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Discussion Paper No. 2009-E-10

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JAPAN

IMES Discussion Paper Series 2009-E-10
March 2009

The Evolution of Loan Rate Stickiness Across the Euro Area

Jouchi Nakajima* and Yuki Teranishi**

Abstract

To investigate the banking sector integration across euro area countries in terms of loan interest rate stickiness, we estimate structural loan rate curves for 12 euro area countries using time-varying regressions with stochastic volatility. Our results show that the loan rates are sticky to a policy interest rate in all countries for all loan maturities, the degree of stickiness differs across the countries, and the degree of difference is more prominent for longer loan maturities. For short-term loans, the loan rate stickiness decreases and for intermediate- and long-term loans the loan rate stickiness converge to average levels during the sample periods. Banking integration in the euro area is not yet complete, but the degree of heterogeneity in the loan rate stickiness decreases.

Keywords: banking integration; sticky loan interest rate; Bayesian analysis; time-varying regression; Markov chain Monte Carlo

JEL classification: C11, C13, E43, E44

***** Economist, Institute for Monetary and Economic Studies, Bank of Japan (E-mail: jouchi.nakajima-1 @boj.or.jp)

******Associate Director, Institute for Monetary and Economic Studies, Bank of Japan (E-mail: yuuki.teranishi @boj.or.jp)

We thank Klaus Adam, Lawrence Christiano, and seminar participants at the Bank of Japan for insightful comments. Views expressed in this paper are those of the authors and do not necessarily reflect the official views of the Bank of Japan.

1 Introduction

"*Financial integration is of key importance for the conduct of the single monetary policy, as a well-integrated financial system enhances the smooth and effective transmission of monetary policy impulse through the euro area. The degree of integration is found to vary considerably across the different market segments, depending also on the degree of integration of the respective market infrastructure.*" ECB(2008)

Financial market integration is one of the most crucial issues for the European Central Bank (ECB) as emphasized in ECB (2008). This is because the ECB has only one policy rate for the euro area economy. If the financial integration is imperfect, an action of the ECB has different effects on the euro area countries, which makes the monetary policy very complicated. Therefore, many studies investigate whether the euro financial market is perfectly integrated or not (Mojon, 2000; Adam *et al.*, 2002; Sørensen and Werner, 2006; ECB, 2006; ECB, 2008; Gropp and Kashyap, 2009; van Leuvensteijn *et al.*, 2008). They conclude that after the establishment of the ECB, financial markets have become more integrated across countries, but the loan market integration is substantially incomplete.[1]

One of the important properties in the loan market is a sticky adjustment of the loan rate to the policy rate as shown by many papers such as Slovin and Sushka (1983) and Berger and Udell (1992) for the US economy, Sørensen and Werner (2006) and Gambacorta (2008) for the euro area economy, and BOJ (2007) for the Japanese economy.[2] This point has direct implications for evaluating imperfect loan markets integration in terms of the stickiness of loan rates across countries. If banking integration is complete, the adjustment

[1] For example, Adam *et al.* (2002) and ECB (2008) report that integration in the bond and stock markets are well advanced in the euro area. They conclude, however, that corporate loan market integration is extremely limited. They point out that a reason for incomplete integration is a different legal system of each country for a financial market.

[2] Slovin and Sushka (1983) and Berger and Udell (1992) point out that the private banks need two or perhaps more quarters to adjust loan rates using micro level data in the US. Sørensen and Werner (2006) shows incomplete pass-through from the policy rate to the loan rates using error correction models for macro level data for the euro area economies. Moreover, they show that the degree of incomplete pass-through differs across the countries. Gambacorta (2008) shows sticky adjustment of the loan rate for Germany. BOJ (2007) and BOJ (2008) report that the major city (local) banks need five (seven) quarters to adjust loan rates.

speeds of loan rates should be the same in all countries because all loan rates uniformly respond to the policy rate. As studies similar to this paper, Mojon (2000), Sørensen and Werner (2007), and van Leuvensteijn *et al.* (2008) empirically find huge heterogeneity in loan rate adjustments for euro area countries using econometric models. However, they can only reveal the situation of the banking sector integration across euro area countries on average because they assume time-invariant parameters for regressions.

In this paper, we estimate structural loan rate curves using a time-varying regression with stochastic volatility (TVR-SV) for 12 euro area countries. Such a time-varying regression model has recently become popular in empirical macroeconomics (*e.g.,* Primiceri, 2005). This nonlinear structure with a drifting coefficient can show a progress for loan market integration in the euro area in real time.

Our main findings are as follows. The loan rates are sticky to the policy rate in all euro area countries for all loan maturities. However, the stickinesses differs across the countries. Moreover, the degree of heterogeneity in loan rate stickiness is more prominent for longer maturity loans. We cannot find evidence of complete convergence in loan rate stickiness, which implies that banking sector integration is incomplete even 10 years after the euro area was established. However, we find that loan rate stickiness is stable and slowly decrease across countries during the sample period for short-term loans. For intermediate- and long-term loans, we find that loan rate stickiness oscillates widely and converges to average levels rather than converges to a smaller level. These are signs of a movement toward perfect banking integration. Our estimations are fairly robust for different specifications.

