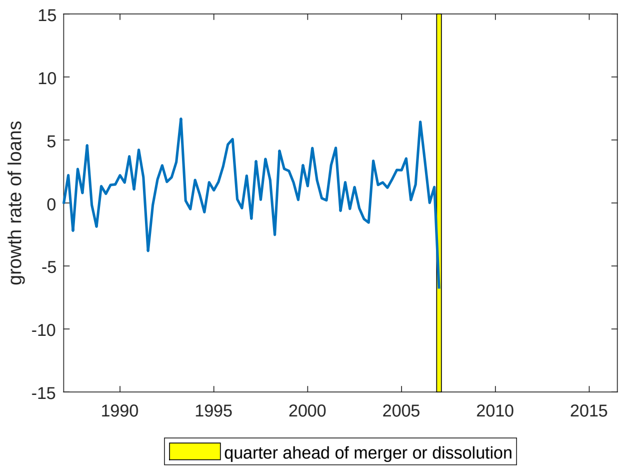
[8]In 2 cases we removed the very few observations of the second sub-sample.

[9]For four banks, the last part of the observation period was marked by statistical outliers. Therefore, in these cases we removed all observations for this period.

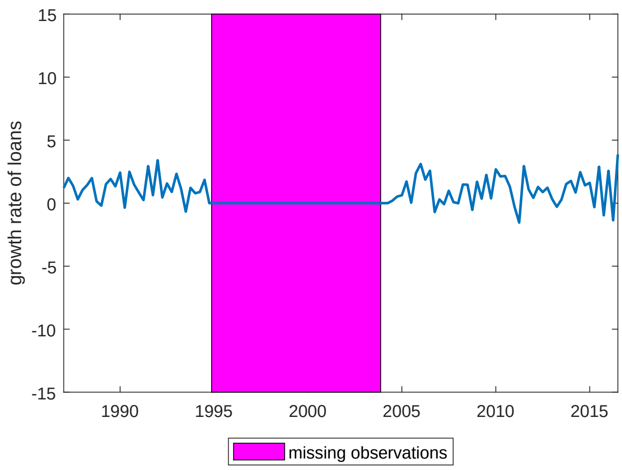
Figure 2 – Outliers and missing observations: Examples



(a) Mergers and acquisitions and statistical outliers

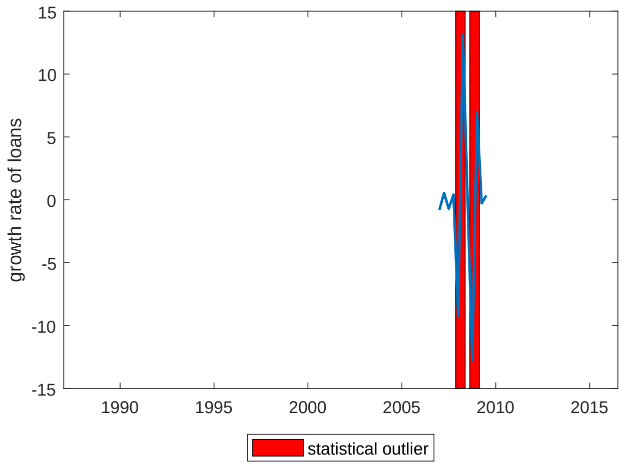


(b) Unusual loan growth before a merger or dissolution



(c) Missing observations for the middle of the sample period

Figure 2 – Outliers and missing observations: Examples cont'd

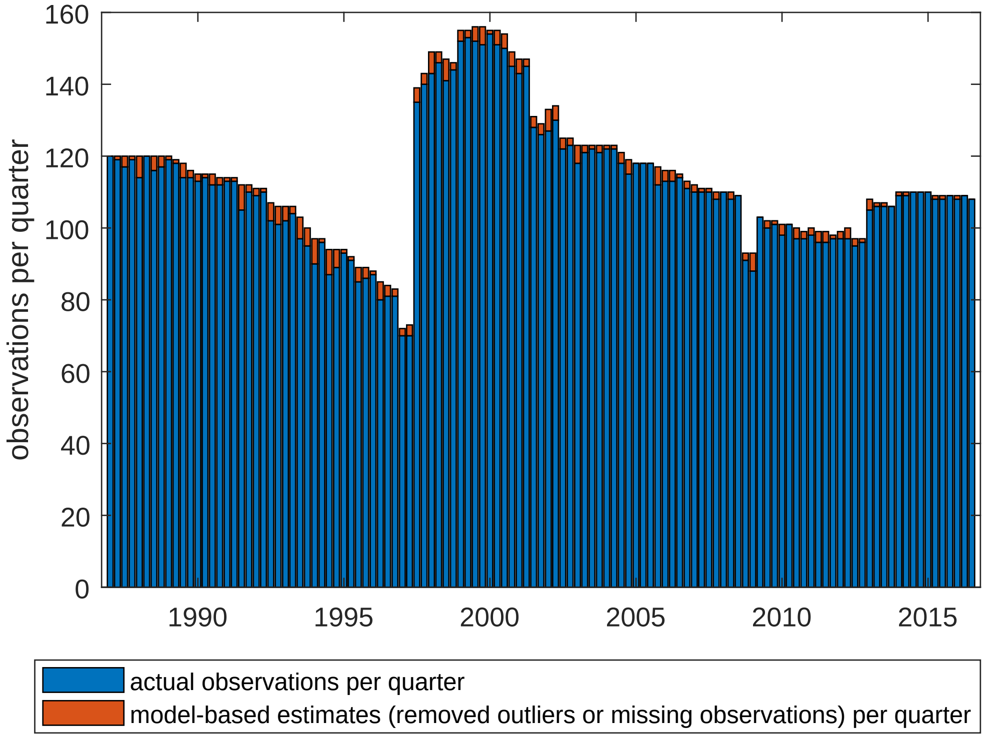


(d) Too many outliers relative to observed values

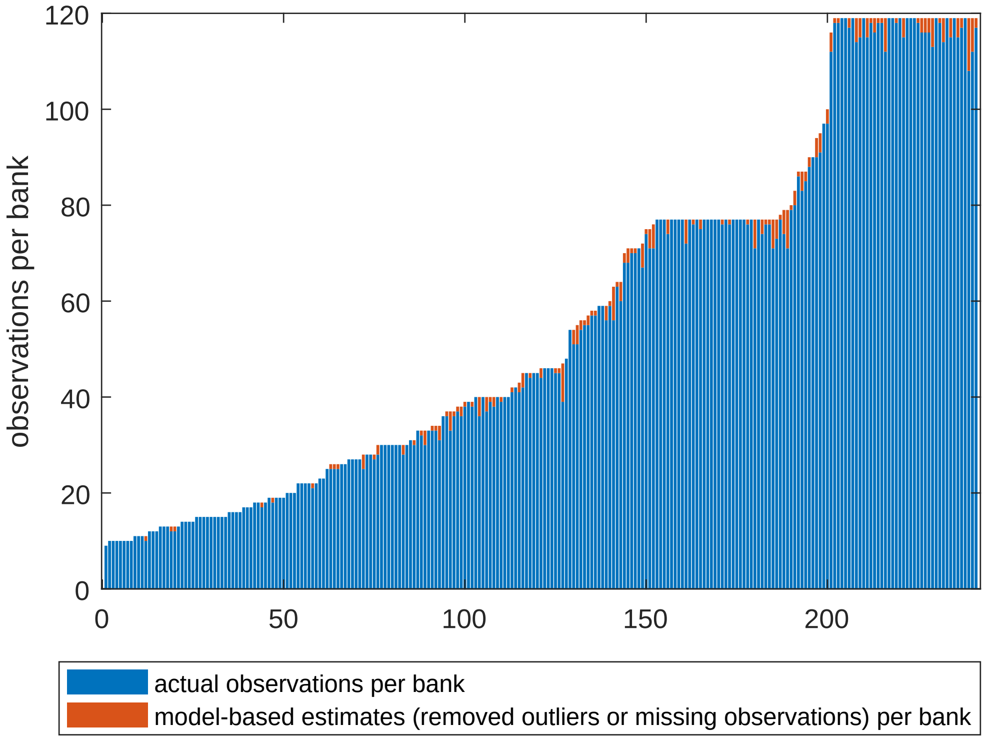
values relative to actual observations is small. On average, only one of the average sample lengths of 56 observations is identified as missing or outlying. For illustration, Panel 3a plots the number of missing or outlying observations against observed values per quarter (time dimension), and Panel 3b shows the relative number of missing or outlying observations per bank (cross-section dimension), with banks ranked in ascending order of the number of observations. The figure also illustrates the trade-off of working with a balanced panel. Either only a few banks (40 banks) would be left for estimation over the entire sample period or the sample period would be substantially shorter for a larger balanced cross-section. Panel 3a shows that the number of period-specific observations decreases during the 1990s, reflecting the consolidation of the Swiss banking industry. The sudden jump occurring in 1998 is due to an extension of the reporting population. Thereafter, from the peak occurring in the early 2000s, ongoing consolidation again led to a decline in period-specific observations.

In analyzing the results, we consider banks' liquidity and capital situation and measures reflecting an individual bank's main business model. To capture banks' liquidity situation, we calculate a broad asset liquidity ratio as the sum of cash and cash equivalents, demand funds, receivables with a maturity of up to 12 months and securities trading portfolios denominated in Swiss francs divided by the CHF asset total. In addition, we calculate three indicators to capture a bank's business model. The ratio of domestic loans and the

Figure 3 – Actual observations versus model-based estimates



(a) Actual observations and model-based estimates per quarter



(b) Actual observations and model-based estimates per bank ratio of Swiss franc denominated core deposits (amounts due to customers in savings or deposit accounts), both in terms of the CHF asset total, indicate to what extent a bank is focused on domestic credit and deposit markets. Next, the ratio of net interest income to the earnings total is an indicator of the importance of traditional financial intermediation in a bank's business model. Finally, we measure banks' capital positions as the ratio of book equity to the asset total. The sample mean and median of these key balance sheet figures are shown in Table 11 in Appendix A.1.