The paper is organized as follows. Section 2 shows the structural model. Section 3 reports the estimation results. We check the estimation robustness in Section 4. Section 5 concludes the paper.

2 Structural model

In contrast with previous studies that estimate econometric models, we aim to estimate structural parameters of the loan rate curve to evaluate loan rate stickiness.

Teranishi (2008) develops a structural model of a loan rate curve with micro-foundations.

In the model, private banks receive deposits at a policy rate, *i.e.,* the call rate, from consumers and lend these deposits to firms at loan rates with markups over the policy rate. Firms finance the costs of productions using loans. The bank loan market is monopolistically competitive, so the loan rates offered by private banks can differ according to borrowers. Moreover, the loan rate contract is set under the Calvo (1983) adjustment scheme. Thus, this structural model includes a stickiness in the loan rate to the policy rate, which is consistent with the former empirical studies (Slovin and Sushka, 1983; Berger and Udell, 1992; Sørensen and Werner, 2006; Gambacorta, 2008; BOJ, 2007). The loan rate curve is given as:

$$R_t = \lambda_1 \mathrm{E}_t R_{t+1} + \lambda_2 R_{t-1} + \lambda_3 i_t. \tag{1}$$

R_t is the loan rate at time t, E_t is the expectation operator, and i_t is the policy rate. λ_1, λ_2, and λ_3 are positive parameters given as $\lambda_1 \equiv \frac{\varphi\beta}{1+\varphi^2\beta}$, $\lambda_2 \equiv \frac{\varphi}{1+\varphi^2\beta}$, and $\lambda_3 \equiv \frac{(1-\varphi\beta)(1-\varphi)}{1+\varphi^2\beta}$, where φ is the Calvo parameter determining the probability that a private bank does not reset a loan rate and β is a discount factor. All variables are log-linearized around the steady state. For example, when the Calvo parameter φ is 0.4, the probability of changing the loan rate is 60 percent in each period. As the probability of resetting the loan rate, $1-\varphi$, decreases, the inertia in the loan rate dynamics, *i.e.,* λ_2, increases.

Note that the firms finance all costs of productions by loans in this basic setting. We relax this assumption in the robustness check.

3 Estimation

3.1 Data

We use monthly interest rate data of the MFI Interest Rate Statistics, which is released by the ECB.[3] The sample period is from January 2003 to May 2008. We use the outstanding (stock) loans, up to one year (short-term), over one year and up to five years (intermediate-term), and over five years (long-term), from banks to nonfinancial corporations. Table 1 reports the summary statistics of the data. The standard deviation is an average of

[3] See http://sdw.ecb.europa.eu/.

standard deviations across 12 countries in each year and the range is the average of absolute differences between the minimum and maximum values across 12 countries in each year. Table 1 shows that there are level differences in the loan rates for all maturities, which is also reported in ECB (2006). Although the standard deviations and ranges across countries for intermediate-term loans slightly decrease, those for short- and long-term loans do not decrease overall. Even in 2007, the range of the loan rate level across countries is still more than two percent for short and intermediate-term loans and about 1.6 percent for long-term loans.

There seems to be some heterogeneity among the loan markets in euro area countries. As pointed out by previous studies, these loan rate differences come from different degrees of loan rate stickiness (Mojon, 2000; Sørensen and Werner, 2007; van Leuvensteijn *et al.*, 2008) and different markups from the policy rate to the loan rates (Gropp and Kashyap, 2009; van Leuvensteijn *et al.*, 2008) across the countries. In this paper, we focus our analysis on the effect of loan rate stickiness on the loan rate dynamics. Thus, in estimations, we use series that are log-detrended by the HP filter with regular monthly criteria (14,400) to eliminate the effect of the markup on loan rate dynamics. This is consistent with our model that does not include the markup factor because the model is log-linearized around the steady state as shown in equation (1).

3.2 Methodology

We estimate the structural loan curve defined by equation (1) using the TVR-SV model. The estimated equations are formulated by:

(Regression)

$$\Delta R_t \;=\; \beta \Delta R_{t+1} + \tilde{\lambda}_t (i_t - R_t) + \varepsilon_t, \quad \varepsilon_t \sim N(0,\, v_t^2), \quad t = 1, \ldots, n.$$

(Time-varying coefficient)

$$\begin{aligned} \tilde{\lambda}_{t+1} \;&=\; \tilde{\lambda}_t + u_t, \quad u_t \sim N(0,\, \sigma_u^2), \qquad t = 1, \ldots, n-1, \\ \tilde{\lambda}_t \;&>\; 0, \qquad t = 1, \ldots, n. \end{aligned}$$

(Stochastic volatility) $\quad h_t = \log v_t^2,$

$$h_{t+1} = h_t + \eta_t, \quad \eta_t \sim N(0,\, \sigma_\eta^2), \quad t = 1, \ldots, n-1,$$

where $\tilde{\lambda}_t \equiv \frac{(1-\varphi_t)(1-\varphi_t\beta)}{1+\varphi_t^2\beta}$ is a time-varying coefficient, φ_t is a time-varying version of the Calvo parameter defined in the theoretical model, and h_t is stochastic volatility. We model the time-varying coefficient, where the stochastic volatility follows a random walk process to allow permanent shifts. The drifting coefficient is meant to capture a possible nonlinearity, such as a gradual change or a structural break (Primiceri, 2005). The stochastic volatility identifies a volatility clustering of shocks over the sample period. The TVR-SV model forms a nonlinear Gaussian state space model. We take a Bayesian approach using the Markov chain Monte Carlo (MCMC) method (Chib and Greenberg, 1996) for a precise and efficient estimation of the TVR-SV model. We show a summary of the estimation algorithm in the appendix.

Note that for our purpose of assessing the time-varying structure of the loan rate curve, it is reasonable to assume the coefficient is restricted to vary over only the positive domain thanks to the restriction in the theoretical model.[4] Moreover, we have a nonlinear relation between the parameter $\tilde{\lambda}_t$ in the regression and the Calvo parameter in $\tilde{\lambda}_t$. It may be difficult to estimate φ_t using a classical method, although the posterior distribution of φ_t can be easily obtained in the context of Bayesian inference. In our analysis, the following prior distributions are assumed: $\sigma_u^{-2} \sim \text{Gamma}(5,\, 10^{-3})$, $\sigma_\eta^{-2} \sim \text{Gamma}(2,\, 0.1)$, $\tilde{\lambda}_1 \sim N(0,\, 10)$, and $h_1 \sim N(0,\, 10)$. These priors are rather diffuse except the one for σ_u.[5] We draw 10,000 samples after the initial 1,000 samples are discarded. We conclude that

[4] This restriction can be easily incorporated into the estimation procedure by rejecting the drawn sample that does not satisfy the restriction throughout the MCMC iterations. In our experiments, the rejection probability is not so high, which implies that the restriction may not make the estimation procedure inefficient.

[5] We use a model with a time-varying coefficient and volatility. The identification problem may arise in such a fully flexible model. However, with the advantage of Bayesian inference, the proper prior for the variance of the sequence of time-varying parameters can produce the identified posterior distribution. Thus, we set a slightly tighter prior for σ_u. We check the prior sensitivity and the case of constant volatility for the disturbance term in the regression. Through these additional estimations, we confirm that the estimation results are robust with respect to both the different prior and volatility specifications.

this iteration size is enough to estimate the posterior distribution of the TVR-SV model with our data set (The appendix shows the diagnostics and figures for the convergence check). The discount factor is set as $\beta = 0.99^{1/3}$. The forward variable R_{t+1} is made by fitting an AR(2) model.[6] After we fit an AR(2) model to the entire sample for each loan rate series and obtain the OLS estimate, we make one-month-ahead forecasts using the OLS estimate as the forward variable, which provides in-sample forecasts. Note that it might be more reasonable to use out-of-sample forecasts in the sense that the forecasts should be considered using only the information that is available up to each time period. We estimate the model using out-of-sample forecasts as a robustness check in Section 4.1.[7]

The computational results are generated using Ox version 4.02 (Doornik, 2006).

4 Estimation results

4.1 Stickiness

Figure 1 shows the estimation outcome for short-term loans for 12 countries.[8] The posterior means and one-standard-deviation bands are drawn for each period based on the sample from the MCMC estimation as shown in Primiceri (2005). We report quarter base Calvo parameters in the figure. Note that the posterior distribution itself is estimated using Bayesian estimation, not as the classical method. Thus, the deviation bands indicate the parameter's distribution rather than estimation errors.

The Calvo parameters are sufficiently above zeros in all countries, which implies that the loan rate adjustments are sticky to the policy rate in all euro area countries.[9] This

[6] Thus, we assume adaptive expectations to form the forward variable. Preston (2005), Branch and Evans (2006), and Milani (2007) imply that adaptive expectations (learning) rather than rational expectations can capture enough of the dynamics in the real economy.

[7] Alternatively, an AR model with a time-varying coefficient could be considered to generate the forward variable. However, using a time-varying coefficient for the autoregressive parameter in a single equation may cause an over-fit of the data. For this reason, we use an out-of-sample robustness check with recursive AR forecasts.

[8] Note that we use a constant trend, *i.e.,* average loan rate in the sample period, only for Belgium to secure the estimation outcome.

[9] Note that the event of the ECB keeping the policy rate constant from 2003M07 to 2005M11 does

finding is consistent with previous studies on loan rate stickiness in euro area countries.