Table 1 presents an overview of the Swiss banking sector as of the first quarter of 2016. The summary statistics characterize bank observations retained for estimation. The 15 largest banks accounted for roughly 73% of the banking sector's CHF asset total, while the 15 smallest banks' share reached barely 1%. Half of all banks reached only 4% of the banking sector's CHF asset total. We observe that large banks on average were nearly three times as liquid as the smallest banks, and the latter again show less variation in liquidity shares than large banks. However, the average liquidity share of large banks equals that of the lower half of all banks.

The table further reveals that the large(st) banks also dominated the Swiss loan market. While banks above the 50th percentile reached a market share of 95%, the 15 largest banks still reached 72%. On the other hand, the small banks' market share was negligible. Interestingly, the average domestic loan share was considerably lower for large banks. This shows that bank lending was an important facet of smaller banks' business models even though the absolute size of loans was significantly less than that of large banks. A comparison of loan shares over time reveals interesting patterns (not shown) with values increasing over the first 20 years of the sample period. Over the last 10 years, the largest banks' loan share has been decreasing while that of smaller banks has broadly stagnated. In contrast, the liquidity share of all but the smallest banks has grown substantially since the onset of the financial crisis. These changes reflect an increase in banks' liquidity reserves at the central bank over the last few years under an expansionary monetary policy.

While the average Swiss franc core deposits ratio of large banks increased only slightly over time, it rose by roughly 50% for banks below the 50th percentile and more than tripled for the smallest 15 banks (not shown). The average ratio of net interest income to total earnings was clearly higher for small banks than for large banks.

Average book equity and Swiss franc core deposits ratios were higher for smaller banks. However, the highest deposit ratio was reported by one of the largest 15 banks. Interestingly, deposit financing seems to have been important for both the largest and smallest banks.

In addition, we use data on the Swiss economy to control for demand effects in our empirical analysis. We include Swiss CPI inflation, the output gap, the term spread, the change in immigration and an economic uncertainty indicator. Inflation is measured as the quarterly change in the seasonally adjusted CPI. The CPI (not seasonally adjusted) is taken from the Swiss Federal Statistical Office (SFSO). The output gap is based on the Cobb-Douglas production function approach and computed by the SNB. The term spread is measured as the difference between the 10-year government bond yield and the 3M Libor. Interest rate series were constructed using averages of SNB internal daily data. The change in immigration is defined as the change in the permanent foreign resident population as reported by the SFSO. To measure economic uncertainty, we use the Theil disagreement indicator published by the KOF Swiss Economic Institute based on their company survey.

Table 1 – Summary statistics (in million CHF), 2016 Q1

	Total	Absolute size		Relative size	
		largest 15 banks	smallest 15 banks	above 50th percentile	below 50th percentile
Number of banks	109	15	15	54	54
CHF asset total	1’482’272	1’085’061	7017	1’422’699	56’758
Market share		73.2	0.5	96.0	3.8
Average size	13’599	72’337	468	26’346	1’051
(min, max)	(376, 291’461)	(22’539, 291’461)	(376, 579)	(2’830, 291’461)	(376, 2’485)
Average CHF broad liquidity / CHF asset total	20.2	18.9	6.9	22.7	18.0
(min, max)	(2.1, 97.5)	(7.4, 49.0)	(3.5, 11.4)	(2.1, 87.0)	(3.5, 97.5)
Domestic loans (market share)	909’611	71.5	0.7	95.2	4.6
Average domestic loans / CHF asset total	73.4	68.2	89.1	66.3	80.2
(min, max)	(4.5, 181.3)	(10.3, 88.2)	(85.1, 93.1)	(4.5, 91.8)	(9.0, 181.3)
Average CHF core deposit / CHF asset total	56.9	61.5	67.2	53.8	59.7
(min, max)	(2.9, 95.2)	(32.4, 95.2)	(56.6, 85.7)	(2.9, 95.2)	(5.9, 85.7)
Average net interest income / total earnings	65.8	63.1	87.1	60.3	71.1
(min, max)	(2.0, 95.1)	(31.3, 79.0)	(80.2, 93.9)	(6.3, 95.1)	(2.0, 93.9)
Average book equity / asset total	7.7	6.5	8.2	7.4	8.1
(min, max)	(1.6, 16.3)	(2.9, 9.5)	(5.3, 13.9)	(2.9, 15.3)	(1.6, 16.3)

Notes: Results are based on the SNB’s banking and loan statistics. The asset total covers all assets in CHF whereas the CHF asset total covers all assets denominated in CHF. Broad liquidity is the sum of cash and cash equivalents, demand funds, receivables with a maturity of up to 12 months and securities trading portfolios denominated in CHF. Domestic loans are the sum of domestic client and mortgage loans. Core deposits include amounts in CHF due to customers in savings or deposit accounts. Total earnings are the sum of results from interest business (net interest income), commission business and services, trading activities and other result from ordinary activities. Book equity is net of immaterial assets. Group-specific smallest and largest values are indicated in parentheses.

3 The model and its estimation

3.1 Model specification

To analyze the data, we setup the following model for the period-t_i growth rate in loans of bank i, y_{it_i}:

$$\begin{aligned} y_{it_i} &= \sum_{j=0}^{q} \beta^{S_i}_{I_{t_i},j} x_{t_i-j} + \sum_{j=1}^{p} \phi^{S_i}_{I_{t_i},j} y_{i,t_i-j} + \sum_{j=1}^{m} \alpha_j \mathrm{X}_{jt_i} + \alpha_0 + \varepsilon_{it_i} \\ & \varepsilon_{it_i} | \lambda_i \sim N(0, \sigma^2/\lambda_i),\ i = 1, \ldots, N \\ & t_i \in \tau_i, \tau_i = \{j | j \in \{1, \ldots, T\}\,; (y_{ij}, y_{i,j-1}, \ldots, y_{i,j-p}) \text{ all observed}\} \end{aligned} \tag{1}$$

where N and T denote, respectively, the number of banks included in the sample and the maximum length of the sample size. The bank-specific set τ_i includes the periods for which current and past values $(y_{it_i}, y_{i,t_i-1}, \ldots, y_{i,t_i-p})$ are observed. The number of observations for bank i is $T_i = \sum_{j=1}^{T} \delta\{j \in \tau_i\}$ with $\delta\{E\} = 1$ if E is true and equaling 0 otherwise.

Variables x_t and X_{jt} denote, respectively, the change in the 3M Libor and included control variable j. Controls comprise variables that measure the economic stance, such as inflation and the output gap, financial conditions and economic uncertainty. We expect the included controls to capture contemporaneous demand-side effects and lagged loan growth rates to reflect bank-specific lagged market conditions. Therefore, the βs represent the marginal effects of interest rate, or in other words, monetary policy changes.[10] The specification closely follows Frühwirth-Schnatter and Kaufmann (2006) in pooling state-specific individual bank lending dynamics. Bank i classifies into one of G groups, $S_i \in \{1, \ldots, G\}$. Across groups, state indicator $I_t \in \{1, \ldots, K\}$ is common to all groups and governs changing lending dynamics over time. Hence, coefficients $\beta^{S_i}_{I_t,j} = \beta^{g}_{k,j}$ and $\phi^{S_i}_{I_t,j} = \phi^{g}_{k,j}$, if $S_i = g$ and $I_t = k$ capture the bank-period-specific effects of, respectively, interest rate changes and autoregressive dynamics. Both sources of heterogeneity are latent (unobserved) and estimated. Finally, bank-specific error volatility $\sigma_i^2 = \sigma^2/\lambda_i$ captures remaining cross-section heteroskedasticity.

From early empirical analyses of the bank lending channel onwards (Kashyap and

[10]Including a bank-customer-specific measure would be best to control for bank-individual demand. Unfortunately, in Switzerland such granular figures are neither broadly surveyed nor reported to the SNB.

Stein 1995, 2000), one approach to managing cross-section heterogeneity has involved pre-classifying banks into groups according to bank characteristics such as, among others, size, liquidity shares, and capital ratios. Another approach involves interacting the change in the policy rate with these bank characteristics (De Bondt 1999). In pursuing this avenue, results for US data have generally been consistent with theoretical predictions of the bank lending channel (Stein 1998), while results for European data have been more mixed (Angeloni et al. 2003). Against the background for similarly inconclusive results for Swiss data (Steudler and Zurlinden 1998, Bichsel and Perrez 2005), we re-visit the bank lending channel and assume that cross-section heterogeneity is unobserved. As in Frühwirth-Schnatter and Kaufmann (2006), the relevant grouping of individual bank lending dynamics is part of our model estimation. We obtain a characterization of cross-section heterogeneity by confronting estimated bank classifications with e.g. bank-specific characteristics or business models. Therefore, to reflect the fact that the bank characteristic relevant for classification is unknown a priori, we specify an uninformed, i.e. fixed group-specific, prior classification probability, $P(S_i = g) = \eta_g,\ g = 1, \ldots, G$, $\sum_{g=1}^{G} \eta_g = 1$.[11]

On the other hand, since Hamilton (1990) first introduced a latent Markov switching parameter specification to analyze asymmetric time series processes, the latent specification of changing dynamics over time has become standard. Here too we remain agnostic to what drives the transition between states and specify homogeneous state-specific transition probabilities for the process I_t, $P(I_t = k | I_{t-1} = j) = \xi_{jk},\ j, k = 1, \ldots, K$, $\sum_{k=1}^{K} \xi_{jk} = 1$, $\forall j$.

We apply Bayesian Markov chain Monte Carlo sampling methods where a hierarchical approach including data augmentation facilitates model estimation with two latent variables.[12]

[11] An informed, bank-specific prior classification probability may be obtained via logit specification

$$\eta_{ig} = \frac{\exp(\gamma_{0g} + \gamma_{1g} C_i)}{1 + \sum_{j=2}^{G} \exp(\gamma_{0j} + \gamma_{1j} C_i)}, \text{ with } g_{01} = g_{11} = 0$$

while including bank-specific characteristic C_i as a determining covariate.

[12] A maximum likelihood approach would be computationally much more involved, requiring integration over $G^N K^T$ latent state specifications.

3.2 Bayesian setup

To briefly describe posterior model inference, we introduce the following notation. All model parameters are collected in $\boldsymbol{\theta} = \left\{\boldsymbol{\beta}, \boldsymbol{\phi}, \boldsymbol{\alpha}, \sigma^2, \boldsymbol{\lambda}, \boldsymbol{\eta}, \boldsymbol{\xi}\right\}$ where sub-components collect the respective parameters.[13] Extended parameter vector $\boldsymbol{\vartheta} = \{\boldsymbol{\theta}, \boldsymbol{S}, \boldsymbol{I}\}$ includes latent variables $\boldsymbol{S} = (S_1, \ldots, S_N)$ and $\boldsymbol{I} = (I_1, \ldots, I_T)$. Left-hand, bank-individual lending data are collected in $\mathbf{Y} = (\mathbf{y}_1', \ldots \mathbf{y}_N')'$ with vector elements $\mathbf{y}_i = \{y_{i,t_i} | t_i \in \tau_i\}$ and right-hand variables in matrix $\mathbf{X} = [\mathbf{X}_1, \ldots, \mathbf{X}_N]'$ with bank-specific observation matrix $\mathbf{X}_i = \{\text{vec}\left(\mathbf{x}_{it_i}, \mathbf{X}_{t_i}\right) | t_i \in \tau_i\}$, $\mathbf{x}_{it_i} = (x_{t_i}, \ldots, x_{t_i - q}, y_{i,t_i-1}, \ldots, \ y_{i,t_i-p})'$, $\mathbf{X}_{t_i} = (X_{1t_i}, \ldots, X_{mt_i}, 1)'$ where vec(a, b) stacks column vectors a and b. Bayesian model inference updates prior distributions with data likelihood

$$\pi\left(\boldsymbol{\vartheta}|\mathbf{Y}, \mathbf{X}\right) \propto L\left(\mathbf{Y}|\mathbf{X}, \boldsymbol{\vartheta}\right) \pi\left(\boldsymbol{I}|\boldsymbol{\xi}\right) \pi\left(\boldsymbol{S}|\boldsymbol{\eta}\right) \pi\left(\boldsymbol{\theta}\right)$$

where the complete data likelihood factorizes

$$L\left(\mathbf{Y}|\mathbf{X}, \boldsymbol{\vartheta}\right) = \sum_{i=1}^{N} \sum_{t_i \in \tau_i} f\left(y_{it_i} | \mathrm{m}_{I_{t_i}}^{S_i}, \sigma^2/\lambda_i\right)$$

where $f(\cdot)$ denotes the bank-period-specific normal observation density with mean $\mathrm{m}_{I_{t_i}}^{S_i}$ and variance σ^2/λ_i,

$$f\left(y_{it_i} | \mathrm{m}_{I_{t_i}}^{S_i}, \sigma^2/\lambda_i\right) = \frac{1}{\sqrt{2\pi\sigma^2/\lambda_i}} \exp\left\{\frac{1}{2} \frac{\left(y_{it_i} - \mathrm{m}_{I_{t_i}}^{S_i}\right)^2}{\sigma^2/\lambda_i}\right\} \tag{2}$$

with

$$\mathrm{m}_{I_{t_i}}^{S_i} = \sum_{j=0}^{q} \beta_{I_{t_i},j}^{S_i} x_{t_i - j} + \sum_{j=1}^{p} \phi_{I_{t_i},j}^{S_i} y_{i,t_i-j} + \sum_{j=1}^{m} \alpha_j \mathrm{X}_{jt_i} + \alpha_0 \tag{3}$$

Conditional on $\boldsymbol{\xi}$ and $\boldsymbol{\eta}$, we obtain the following prior specification for the latent state variables:

$$\pi\left(\boldsymbol{S}|\boldsymbol{\eta}\right) = \prod_{g=1}^{G} \eta_g^{\#\{S_i = g\}}, \ \pi\left(\boldsymbol{I}|\boldsymbol{\xi}\right) = \prod_{j=1}^{K} \prod_{k=1}^{K} \xi_{jk}^{\#\{I_t = k, I_{t-1} = j\}}$$

[13] $\boldsymbol{\beta} = \left\{\beta_{k,j}^g | g = 1, \ldots, G; k = 1, \ldots, K; j = 1, \ldots, q\right\}$, $\boldsymbol{\phi} = \left\{\phi_{k,j}^g | g = 1, \ldots, G; k = 1, \ldots, K;\right.$ $\left. j = 1, \ldots, p\right\}$, $\boldsymbol{\alpha} = \{\alpha_j | j = 0, \ldots, m\}$, $\boldsymbol{\lambda} = \{\lambda_i | i = 1, \ldots, N\}$, $\boldsymbol{\eta} = \{\eta_g | g = 1, \ldots, G\}$ and $\boldsymbol{\xi} = \{\xi_{jk} | j, k = 1, \ldots, K\}$.

where $\#\{E\}$ denotes the number of occurrences of event E. To complete the setup, we assume independent prior specifications for model parameters:

$$\pi(\boldsymbol{\theta}) = \pi(\boldsymbol{\beta}, \boldsymbol{\phi}, \boldsymbol{\alpha})\, \pi(\sigma)\, \pi(\boldsymbol{\lambda})\, \pi(\boldsymbol{\eta})\, \pi(\boldsymbol{\xi})$$

All prior distributions are standard conjugate. To reflect our agnostic views on group and state ordering, we formulate exchangeable priors on group- and state-specific parameters, which leads to following prior distributions:

- Normal for group and state specific parameters $\boldsymbol{\beta}_k^g = (\beta_{k1}^g, \ldots, \beta_{kq}^g)'$, $\boldsymbol{\phi}_k^g = (\phi_{k1}^g, \ldots, \phi_{kp}^g)'$ and fixed effect parameters $\boldsymbol{\alpha} = (\alpha_1, \ldots, \alpha_m, \alpha_0)'$

$$\left.\begin{aligned} \pi\left(\boldsymbol{\beta}_k^g\right) &= N(0, B_0) \\ \pi\left(\boldsymbol{\phi}_k^g\right) &= N(0, P_0) \end{aligned}\right\} \forall g, k, \quad \pi(\boldsymbol{\alpha}) = N(0, A_0)$$

  where B_0, P_0 and A_0 are group- and state-independent diagonal matrices of dimension q, p and $m+1$, respectively.

- Inverse Gamma and Gamma for, respectively, the error variance and bank-individual weights:

$$\pi\left(\sigma^2\right) = IG(s_0, S_0), \;\; \pi(\lambda_i) = G(\nu_0/2, \nu_0/2), \forall i$$

- Dirichlet prior for classification probabilities

$$\pi(\boldsymbol{\eta}) = D(e_0, \ldots, e_0)$$

- Dirichlet prior for state transition probabilities

$$\pi(\boldsymbol{\xi}) = \prod_{k=1}^{K} D(u_{0,k1}, \ldots, u_{0,kK})$$

  where $u_{0,jj} = u_{0a}, \forall j = 1, \ldots K$ and $u_{0,jk} = u_{0b}, \forall j, k = 1, \ldots, K$ and $j \neq k$.

3.3 Posterior sampling

Based on conjugate prior distributions, the sampler is based on full posterior distributions. To obtain a sample from posterior $\pi(\boldsymbol{\vartheta}|\mathbf{Y},\mathbf{X})$, we iteratively draw:

- The group indicator, $\pi(\boldsymbol{S}|\mathbf{Y},\mathbf{X},\boldsymbol{I},\boldsymbol{\theta})$, from a discrete and update the classification probability, $\pi(\boldsymbol{\eta}|\boldsymbol{S})$, from a Dirichlet posterior distribution.

- The state indicator, $\pi(\boldsymbol{I}|\mathbf{Y},\mathbf{X},\boldsymbol{S},\boldsymbol{\theta})$, by multi-move sampling from a discrete and update the transition probabilities, $\pi(\boldsymbol{\xi}|\boldsymbol{I})$, from Dirichlet posterior distributions.

- The regression parameters, $\pi(\boldsymbol{\beta},\boldsymbol{\phi},\boldsymbol{\alpha}|\mathbf{Y},\mathbf{X},\boldsymbol{S},\boldsymbol{I},\sigma,\boldsymbol{\lambda})$, from normal posterior distributions.

- The error variance, $\pi(\sigma|\mathbf{Y},\mathbf{X},\boldsymbol{S},\boldsymbol{I},\boldsymbol{\beta},\boldsymbol{\alpha},\boldsymbol{\phi},\boldsymbol{\lambda})$, from an inverse Gamma and the bank-individual weights, $\pi(\boldsymbol{\lambda}|\mathbf{Y},\mathbf{X},\boldsymbol{S},\boldsymbol{I},\boldsymbol{\beta},\boldsymbol{\alpha},\boldsymbol{\phi},\sigma)$, from individual Gamma posterior distributions.

The interested reader can find detailed derivations of all posterior moments in Appendix A.

The sampler ends with a random permutation of groups and states to enforce label switching and obtain a sample from unconstrained multimodal posterior (Frühwirth-Schnatter 2001). Define $\varrho^G = (\varrho^G_1,\ldots,\varrho^G_G)$ and $\varrho^K = (\varrho^K_1,\ldots,\varrho^K_K)$ as random permutations of, respectively, $\{1,\ldots,G\}$ and $\{1,\ldots,K\}$. The sampler terminates by applying the permutations to group- and state-specific parameters and latent variables:

- $\varrho^G(\boldsymbol{\beta},\boldsymbol{\phi})$: $\left\{\boldsymbol{\beta}^j_k,\boldsymbol{\phi}^j_k\right\} := \left\{\boldsymbol{\beta}^{\varrho^G_j}_k,\boldsymbol{\phi}^{\varrho^G_j}_k|j=1,\ldots,G;k=1,\ldots,K\right\}$;
  $\varrho^G(\boldsymbol{S})$: $S_i := \varrho^G_{S_i}$; $\varrho^G(\boldsymbol{\eta}): \eta_g := \eta_{\varrho^G_g}$
- $\varrho^K(\boldsymbol{\beta},\boldsymbol{\phi})$: $\left\{\boldsymbol{\beta}^g_j,\boldsymbol{\phi}^g_j\right\} := \left\{\boldsymbol{\beta}^g_{\varrho^K_j},\boldsymbol{\phi}^g_{\varrho^K_j}|j=1,\ldots,K;g=1,\ldots,G\right\}$;
  $\varrho^K(\boldsymbol{I})$: $I_t := \varrho^K_{I_t}$; $\varrho^K(\boldsymbol{\xi}): \xi_{jk} := \xi_{\varrho^K_j\varrho^K_k}$

This allows us to explore the full posterior distribution and determine parameters that discriminate well between groups and states.