Figures 2 and 3 show the estimation outcomes for the intermediate- and long-term loans, respectively.[10] We find that the loan rates are sticky for loans of these maturities. An additional finding is that average stickiness, which is given by an average of the posterior means of the Calvo parameters across countries,[11] for longer maturities tends to be larger as shown in Figure 4.[12] However, the loan rate stickiness for the intermediate- and long-term loans is not so different from that for short-term loans. We find a similar result in each country. One reason for this is that loan rates are indexed to the market rate, as prime rates and government bond rates, in the euro area. Thus, the loan rates for long maturities are quickly adjusted against the length of maturity.[13] Note that, in Austria, Greece, and Italy, longer maturity loans have less loan rate stickiness than shorter maturity loans do. This is because of the indexation of the loan rate and economic situation in each country. In these three countries, longer maturity loans have lower loan rate levels than the shorter maturity loans do.

4.2 Heterogeneity

In Table 2, to measure the heterogeneity in stickiness across countries, we calculate the distribution of the difference in the Calvo parameters for all combinations of two countries in January of each year. This distribution is computed using the MCMC outputs that we draw in the estimation. The probability difference, $p_{ij} = \Pr(\tilde{\psi}_t^{(i)} - \tilde{\psi}_t^{(j)} > 0)$, measures

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not distort our estimation results. This is because the loan rates still move enough in such the periods. Moreover, equation (1) always holds even when $i_t = 0$, so we can measure loan rate stickiness.

[10] Note that for the intermediate-term loans, we reduce the sample period from 2003M1 to 2005M3 for Ireland because there is a clear jump from 2005M3 to 2005M4 in the data, which makes estimation very difficult.

[11] Although we have many ways of identifying the posterior distributions, we follow the dynamics of the Calvo parameter with respect to its posterior mean. As we report in the appendix, the shape of the posterior distribution for the Calvo parameter is unimodal, so we can alternatively follow the modes or medians of the posterior distribution although the insights regarding the results do not change.

[12] We exclude Ireland for intermediate-term loans in Figure 4.

[13] This point can also be confirmed by figures showing dynamics of the loan rates in the euro area. These figures are available by request.

the degree of difference with respect to the estimated parameter distributions, where $\tilde{\psi}^{(k)}$ is the Calvo parameter for the k-th country. The table shows the number of sets of two countries where the measure $\max(p_{ij},\, 1-p_{ij})$ satisfies the criteria of 60, 65, 70, 75, 80, 85, 90, and 95 percent. The two parameter distributions do not overlap for the 100 percent criteria and are identical for the 50 percent criteria. We have 66 calculations overall from 12 countries for each loan maturity.[14]

Table 2 shows that there are heterogeneities for all loan maturities. For the short-term loans, however, the degree of heterogeneity is not so strong through the sample periods. The number of higher probability differences are not as large as for the short-term loans. For the posterior means of the Calvo parameters, for example, France and Portugal show more stickiness, but Germany and Ireland show less stickiness for the short-term loans, as in Figure 1. The difference between the two groups is around 20% through the sample periods. For the long-term loans, the heterogeneity is clearer. Table 2 shows that the number of higher probability differences is large for the long-term loans. For the posterior means of the Calvo parameters, for example, Germany and Netherlands show more stickiness, but Greece and Italy show less stickiness for the long-term loans, as in Figure 3. The difference between the two groups is around 30%. For the intermediate-term loans, the probability differences of the parameter distributions are larger than those for the short-term loans in the sense that the numbers in the 60 to 70 percent criteria are larger for the intermediate-term loans regardless of the smaller samples. However, this does not hold for the over 70 percent criteria.

These results imply that the banking sector integration across euro area countries is still far from perfect, in particular for longer maturity loans, which is consistent with the outcomes of previous studies using different econometric techniques (Mojon, 2000; Sørensen and Werner, 2006; van Leuvensteijn *et al.*, 2008). The ECB (2006) provides some reasons for this heterogeneity, such as differences in the average period of initial rate fixation, in collateral practices, and in market environments by firm size among the countries. The heterogeneous loan rate adjustment induces a monetary policy trade-off for

[14] For the intermediate-term loans, we exclude Ireland from the observation. Thus, we have 55 samples.

the ECB because the best monetary policy for one country is not necessarily the best for other countries.

4.3 Convergence

The last subsection shows that the heterogeneities in the loan rates do not disappear. However, is there some evidence of perfect banking integration? Time-varying estimation investigates this issue.

Table 2 shows that the probability difference in the parameter distributions disappears for all maturity loans because the number of high probability differences decreases in recent years.

To reveal how the heterogeneities disappear, Table 3 shows the inference on the average difference in the posterior means of the Calvo parameters between the first half sample, from 2003M03 to 2005M09, and the last half sample, from 2005M10 to 2008M04, for each country.[15] D denotes "decrease", I denotes "increase", and U denotes "unchanged" in the inferences.