4 Baseline model

4.1 Specification and overall results

A preliminary analysis advises us to set both the number of groups and states as equal to two in our baseline specification. Moreover, we include the contemporaneous and lagged value of the change in the 3M Libor ($q = 1$) and one lag of the change in loan growth ($p = 1$) in the estimation. The sample includes in total 241 banks and covers quarterly observations for 1987 to 2016. In total, the unbalanced panel contains approximately 13,600 observations. Some additional results confirm that our results are robust with respect to modeling choices.

For posterior inference, we iterate 17,000 times over the sampler, discard the first 8,000 draws to remove dependence on initial values and retain every second draw. MCMC output post-processing reveals that groups are well discriminated by the group-specific autoregressive lag. In a first round, we re-order group-specific draws to fulfill restriction $\phi_1^1 < \phi_1^2$. States are best discriminated by the reaction to interest rate changes, and in a second round we re-order draws to fulfill $\beta_{1,0}^2 < \beta_{2,0}^2$. After re-ordering, we obtain well-identified group- and state-specific parameter estimates; see for an illustration Figure 8 in Appendix A.3.

Table 2 shows the posterior mean of parameter estimates, which is computed by taking the average over values sampled from the posterior with the shortest 95% highest posterior density interval (HPDI) indicated in parentheses. Overall, the results document that bank lending is significantly affected by all included covariates and especially by changes in the three-month Swiss franc Libor. All effects of the control variables have the expected sign. A favorable economic stance – as reflected in higher inflation and a positive output gap – and strong immigration positively affect loan growth. A larger term spread decreases loan growth. This result is not surprising since mortgages with fixed five- to ten-year rates account for a large share of loans in Switzerland. Finally, economic uncertainty negatively affects loan growth.

In the following, we first assess whether the results for our baseline model yield evidence for heterogenous and state-dependent bank lending reactions. We then examine whether (i) specific balance sheet indicators characterize heterogenous lending reactions and whether (ii) states of different lending reactions can be related to certain economic conditions (e.g. to boom and bust periods).

4.2 Heterogenous bank lending responses

Table 2 displays the posterior mean effect of variables along with the shortest 95% HPDI interval given in parentheses. The table shows that we are able to discriminate between two bank groups and two states. Interestingly, the bank groups are identified based on their autoregressive dynamics (in State 1 or State 2); see effects of Δ loans_{t-1}. Overall, posterior inference discriminates well between the two groups. In total, 165 banks (or 68% of all banks) are with a probability of more than 90% assigned to one of the groups. Only 14 banks (or 6% of all banks) are with a probability of less than 60% assigned to one of the groups. Group 1 displays negative autocorrelation (-0.20) and Group 2 shows positive autocorrelation (0.22), which means that the full, long-run effect of 3M Libor changes accumulates and is amplified over time for the banks in Group 2, while the banks in Group 1 counteract the first-round effects of 3M Libor changes. Both groups react negatively to 3M Libor changes (100bp) over the short run with values of -0.48 pp and -0.72 pp found for Groups 1 and 2, respectively. The mean long-run effect on the 82 banks in Group 1 (-0.40) is considerably smaller (in absolute value) than that on the 159 banks in Group 2 (-0.92), which adjust loans nearly one-to-one to interest rate changes.

State-dependent effects and states are identified based on the 3M Libor effect for Group 2, i.e. posterior draws are re-ordered to fulfill the restriction that the effect in State 1 is less than that in State 2. The persistence of states, 0.78 and 0.67 is considerable. Surprisingly, the total short-run effect of 3M Libor changes is counter-intuitively positive for both groups at 0.87 and 0.53 for, respectively, Groups 1 and 2, in State 2. Considering dynamics, the long-run effect is similar at nearly 0.80 and still significantly positive for both bank groups, which clearly requires further investigation and indicates that we must, in particular, characterize states properly to interpret these results, as discussed in further detail in Subsections 4.4 and 5.

Based on the significantly different lending responses between groups in State 1, we examine whether the groups differ in certain balance sheet indicators related to the bank

Table 2 – Estimation results of the baseline model. Posterior mean effect on loan growth. The shortest 95% HPDI is indicated in parentheses.

	State 1		State 2	
	Group 1	Group 2	Group 1	Group 2
Δ 3M Libor$_t$	-0.10	-0.27	0.63	0.39
	(-0.49 0.28)	(-0.44 -0.11)	(0.19 1.14)	(0.19 0.60)
Δ 3M Libor$_{t-1}$	-0.38	-0.45	0.24	0.14
	(-0.81 0.11)	(-0.62 -0.24)	(-0.19 0.70)	(0.00 0.28)
sum	-0.48	-0.72	0.87	0.53
	(-1.01 0.06)	(-0.91 -0.52)	(0.34 1.44)	(0.38 0.69)
Δ loans$_{t-1}$	-0.20	0.22	-0.11	0.33
	(-0.25 -0.14)	(0.17 0.26)	(-0.18 -0.04)	(0.29 0.37)
long-run effect	-0.40	-0.92	0.78	0.79
	(-0.86 0.04)	(-1.16 -0.67)	(0.28 1.27)	(0.57 1.01)
ξ_{11} | ξ_{22}	0.78		0.67	
	(0.65 0.90)		(0.49 0.86)	
ξ_{12} | ξ_{21}	0.22		0.33	
	(0.10 0.35)		(0.14 0.51)	
inflation$_t$	0.06			
	(-0.02 0.15)			
output gap$_t$	0.05			
	(0.03 0.08)			
Δ term spread$_t$	-0.15			
	(-0.28 -0.01)			
Δ immigration$_t$	0.07			
	(0.04 0.10)			
economic uncertainty$_t$	-0.06			
	(-0.12 -0.02)			
constant	0.65			
	(0.58 0.72)			
number of banks	82	159		

Notes: Posterior draws are re-ordered to identify groups based on the autoregressive coefficient of State 1, $\phi_1^1 < \phi_1^2$, and based on the effect of current interest rate changes in Group 2 to identify states, $\beta^2_{1,0} < \beta^2_{2,0}$.

lending channel.

4.3 Is there evidence of a bank lending channel?

Table 3 compares group-specific median values of five key balance sheet figures. The banks in Group 2 are substantially less liquid, and their CHF broad liquidity ratio is four times smaller than the ratio of Group 1 banks. The banks in Group 2 also display a lower book equity ratio of 6% than the book equity ratio of 8% found for the banks in Group 1.

Interestingly, the banks in Group 2 have a domestic loan and CHF core deposit share (in terms of the CHF asset total) that are more than twice as large as the corresponding shares of the banks in Group 1. Net interest income in terms of the earnings total is more than two and a half times higher than it is for the banks in Group 1. Apparently, the

Table 3 – Median of group-specific key balance sheet figures.

Variables/Groups	Group 1	Group 2	G1/G2
CHF broad liquidity / CHF asset total	0.20	0.05	3.93*
	(0.10, 0.28)	(0.03, 0.08)	
domestic loans / CHF asset total	0.26	0.85	0.30*
	(0.14, 0.59)	(0.75, 0.88)	
CHF core deposits / CHF asset total	0.27	0.57	0.48*
	(0.13, 0.46)	(0.47, 0.64)	
net interest income / total earnings	0.35	0.75	0.46*
	(0.23, 0.61)	(0.58, 0.84)	
book equity / asset total	0.08	0.06	1.27*
	(0.06, 0.12)	(0.05, 0.08)	

Notes: Results are based on the SNB's banking and loan statistics. The asset total covers all assets in CHF whereas the CHF asset total covers all assets denominated in CHF. Broad liquidity is the sum of cash and cash equivalents, demand funds, receivables with a maturity of up to 12 months and securities trading portfolios denominated in CHF. Domestic loans are the sum of domestic client and mortgage loans. Core deposits consist of amounts in CHF due to customers in savings or deposit accounts. Total earnings are the sum of results from the interest business (net interest income), commission business and services, trading activities and other ordinary activities. Book equity is net immaterial assets. We first compute the bank-specific average before evaluating the cross-section median. The 25th and 75th percentiles are indicated in parentheses. * denotes significantly different medians at the 1% level (Mood 1950).

banks in Group 2 are more involved in the traditional margin business and domestic loan market and thus more exposed to monetary policy effects than the banks in Group 1.[14] According to Mood's test (Mood 1950), the medians of all five key balance sheet figures differ significantly across groups. Moreover, roughly 75% of banks in each group have a (at most one) balance sheet figure that falls under the respective interquartile range of the other group, which shows that the overlap between groups with respect to the most important balance sheet positions is small.

In Table 4 we display the state-specific median CHF broad liquidity and book equity ratios for each group.[15] Balance sheet conditions are essentially the same across states. Therefore, we could expect bank lending responses to also be different across groups in State 2. Moreover, the counter-intuitive change in lending responses observed in State 2 is not reflected in changes in balance sheet conditions. This finding reinforces the need to provide a proper interpretation of State 2 in particular, which we discuss in Section 4.4

[14]The analysis is based only on assets denominated in CHF where available. The use of assets denominated in all currencies instead does not alter the conclusions. The broad liquidity, domestic loan and core deposit share (in terms of the asset total) remain practically unchanged for Group 2. For Group 1, two balance sheet figures are slightly different. On one hand, the core deposit ratio rises from 0.27 to 0.40 and on the other hand, the domestic loan share falls from 0.26 to 0.10. This finding reflects the different business models of banks in the two groups.

[15]The figures are also practically identical across states for the other balance sheet indicators listed in Table 3 (available upon request).

Table 4 – Median of group- and state-specific key balance sheet figures.

Variables/Groups	Group 1		Group 2	
States	State 1	State 2	State 1	State 2
CHF broad liquidity / CHF asset total	0.20	0.20	0.05	0.05
	(0.10, 0.29)	(0.10, 0.29)	(0.03, 0.8)	(0.04, 0.07)
book equity / asset total	0.09	0.08	0.07	0.06
	(0.06, 0.13)	(0.06, 0.11)	(0.05, 0.08)	(0.04, 0.08)

Notes: Results are based on the SNB's banking and loan statistics. The asset total covers all assets in CHF whereas the CHF asset total covers all assets denominated in CHF. Broad liquidity is the sum of cash and cash equivalents, demand funds, receivables with a maturity of up to 12 months and securities trading portfolios denominated in CHF. Book equity is net immaterial assets. We first compute the bank-specific average before evaluating the cross-section median. The 25th and 75th percentiles are indicated in parentheses.

and investigate further in Section 5.

The reported results are consistent with the empirical literature on the bank lending channel. The role of liquidity and equity in heterogeneous monetary policy transmission has been documented quite extensively in the literature though with mixed outcomes. Early studies using panel data on US banks show that liquidity or capital ratios determine monetary policy transmission with less liquid or undercapitalized banks reacting more strongly to policy changes (Kashyap and Stein 2000, Kishan and Opiela 2000). These studies also identify size, which is not relevant for our sample, as a determining factor. For European countries, evidence of a bank lending channel has been mixed. According to De Bondt (1999), the liquidity share plays a role only in three out of six countries and namely for Belgian, German and Dutch banks. Altunbaş et al. (2002) find that across EMU countries, the lending of undercapitalized banks reacts more strongly to monetary policy changes. Likewise, some investigations based on country-specific data find evidence of this specific bank lending channel. For example, Gambacorta and Mistrulli (2004) find that well-capitalized Italian banks can better shield their lending portfolios from monetary policy shocks. Bank deposits have also been highlighted as a key driving force by monetary policy transmission through banks. The empirical evidence indicates that monetary policy tightening is associated with a deposit outflow, leading to contraction in lending as banks rely heavily on deposits for their funding (Kashyap and Stein 1995, Drechsler et al. 2017).

For Switzerland, Bichsel and Perrez (2005) find evidence in favor of a bank lending channel with capitalization, but not liquidity, affecting banks' lending reactions. Based on recent data, Beutler et al. (2020) draw similar conclusions and emphasize the importance of a bank's interest rate risk exposure for the impact of an interest rate shock on bank lending.

One could argue that the different lending reactions across estimated groups could be driven by group-specific customers. However, the distinction of bank groups by the business model, where for example the share of net interest income of total earnings of Group 1 banks is roughly one-third of the corresponding share for Group 2 banks, suggests that banks specialize in business types and not in customers. Given that the variable we analyze consists mainly of mortgage loans to firms and households (cf. Section 2.2.), customers and banks of both bank groups face similar aggregate and demand conditions, respectively.[16]

4.4 State-dependent bank lending responses

As mentioned above, the state-dependent effect is best discriminated based on draws for the effect of the current change in the 3M Libor on lending for Group 2. Table 2 reports that unlike in State 1 in which the banks in Group 1 react more strongly to interest rate changes, both groups react similarly in the long run in State 2. Moreover, the overall short-run positive reaction observed for State 2 is counter-intuitive and calls for a proper interpretation of both states.

Figure 4 plots the mean posterior probabilities for State 1 for the sample period. Overall, posterior inference discriminates well between states, as posterior probabilities are either close to 1 or 0 except in periods following the financial crisis (2010 to 2012) and in more recent periods (2015-2016). As reported in Table 2, State 1 is more persistent (0.78) than State 2 (0.67). Conditional on a threshold of 0.5, roughly 60% of the quarters are assigned to State 1. State 1 covers the early 1990s; most of the second half of the 1990s; the period from 2004 to the start of 2009 and the recent years of 2013, 2014 and 2016. The start of the sample period (1987-1990), three episodes in the 1990s, the years 2002 and 2003, the four years following the onset of the Great Recession and 2015 are assigned to State 2.

Figure 5 plots the output gap and changes in the 3M Libor for the sample period. Except in the first period running from 1987 to 1990, State 2 is characterized by poor

[16] The share of mortgages in domestic lending of Group 1 banks is less than that for Group 2 banks, which might be attributed to the fact that these Group 1 banks offer different credit products. While a differentiated analysis across credit products could provide further insights (see e.g. Ivashina et al. 2020), we lack the data for such an analysis.

Table 5 – State-specific mean of macroeconomic variables.

Macro Variables	State 1	State 2	*State 2**
Δ 3M Libor	-0.03	-0.05	*-0.22*
inflation	0.29	0.35	*0.20*
output gap	0.02	-0.43	*-1.27*
Δ term spread	0.01	-0.00	*0.09*
Δ immigration	2.44	2.60	*2.37*
uncertainty index	0.31	0.24	*0.69*

Notes: *Excluding all periods assigned to State 2 during the housing boom before Q2 1990

economic development and strong decreases in the 3M Libor whereas State 1 mainly relates to economic recovery periods. Observed differences in the economic conditions of the states are also reflected in state-specific average values of variables included in the model. The values are shown in Table 5. At a first glance, differences between the states appear rather minor. However, State 2 values deteriorate markedly when we exclude all quarters assigned to State 2 for 1987 to 1990, i.e. all periods during which Switzerland experienced a pronounced housing boom. Compared to that in State 1, inflation in State 2 is lower (0.20 versus 0.29), the output gap is large and negative (-1.27 versus 0.02), and the term spread and especially the uncertainty index are higher (0.09 versus 0.01 and 0.69 versus 0.31, respectively).[17] Moreover, when excluding the housing boom to compute averages, State 2 is characterized by considerably strong declines in the 3M Libor (-0.22 on average). During the housing boom, the 3M Libor increased continuously while economic uncertainty was low (see Figure 6). This finding means that the positive effect of 3M Libor changes in State 2 led to positive loan growth during the housing boom and to negative loan growth after 1990 and hence to de-leveraging in the latter case. Apparently, during these critical periods, the transmission channel is counter-acted by additional forces.

A recent study by Alessandri and Bottero (2020) documents the importance of economic uncertainty for banks' lending. Given that economic uncertainty was unusually low and high during, respectively, the housing boom and critical periods after 1990, we investigate its role in more detail in the next section.

[17]In fact, during the housing boom, the economy was overheating and economic uncertainty was assessed to be extremely low.

Figure 4 – Mean posterior probabilities of State 1. Baseline specification.

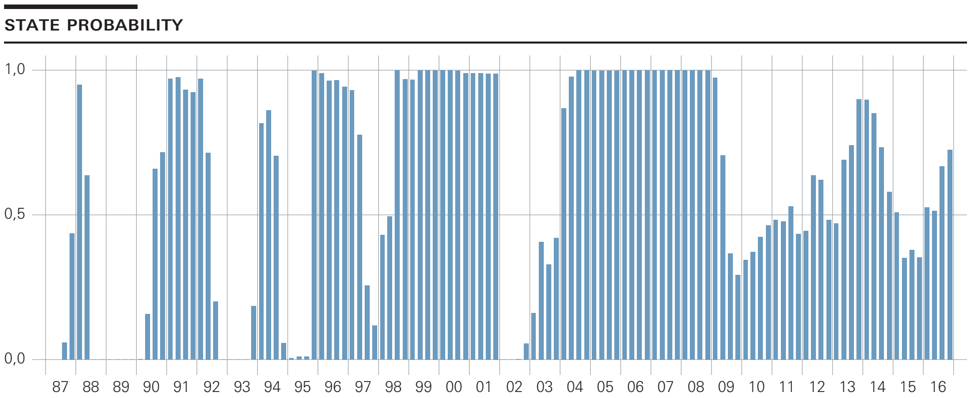


Figure 5 – Output gap and change in 3M Libor.

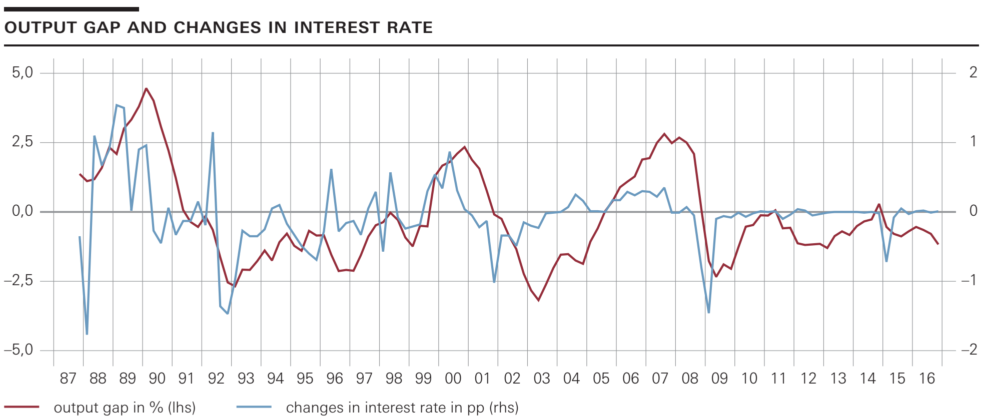
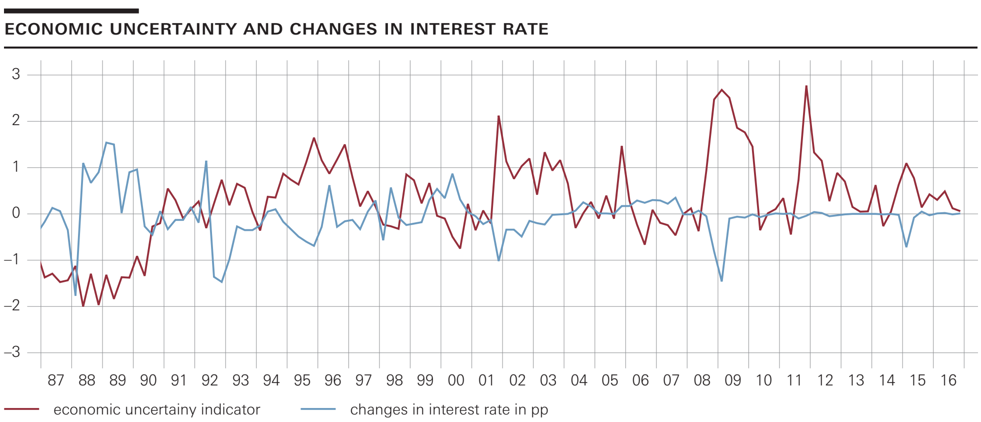


Figure 6 – Economic uncertainty and change in 3M Libor.