For the short-term loans, loan rate stickiness decreases in almost all countries except Italy and Portugal in the last few years as shown in the second column of Table 3. Eventually, the stickiness of the loan rates decreases even on average across the countries. We confirm this point even in Figure 4, which reports the transition of the average of the posterior means of the Calvo parameters across countries. Thus, the heterogeneities in loan rate stickiness decrease because the loan rate stickiness decreases. This fact provides evidence for the discussions in Sander and Kleimeier (2004), Gropp *et al.* (2006), and van Leuvensteijn *et al.* (2008). They imply that more market competition lowers loan rate stickiness. The euro area faces such a situation as financial market competition increases because of less regulation on cross border financial business as pointed out by these papers.

For longer maturity loans, we cannot find trends that show reductions across countries in loan rate stickiness as shown in the third and fourth columns of Table 3. The loan rate stickiness for the intermediate- (long-) term loans increases in six (five) countries, decreases

[15] For Ireland, we define the first half sample from 2005M04 to 2006M10 and the last half sample from 2006M11 to 2008M04.

in three (five) countries, and does not change in three (two) countries . As a result, average loan rate stickiness across the countries does not change between the first and last half of the sample for the long-term loans and slightly increases but negligibly for intermediate-term loans as seen in Table 3. We confirm this point even in Figure 4. However, other than reductions in loan rate stickiness, we see that the variance of the posterior means of the Calvo parameters across countries decreases. The mean, standard deviation, and t statistics for inference on the increase in the variance of the posterior means of the Calvo parameters among countries for long-term loans and for intermediate-term loans are (–0.0004, 0.000098, –3.9) and (–0.0016, 0.00064, –2.4), respectively.[16] This implies that loan rate stickiness converges to the average level of loan rate stickiness across the countries. This is a different type of evidence of convergence in the loan market, which eventually induces reductions in heterogeneity in loan rate stickiness.

4.4 Dynamics

Our estimation technique can reveal the dynamic properties of loan rate stickiness with respect to the economic situation in each country.

Figure 1 shows that the posterior means of loan rate stickiness do not change more than 5% in all countries except Austria during the sample periods for the short-term loans. Thus, loan rate stickiness does not change much according to the economic situation in the country. However, Figures 2 and 3 show that the posterior means of loan rate stickiness oscillate widely for the longer maturity loans. In almost all countries, loan rate stickiness moves more than 5% during the sample period. For example, in Spain (Finland), the posterior mean of loan rate stickiness changes 10% (13%) and 15% (13%) for the intermediate- and long-term loans, respectively, compared with 3% (4%) for the short-term loans. This implies that loan rate stickiness changes according to economic conditions for the longer maturities. These findings are consistent with yield curves. It is well known that longer maturity loan rates change their dynamics more dramatically

[16] For the short-term loans, the variance of the posterior means of the Calvo parameters among the countries does not change. The mean, standard deviation, and t statistics for inference on the increase of the variance for short-term loans are (0.000009, 0.000024, 0.39).

than shorter maturity loan rate do because of a term premium depending on the market expectation that is very vulnerable to economic conditions.

It has sometimes been argued that there might be asymmetric adjustment speeds in the loan rates depending on whether the adjustments are towards higher or lower rates. In particular, the private banks are likely to quickly increase loan rates when the ECB increases the policy rate because the private banks want to add increased funding costs on the loan rates to secure their profits. We check this point. During the first half of the sample, the ECB decreased or fixed the policy rate but the ECB increased the policy rate during the last half of the sample. Thus, Table 2 provides insights to asymmetric adjustment. For the short-term loans, we can see asymmetric adjustment because loan rate stickiness decreases in many countries following an increase in the loan rates. This asymmetric adjustment could be the reason for the reductions in loan rate stickiness. For intermediate- and long-term loans, however, we see reductions in loan rate stickiness in some countries, but we cannot say that loan rate stickiness decreases in many countries in Table 2.

5 Robustness

In this section, we show that the findings in the last section are robust for different model specifications. In particular, we consider the case of Germany as a robustness check.[17]

5.1 Forward variable based on out-of-sample forecasts

As a robustness check for our estimation result, we estimate the TVR-SV model using the out-of-sample forecasts for the forward variable, R_{t+1}. To generate the out-of-sample forecasts, we fit an autoregressive model to the historical data up to time t, while the in-sample forecasts are made by fitting one to the entire sample. Because the original data starts from January 2003, we firstly use the data from January 2003 to February 2004 to forecast the forward variable to March 2004 by fitting an AR(2) model. We recursively update the historical data (from January 2003 to month t) to fit the AR(2) model and the

[17] The outcomes for other countries and analyses on these outcomes are available by request.

corresponding OLS estimator is used for forecasts. We label this method as a recursive AR(2).