5 The role of economic uncertainty

As discussed in Subsections 4.2 and 4.4, the overall positive effect of 3M Libor changes for both bank groups in State 2 calls for a careful analysis of state characteristics and a re-assessment of bank lending transmission. In the previous Subsection we observed that State 2 periods are associated with a housing boom and persistent interest rate increases before 1990 and with poor economic conditions and strong interest rate decreases after 1990, during which economic uncertainty was generally unusually low and high, respectively. These conditions may reflect periods in which critical macro-economic conditions may offset the traditional bank lending channel.

Motivated by Alessandri and Bottero (2020), who study the impact of economic uncertainty on bank lending in Italy from 2004 to 2012, we re-assess the importance of economic uncertainty by allowing it to have group- and state-specific effects on lending.[18] If present, including non-linear effects may partially or even fully account for the estimated counter-intuitive positive effect of 3M Libor changes.[19]

Table 6 presents the results. Group- and state-specific autoregressive dynamics remain unchanged. Economic uncertainty has a stronger mean effect for the banks in Group 1 than the banks in Group 2. Interestingly, in State 1 the effect is marginally positive and renders the interest rate effect insignificant for Group 1. For Group 2, the inclusion of economic uncertainty, itself having a small, insignificant effect, reduces the mean interest rate effect to nearly one-third of the baseline specification (-0.34 versus -0.92), which corroborates our interpretation that banks classify into groups according to their business models.

In State 2, economic uncertainty has a strong, economically meaningful negative effect on bank lending. The inclusion of economic uncertainty reduces the mean long-run interest rate effect considerably to 40% and 27% of the baseline effect for, respectively, Group 1 and Group 2. Still, reactions to 3M Libor changes, although marginally significant, are

[18] Alessandri and Bottero (2020) find that higher economic uncertainty – measured by the Economic Policy Uncertainty (EPU) index Baker et al. (2016) or forecast disagreement constructed from forecasts published by Consensus Economics – renders banks less responsive to fluctuations in short-term interest rates, i.e. weakens the bank lending channel. According to their results, the impact of uncertainty is quantitatively similar to that of the short-term interest rate.A high capital buffer dampens its negative effect. Alessandri and Bottero (2020) do not examine time-varying effects of uncertainty, however.

[19] For this specification, the mean effect of the term spread still is positive but insignificant overall. Therefore, we exclude it from estimation.

Table 6 – Posterior mean effect on loan growth. The shortest 95% HPDI is indicated in parentheses.

	State 1		State 2	
	Group 1	Group 2	Group 1	Group 2
Δ 3M Libor$_t$	0.23	-0.04	0.37	0.18
	(-0.19 0.66)	(-0.21 0.13)	(0.00 0.68)	(0.08 0.28)
Δ 3M Libor$_{t-1}$	-0.07	-0.21	-0.01	-0.03
	(-0.44 0.33)	(-0.39 -0.00)	(-0.32 0.28)	(-0.13 0.11)
sum	0.16	-0.26	0.35	0.15
	(-0.43 0.71)	(-0.51 0.00)	(-0.09 0.81)	(-0.00 0.33)
Δ loans$_{t-1}$	-0.17	0.25	-0.13	0.30
	(-0.23 -0.12)	(0.21 0.29)	(-0.20 -0.06)	(0.26 0.34)
long-run effect	0.13	-0.34	0.31	0.21
	(-0.35 0.62)	(-0.71 -0.03)	(-0.09 0.71)	(-0.01 0.47)
uncertainty index$_t$	0.23	0.03	-0.67	-0.47
	(-0.04 0.56)	(-0.03 0.15)	(-1.15 -0.27)	(-0.61 -0.35)
$\xi_{11} \mid \xi_{22}$	0.85		0.73	
	(0.72 0.95)		(0.55 0.91)	
$\xi_{12} \mid \xi_{21}$	0.15		0.27	
	(0.05 0.28)		(0.09 0.45)	
inflation$_t$	0.08			
	(-0.00 0.16)			
output gap$_t$	0.04			
	(0.01 0.07)			
Δ immigration$_t$	0.06			
	(0.03 0.09)			
constant	0.59			
	(0.51 0.67)			
number of banks	82	159		

Notes: Posterior draws are re-ordered to identify groups based on the autoregressive coefficient of State 1, $\phi_1^1 < \phi_1^2$, and based on the effect of current interest rate changes in Group 2 to identify states, $\beta_{1,0}^2 < \beta_{2,0}^2$.

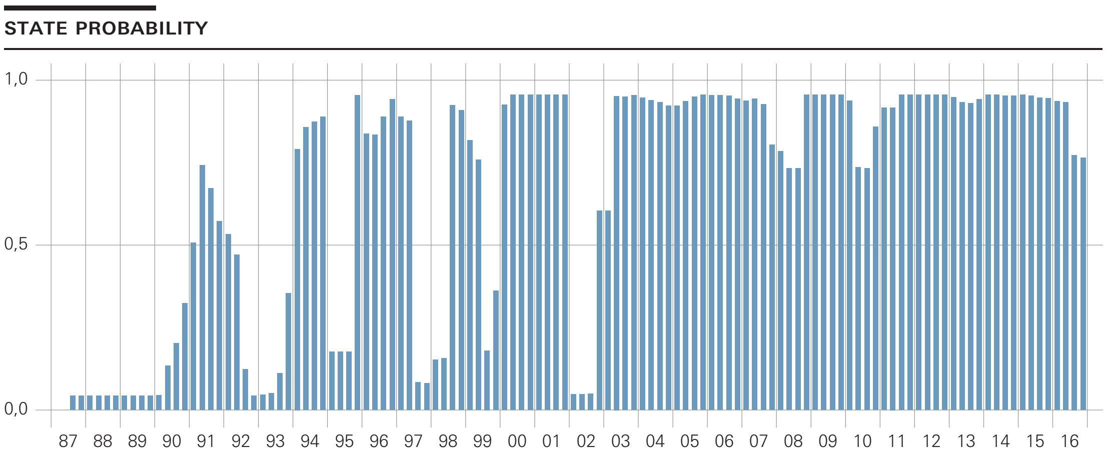
consistent with leveraging (when interest rates rise) or de-leveraging (when interest rates decrease) during these periods.

Figure 7 shows posterior mean probabilities of State 1. Compared to estimates of the baseline specification (Figure 4), most recent periods are now clearly classified into State 1. This finding suggests that the bank lending channel has not been subject to changes since the mid 2000s.

Our results are consistent with reported evidence of asymmetric effects of monetary policy over time. Mumtaz and Surico (2015) and Tenreyro and Thwaites (2016) document that US monetary policy is less effective in times of recession, while Aastveit et al. (2017), Castelnuovo and Pellegrino (2018) find the same in times of heightened uncertainty. [20]

[20] The results of Pellegrino (2018) suggest that in the euro area the effects of monetary policy shocks are weaker during uncertain times, which contrasts with those of Peersman and Smets (2002), who find evidence of more effective monetary policy during euro area recessions.

Figure 7 – Mean posterior probabilities of State 1. State-specific uncertainty.



Moreover, Albrizio et al. (2019) provide evidence of a weaker impact of US monetary policy on cross-border bank lending when global uncertainty is higher.

6 Robustness analyses

We check the robustness of our baseline results with respect to various model dimensions and the sample period.[21] In the following, we show only posterior inference on the parameters. Posterior mean state probabilities are essentially similar to those given Figure 4 and therefore are not displayed to save space.

First, we examine the impact of control variables included in the model in addition to inflation and the output gap. The inclusion of inflation should correct for changes in nominal loan growth that is only attributable to movements in the price level, whereas the output gap (or real GDP growth) is often used as proxy to capture demand-driven fluctuations in loan growth. Table 7 shows that the results remain unchanged when we include only these controls.

Second, we allow for three bank groups instead of two.[22] The results are shown in Table 8.[23] Group 3 is the largest group (155 banks) and displays similar effects as Group 2 in the baseline estimate with a smaller effect of 3M Libor changes, however. For this specification,

[21]For all but the last robustness check we exclude the term spread, as its effect is insignificant.

[22]Allowing for three states blurred the inference on mean posterior probabilities, i.e. three states cannot be discriminated well, which corroborates our selection of two states.

[23]All effects of the lagged 3M Libor with the exception of one were statistically insignificant. Therefore, we excluded Δ 3M Libor$_{t-1}$ from this specification.

Table 7 – Including only inflation and the output gap as controls. Mean posterior effect on loan growth. The shortest 95% HPDI is indicated in parentheses.

	State 1		State 2	
	Group 1	Group 2	Group 1	Group 2
Δ 3M Libor$_t$	0.01	-0.18	0.65	0.43
	(-0.38 0.40)	(-0.34 -0.06)	(0.12 1.18)	(0.24 0.63)
Δ 3M Libor$_{t-1}$	-0.42	-0.55	0.20	0.15
	(-0.86 0.09)	(-0.74 -0.31)	(-0.26 0.68)	(0.00 0.29)
sum	-0.41	-0.73	0.85	0.58
	(-0.97 0.17)	(-0.90 -0.56)	(0.20 1.45)	(0.40 0.72)
Δ loans$_{t-1}$	-0.19	0.20	-0.11	0.35
	(-0.25 -0.14)	(0.16 0.25)	(-0.19 -0.04)	(0.31 0.39)
long-run effect	-0.34	-0.92	0.77	0.88
	(-0.80 0.16)	(-1.12 -0.72)	(0.17 1.30)	(0.65 1.13)
$\xi_{11} \mid \xi_{22}$	0.78		0.71	
	(0.65 0.90)		(0.53 0.88)	
$\xi_{12} \mid \xi_{21}$	0.22		0.29	
	(0.10 0.35)		(0.12 0.47)	
inflation$_t$	0.15			
	(0.07 0.23)			
output gap$_t$	0.08			
	(0.05 0.10)			
constant	0.78			
	(0.73 0.82)			
number of banks	85	156		

Notes: Posterior draws are re-ordered to identify groups based on the autoregressive coefficient of State 1, $\phi_1^1 < \phi_1^2$, and based on the effect of current interest rate changes in Group 2 to identify states, $\beta_{1,0}^2 < \beta_{2,0}^2$.