Figure 5 draws the transition of the Calvo parameters with out-of-sample forecasts of the recursive AR(2) for Germany. The case of fitting a recursive AR(3) model and the original model as the original AR(2) from the Figure 1, 2, and 3 are also reported. For the case of the short- and intermediate-term loans, the transitions of the Calvo parameters under recursive AR forecasts are slightly upward; however, the estimation results are basically the same as the original AR(2). For the long-term loans, the difference from the original estimates is wider than the ones for the other loans. However, the recursive model captures well the sudden change around 2006–2007 as the original AR(2). Therefore, our estimation is robust with respect to the computation of the forward variable.

5.2 Ratio of external finance

In this subsection, we relax the assumption that the firm finances all production costs by loans. When the firm finances only some parts of production costs by loans, the parameter λ_3 is given by $\frac{\epsilon\gamma}{\beta(1-\gamma)+\epsilon\gamma}\frac{(1-\varphi\beta)(1-\varphi)}{1+\varphi^2\beta}$. γ is a ratio of external finance.[18] When γ increases, the effect of the policy rate on the loan rate, *i.e.,* λ_3, increases. ϵ is a parameter reflecting the degree of monopolistic power of private banks to firms in setting loan rates.[19] When ϵ increases, monopolistic power decreases and so the steady state markup from the policy rate to the loan rate, *i.e.,* $\frac{1+\bar{r}}{1+\bar{i}}$, decreases, where $\bar{r}$ and $\bar{i}$ are steady state values of the loan rate and policy rate, respectively. Thanks to the degree of monopolistic power and the ratio of external finance, the model can include more detailed properties of the financial market of each country.

To secure estimation robustness, we choose the case of γ =0.5 and 0.75. There, we calculate ε as it satisfies $\frac{1+\bar{r}}{1+\bar{i}}$ =1.024, 1.018, and 1.024, which are the average values for the short-, intermediate-, and long-term loans, respectively, in the sample periods for Ger-

[18] In the basic setting, $\gamma = 1$. See the details of the derivation in Teranishi (2008).

[19] In the theoretical model, private banks can set different loan rates to firms according to business characteristics differentiated by labor types defined by ϵ, which eventually defines the degree of monopolistic power.

many.[20] Then, for the short-, intermediate-, and long-term loans, we have ε =83.9 when γ =0.5 and ε =56.4 when γ =0.75, ε =111.5 when γ =0.5 and ε =74.2 when γ =0.75, and ε =83.9 when γ =0.5 and ε =56.4 when γ =0.75, respectively.

Figure 6 shows the estimation results with different ratios of external finance. We confirm that our results in previous sections are robust even for this specification.

6 Concluding remarks

This paper shed light on loan rate stickiness and its heterogeneity in the euro area. A time-varying regression with stochastic volatility is applied to structural loan rate curves for 12 euro area countries. The estimation results showed that loan rates are sticky and the stickiness differs across the countries. This result is robust for three types of loan duration. We conclude that the banking sector integration across euro area countries is imperfect in terms of loan rate stickiness. However, the degree of heterogeneity in the loan rate stickiness decreases during the last few years.

[20] We use the relation $\frac{1+\bar{r}}{1+\bar{i}}\frac{\varepsilon}{\varepsilon-1} = \frac{\varepsilon\gamma}{\beta(1-\gamma)+\varepsilon\gamma}$ in the steady state to calculate ε as derived in Teranishi (2008).

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Table 1: Summary statistics for loan data. Standard deviation and range across countries for each year (monthly average).

Year	Short-term loan	Intermediate-term loan	Long-term loan
		Standard deviation	
2003	0.667	0.707	0.621
2004	0.627	0.726	0.648
2005	0.530	0.711	0.598
2006	0.550	0.692	0.510
2007	0.632	0.602	0.527
		Range (max. − min.)	
2003	2.178	2.404	1.714
2004	1.981	2.575	1.909
2005	2.000	2.472	1.773
2006	1.966	2.335	1.618
2007	2.373	2.065	1.630

Table 2: Difference in distributional probability.

Short-term loan	>60	>65	>70	>75	>80	>85	>90	>95
2004	33	25	20	17	9	4	0	0
2005	34	24	20	17	12	8	2	0
2006	38	29	24	20	15	12	4	0
2007	39	34	26	20	18	13	4	0
2008	38	32	24	19	14	4	0	0
Intermediate-term loan	>60	>65	>70	>75	>80	>85	>90	>95
2004	40	32	20	12	8	5	1	0
2005	40	38	27	17	9	7	2	0
2006	39	30	20	12	8	4	0	0
2007	41	31	21	16	13	6	2	1
2008	34	21	10	7	3	1	0	0
Long-term loan	>60	>65	>70	>75	>80	>85	>90	>95
2004	54	48	34	29	24	15	9	4
2005	59	50	44	39	31	23	16	10
2006	54	51	45	36	29	25	16	7
2007	52	47	44	39	36	35	24	9
2008	50	40	32	26	20	10	3	0

Table 3: Posterior mean differences for loans between first and last half samples.