Group 1 of the baseline estimate is divided into Group 1 and 2, which renders the long-run effect of 3M Libor changes insignificant (baseline mean effect of -0.4) and contrasts with the results found for Group 1 under the baseline model, for which the effect is much larger (-0.4) and only very marginally statistically insignificant. As in the baseline specification, the mean long-run effect of 3M Libor changes is the same for all groups. Overall, allowing for three instead of two bank groups does not provide additional key insights.

Third, we estimate the model including data only to 2007Q3 to check whether the results hinge on the recent financial crisis and Great Recession. Relative to those given in Table 2, the results shown in Table 9 are almost unchanged .[24]

Fourth, we investigate the influence of larger loan suppliers, as results could be driven by small banks or banks for which the Swiss loan market is of minor relevance. Table 10 displays the result obtained when only banks with an average loan market share of larger than 0.35% are included in the sample. When imposing this threshold, the number of

[24]Note that fewer banks are included in the sample due to the shorter sample period considered. Immigration is excluded, as it turns insignificant under this specification.

Table 8 – Allowing for three groups. Mean posterior effect on loan growth. The shortest 95% HPDI is indicated in parentheses.

	State 1			State 2		
	Group 1	Group 2	Group 3	Group 1	Group 2	Group 3
Δ 3M Libor$_t$	0.01 (-0.37 0.39)	-0.06 (-0.48 0.38)	-0.35 (-0.46 -0.23)	0.41 (0.00 0.82)	0.80 (0.34 1.24)	0.64 (0.53 0.75)
Δ loans$_{t-1}$	0.52 (0.43 0.60)	-0.22 (-0.27 -0.17)	0.14 (0.10 0.19)	0.55 (0.46 0.65)	-0.12 (-0.19 -0.04)	0.31 (0.26 0.35)
long-run effect	0.03 (-0.71 0.86)	-0.05 (-0.38 0.32)	-0.41 (-0.54 -0.27)	0.92 (-0.04 1.80)	0.72 (0.29 1.12)	0.93 (0.77 1.08)
$\xi_{11} \mid \xi_{22}$	0.78 (0.65 0.90)			0.71 (0.54 0.89)		
$\xi_{12} \mid \xi_{21}$	0.22 (0.10 0.35)			0.29 (0.11 0.46)		
inflation$_t$	0.07 (-0.02 0.15)					
output gap$_t$	0.03 (0.01 0.06)					
Δ immigration$_t$	0.09 (0.07 0.12)					
uncertainty index$_t$	-0.06 (-0.10 -0.01)					
constant	0.60 (0.53 0.66)					
number of banks	14	72	155			

Notes: Posterior draws are re-ordered to identify groups based on the autoregressive coefficient of State 1, $\phi_1^1 < \phi_1^2 < \phi_1^3$, and based on the effect of current interest rate changes in Group 3 to identify states, $\beta_{1,0}^3 < \beta_{2,0}^3$.

included banks falls from 241 to 48 banks. These banks react similarly to changes in the 3M Libor and fall under a single group. Since the mean lending reaction is unchanged relative to the lending reactions of banks in Group 2 under the baseline specification, we conclude that the findings are not driven by small banks.

Table 9 – Excluding the financial crisis (sample Q2 1987–Q3 2007). Mean posterior effect on loan growth. The shortest 95% HPDI is indicated in parentheses.

	State 1		State 2	
	Group 1	Group 2	Group 1	Group 2
Δ 3M Libor$_t$	-0.10	-0.29	0.64	0.38
	(-0.50 0.27)	(-0.46 -0.13)	(0.25 1.00)	(0.20 0.53)
Δ 3M Libor$_{t-1}$	-0.14	-0.52	0.10	0.09
	(-0.63 0.38)	(-0.75 -0.24)	(-0.23 0.49)	(-0.02 0.20)
sum	-0.24	-0.81	0.74	0.47
	(-0.68 0.21)	(-1.04 -0.56)	(0.39 1.11)	(0.28 0.62)
Δ loans$_{t-1}$	-0.22	0.22	-0.11	0.31
	(-0.27 -0.17)	(0.17 0.26)	(-0.18 -0.03)	(0.26 0.36)
long-run effect	-0.19	-1.04	0.67	0.68
	(-0.57 0.17)	(-1.33 -0.74)	(0.35 0.99)	(0.43 0.90)
$\xi_{11} \mid \xi_{22}$	0.76		0.70	
	(0.58 0.92)		(0.50 0.88)	
$\xi_{12} \mid \xi_{21}$	0.24		0.30	
	(0.08 0.42)		(0.12 0.50)	
inflation$_t$	0.25			
	(0.14 0.37)			
output gap$_t$	0.06			
	(0.02 0.09)			
uncertainty index$_t$	-0.19			
	(-0.27 -0.12)			
constant	0.74			
	(0.66 0.81)			
number of banks	87	129		

Notes: Posterior draws are re-ordered to identify groups based on the autoregressive coefficient of State 1, $\phi_1^1 < \phi_1^2$, and based on the effect of current interest rate changes in Group 2 to identify states, $\beta_{1,0}^2 < \beta_{2,0}^2$.

Table 10 – Including only banks with loan market shares of above 0.35%. Mean posterior effect on loan growth. The shortest 95% HPDI is indicated in parentheses.

	State 1	State 2
Δ 3M Libor_t	-0.39	0.26
	(-0.60 -0.19)	(0.06 0.47)
Δ 3M Libor_{t-1}	-0.59	0.15
	(-0.77 -0.40)	(-0.02 0.32)
sum	-0.98	0.41
	(-1.27 -0.70)	(0.23 0.58)
Δ loans_{t-1}	0.15	0.36
	(0.09 0.20)	(0.29 0.43)
long-run effect	-1.15	0.63
	(-1.46 -0.81)	(0.36 0.88)
$\xi_{11} \mid \xi_{22}$	0.73	0.58
	(0.56 0.91)	(0.36 0.80)
$\xi_{12} \mid \xi_{21}$	0.27	0.42
	(0.09 0.44)	(0.20 0.64)
inflation_t	0.03	
	(-0.09 0.17)	
output gap_t	0.06	
	(0.02 0.10)	
Δ term spread_t	-0.23	
	(-0.41 -0.04)	
Δ immigration_t	0.10	
	(0.06 0.15)	
uncertainty index_t	-0.10	
	(-0.17 -0.04)	
constant	0.56	
	(0.45 0.66)	
number of banks	48	

Notes: Posterior draws are re-ordered to identify groups based on the autoregressive coefficient of State 1, $\phi_1^1 < \phi_1^2$, and based on the effect of current interest rate changes in Group 2 to identify states, $\beta_{1,0}^2 < \beta_{2,0}^2$.

7 Conclusion

In this paper, we remain agnostic about which characteristics drive the heterogenous responses of bank lending and assume that cross-section heterogeneity is unobserved. As in Frühwirth-Schnatter and Kaufmann (2006), the relevant grouping of individual bank lending dynamics is part of model estimation. In addition, our model allows for state-dependent changes in lending reactions over time. Here too we remain agnostic in terms of what drives the transition between states and let the estimation procedure endogenously determine periods of different lending reactions.

Using data on Swiss banking populations for the last three decades, we find evidence of heterogeneous bank lending reactions to changes in the 3M Libor, whose rate serves as a reference rate for both the Swiss financial market and for monetary policy. Balance sheet indicators characterizing these heterogeneous lending reactions are consistent with a bank lending channel. In fact, banks show a stronger reaction to changes in the 3M Libor the lower their liquidity or book equity ratios and the higher their core deposit or interest income ratios.

In addition, we find evidence of the changing significance of the bank lending channel. The channel is counteracted in periods of unusually low or high economic uncertainty and in the latter case is most often accompanied by subdued economic performance and sudden declines in 3M Libor rates.

Our results are robust along a number of dimensions. First, our conclusions are robust to sample period adjustments (e.g. excluding the recent period of low interest rates) and included control variables. Second, the presented results are not driven by small banks or banks for which the Swiss loan market is only of marginal relevance. Finally, allowing for three instead of two bank groups does not provide additional key insights.

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A Appendix

A.1 Data

Table 11 – Key balance sheet figures and characteristics of banks

Variables	Mean	Median
CHF broad liquidity / CHF asset total	0.13	0.07
domestic loans / CHF asset total	0.63	0.81
CHF core deposits / CHF asset total	0.45	0.52
net interest income / total earnings	0.59	0.68
book equity / asset total	0.08	0.07

Notes: Results are based on the SNB's banking and loan statistics. The asset total covers all assets in CHF whereas the CHF asset total covers all assets denominated in CHF. Broad liquidity is the sum of cash and cash equivalents, demand funds, receivables with a maturity of up to 12 months and securities trading portfolios denominated in CHF. Domestic loans are the sum of domestic client and mortgage loans. Core deposits consist of amounts in CHF due to customers in savings or deposit accounts. We first compute the bank-specific average before evaluating the cross-section median.

A.2 Posterior distributions

Based on the Bayesian setup detailed in Section 3.2, the posterior update yields the following distributions.

- Group indicator $\boldsymbol{S}$ and classification probabilities $\boldsymbol{\eta}$:
  - A discrete prior distribution, $P\left(S_i = g|\boldsymbol{\eta}\right) = \eta_g$, independent across banks, leads to a bank-specific, discrete posterior distribution, which can be evaluated individually for each bank:

$$P\left(S_i = g|\mathbf{y}_i, \mathbf{X}_i, \boldsymbol{I}, \boldsymbol{\theta}\right) \propto L\left(\mathbf{y}_i|\mathbf{X}_i, \boldsymbol{I}, \boldsymbol{\beta}^g, \boldsymbol{\phi}^g, \boldsymbol{\alpha}, \sigma_i\right)\eta_g \tag{4}$$

$(\boldsymbol{\beta}^g, \boldsymbol{\phi}^g) = \left\{\beta^g_{kj}, \phi^g_{kl}|k = 1, \ldots, K; j = 1, \ldots, q; l = 1, \ldots, p\right\}$ represent bank-i relevant state-specific parameters. The observation density of bank-specific likelihood $L\left(\mathbf{Y}_i|\mathbf{X}_i, \boldsymbol{I}, \boldsymbol{\beta}^g, \boldsymbol{\phi}^g, \boldsymbol{\alpha}, \sigma_i\right) = \sum_{t_i \in \mathcal{T}_i} f\left(y_{it_i}|\mathrm{m}^{S_i}_{I_{t_i}}, \sigma^2/\lambda_i\right)$ is given in (2) and (3). After normalizing (4), draw $U \sim (0,1)$ and set

$$S_i = 1 + \sum_{j=1}^{G} \delta\left\{\left(\sum_{g=1}^{j} P(S_i = g|\cdot)\right) \leq U\right\}$$

  - The update of the Dirichlet prior $\pi\left(\boldsymbol{\eta}\right) = D\left(e_0, \ldots, e_0\right)$ leads to a Dirichlet posterior $\pi(\boldsymbol{\eta}|\boldsymbol{S}) = D(e_1, \ldots, e_G)$, with $e_g = e_0 + \sum_{i=1}^{N} \delta\{S_i = g\}$.