Country	Short-term loan	Intermediate-term loan	Long-term loan
Austria	D (-0.08, -15.6)	D (-0.06, -10.6)	D (-0.03, -5.7)
Belgium	D (-0.02, -13.4)	I (0.01, 3.2)	D (-0.03, -3.9)
Netherlands	D (-0.02, -7.9)	I (0.02, 2.9)	D (-0.04, -5.3)
Finland	D (-0.03, -20.0)	I (0.04, 4.5)	I (0.04, 4.6)
France	D (-0.004, -2.7)	I (0.02, 10.0)	I (0.02, 14.7)
Germany	D (-0.01, -14.1)	I (0.02, 8.9)	U (-0.01, -0.6)
Greece	D (-0.02, -10.0)	D (-0.01, -4.2)	I (0.01, 3.7)
Ireland	D (-0.01, -4.3)	D (-0.04, -13.3)	D (-0.02, -13.9)
Italy	I (0.01, 1.9)	U (0.001, 0.2)	I (0.06, 10.2)
Luxemburg	D (-0.03, -19.8)	U (-0.005, -1.4)	U (0.001, 0.4)
Portugal	I (0.01, 10.0)	U (-0.008, -0.9)	D (-0.03, -5.2)
Spain	D (-0.01, -8.2)	I (0.04, 6.9)	I (0.08, 10.7)
Average of all countries	D (-0.02, -15.3)	I (0.006, 1.9)	U (0.005, 1.2)