- State indicator $\boldsymbol{I}$ and transition probabilities $\boldsymbol{\xi}$:
  - The joint posterior of the state indicator is factorized as

$$\pi(\boldsymbol{I}|\mathbf{Y}, \mathbf{X}, \boldsymbol{S}, \boldsymbol{\theta}) = \pi(I_T|\mathbf{Y}, \mathbf{X}, \boldsymbol{S}, \boldsymbol{\theta}) \prod_{t=1}^{T-1} \pi(I_t|\mathbf{Y}, \mathbf{X}, \boldsymbol{S}, \boldsymbol{\theta}, I_{t+1})$$

    and we obtain a draw $\boldsymbol{I}$ by applying the well-known forward-filtering, backward-sampling algorithm developed by Chib (1996).
  - The Dirichlet prior $\pi(\boldsymbol{\xi}) = \prod_{k=1}^{K} D(u_{0,k1}, \ldots, u_{0,kK})$ leads to a Dirichlet posterior
    $\pi(\boldsymbol{\xi}|\boldsymbol{I}) = \prod_{k=1}^{K} D(u_{k1}, \ldots, u_{kK})$, $u_{kj} = u_{0,kj} + \sum_{t=1}^{T} \delta\{I_t = j|I_{t-1} = k\}$
- Group and state specific parameters $\{\boldsymbol{\beta}_k^g \boldsymbol{\phi}_k^g\}$ and fixed effect parameters $\boldsymbol{\alpha}$, $\theta^{\mathbf{X}} = \text{vec}\left(\beta_1^1, \phi_1^1, \beta_1^2, \phi_1^2, \ldots, \beta_K^G, \phi_K^G, \boldsymbol{\alpha}\right)$: Conditional on a normal prior distribution, the posterior is also normal

$$\pi\left(\theta^{\mathbf{X}}|\mathbf{Y}, \mathbf{X}, \boldsymbol{S}, \boldsymbol{I}, \sigma, \boldsymbol{\lambda}\right) = N(h, H)$$
$$H = \left(\mathcal{X}'\Sigma^{-1}\mathcal{X} + H_0^{-1}\right)^{-1}, \; h = H\left(\mathcal{X}'\Sigma^{-1}\mathbf{Y} + h_0 H_0\right)$$

with diagonal $\Sigma = \text{diag}\left(\sigma_1^2 \otimes I_{T_1}, \ldots, \sigma_N^2 \otimes I_{T_N}\right)$, $\sigma_i^2 = \sigma/\lambda_i$ and $\otimes$ the Kronecker product, and regressor matrix[25]

$$\mathcal{X} = \begin{bmatrix} \mathbf{x}_1 \odot D_1^{(11)} & \mathbf{x}_1 \odot D_1^{(21)} & \mathbf{x}_1 \odot D_1^{(12)} & \ldots & \mathbf{x}_1 \odot D_1^{(GK)} & \mathbf{X}_1 \\ \vdots & & \vdots & & \vdots & \vdots \\ \mathbf{x}_N \odot D_N^{(11)} & \mathbf{x}_N \odot D_N^{(21)} & \mathbf{x}_N \odot D_N^{(12)} & \ldots & \mathbf{x}_N \odot D_N^{(GK)} & \mathbf{X}_N \end{bmatrix}$$

where $\odot$ denotes element-wise multiplication and $\mathbf{x}_i$ is a $T_i \times (p+q)$ matrix containing row vectors $\mathbf{x}'_{it_i}$ and $\mathbf{X}_i$ a $T_i \times (m+1)$ matrix with row vectors $\mathbf{X}'_{t_i}$, $t_i \in \tau_i$. Dummy matrices D_i^{gk} contain a $1 \times (p+q)$ unit vector in row t_i if bank i classifies into group g, $S_i = g$, and state k prevails in period t_i, $I_{t_i} = k$, $t_i \in \tau_i$.

[25] A sequential build-up of the moment matrices can be computationally advantageous: $\mathcal{X}'\Sigma^{-1}\mathcal{X} = \sum_{i=1}^{N} \frac{\lambda_i}{\sigma^2} \mathcal{X}_i'\mathcal{X}_i$ and $\mathcal{X}'\Sigma^{-1}\mathbf{Y}_i = \sum_{i=1}^{N} \frac{\lambda_i}{\sigma^2} \mathcal{X}_i'\mathbf{Y}_i$ where matrix $\mathcal{X}_i$ and vector $\mathbf{Y}_i$ collect the rows in, respectively, $\mathcal{X}$ and $\mathbf{Y}$ correspond to observations of bank i.

- Error variance σ^2 and bank-specific weights $\boldsymbol{\lambda}$:
  - We obtain an inverse Gamma posterior distribution $IG(s, S)$ with posterior moments

$$\begin{aligned}
&\pi\left(\sigma^2|\mathbf{Y}, \mathbf{X}, \boldsymbol{S}, \boldsymbol{I}, \boldsymbol{\beta}, \boldsymbol{\alpha}, \boldsymbol{\phi}, \boldsymbol{\lambda}\right) = IG\left(s, S\right)\\
&s = s_0 + 0.5\sum_{i=1}^{N} T_i,\ S = S_0 + 0.5\left(\Lambda \odot \left(\mathbf{Y} - \mathcal{X}\theta^{\mathbf{X}}\right)\right)'\left(\Lambda \odot \left(\mathbf{Y} - \mathcal{X}\theta^{\mathbf{X}}\right)\right)\\
&\Lambda = \left(\lambda_1 \otimes \iota_{T_1}, \ldots, \lambda_N \otimes \iota_{T_N}\right)',\ \iota_T \text{ a } 1 \times T \text{ unit vector}
\end{aligned}$$

  - Bank specific weights are Gamma distributed

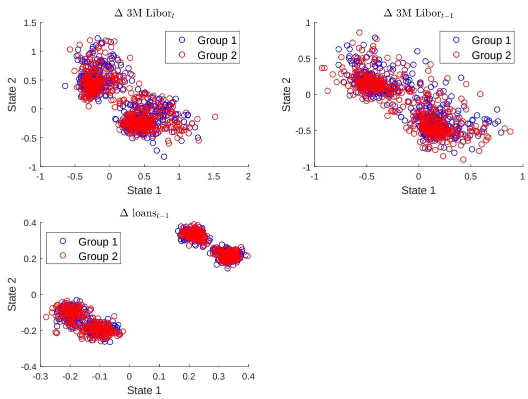
$$\begin{aligned}
&\pi\left(\lambda_i|\mathbf{Y}, \mathbf{X}, \boldsymbol{S}, \boldsymbol{I}, \boldsymbol{\beta}, \boldsymbol{\alpha}, \boldsymbol{\phi}, \sigma\right) = G\left(\nu_i/2, L_i/2\right)\\
&\nu_i = \nu_0 + T_i,\ L_i = \nu_0 + \frac{1}{\sigma^2}\left(\mathbf{Y}_i - \mathcal{X}_i\theta^{\mathbf{X}}\right)'\left(\mathbf{Y}_i - \mathcal{X}_i\theta^{\mathbf{X}}\right)
\end{aligned}$$

  Vector $\mathbf{Y}_i$ and matrix $\mathcal{X}_i$ collect the rows in $\mathbf{Y}$ and $\mathcal{X}$, respectively, corresponding to observations of bank i.

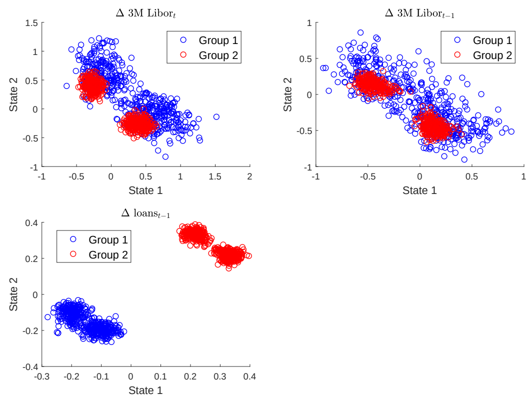
A.3 Posterior sorting

We first identify groups by re-ordering draws to ensure that the autoregressive coefficient (in State 1) of Group 1 is smaller than that of Group 2, $\phi_1^1 < \phi_1^2$; see the re-ordered output in Panel (b). Then, to identify states, we re-order draws by having the contemporaneous interest rate effect of Group 2 be less pronounced in State 1 than in State 2, $\beta_{1,0}^2 < \beta_{2,0}^2$. We in turn obtain the sorted output shown in Panel (c).

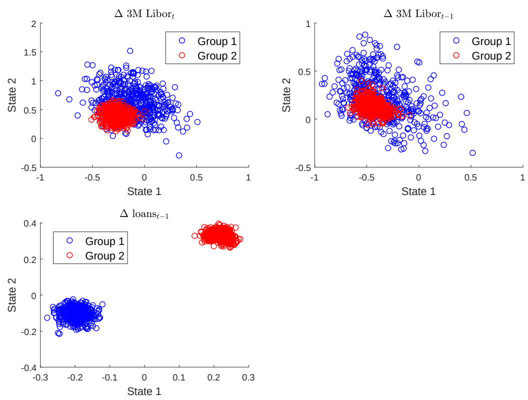
Figure 8 – Posterior processing. Scatter plots of group-specific parameters for State 1 against those for State 2.



(a) Unsorted output



(b) Sorted for groups: $\phi_1^1 < \phi_1^2$



(c) Sorted for states: $\beta_{1,0}^2 < \beta_{2,0}^2$