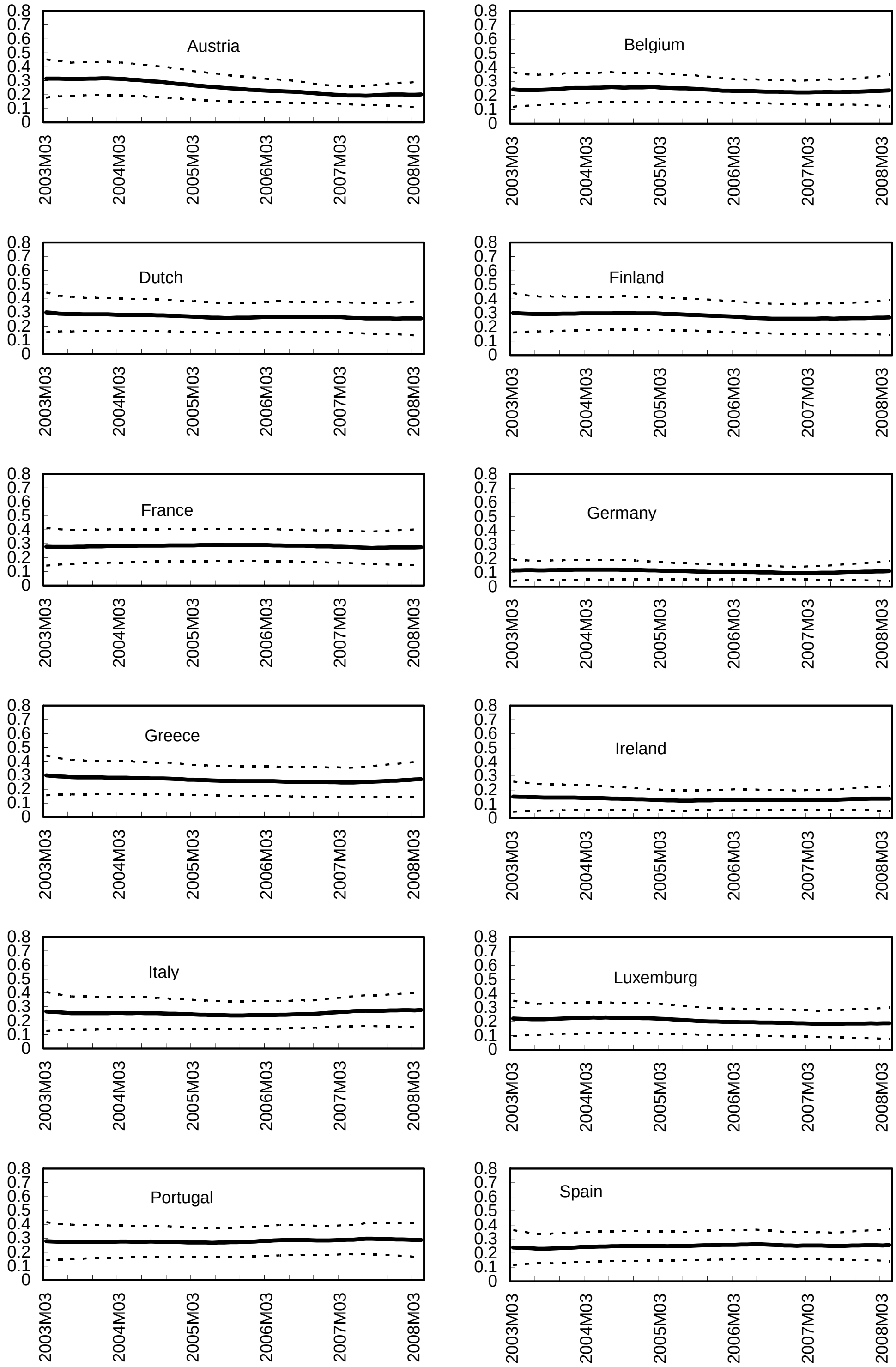

Figure 1: Calvo parameters for the short-term loans. Posterior means (solid) and one-standard-deviation bands (dashed).

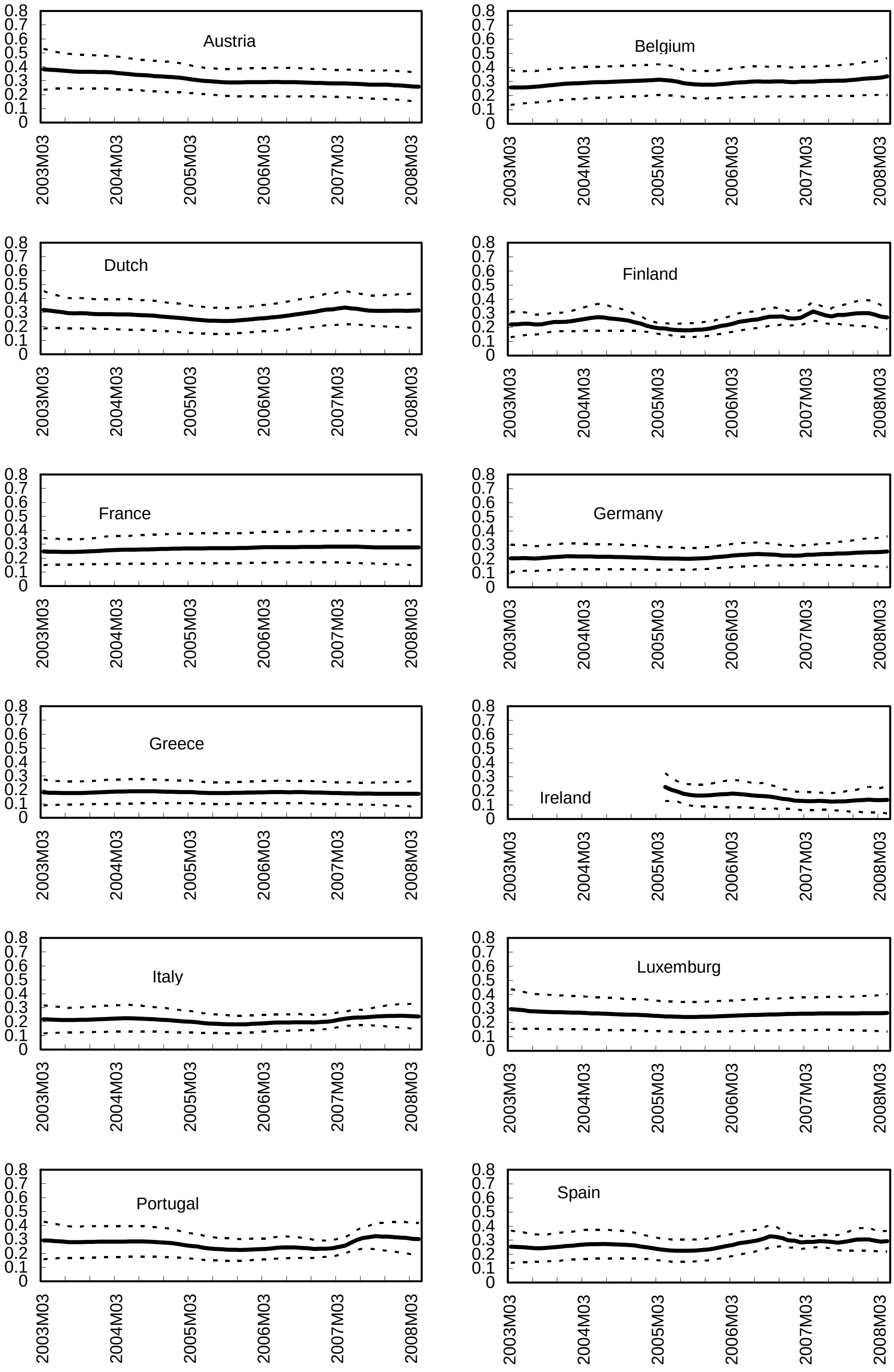

Figure 2: Calvo parameters for the intermediate-term loans. Posterior means (solid) and one-standard-deviation bands (dashed).

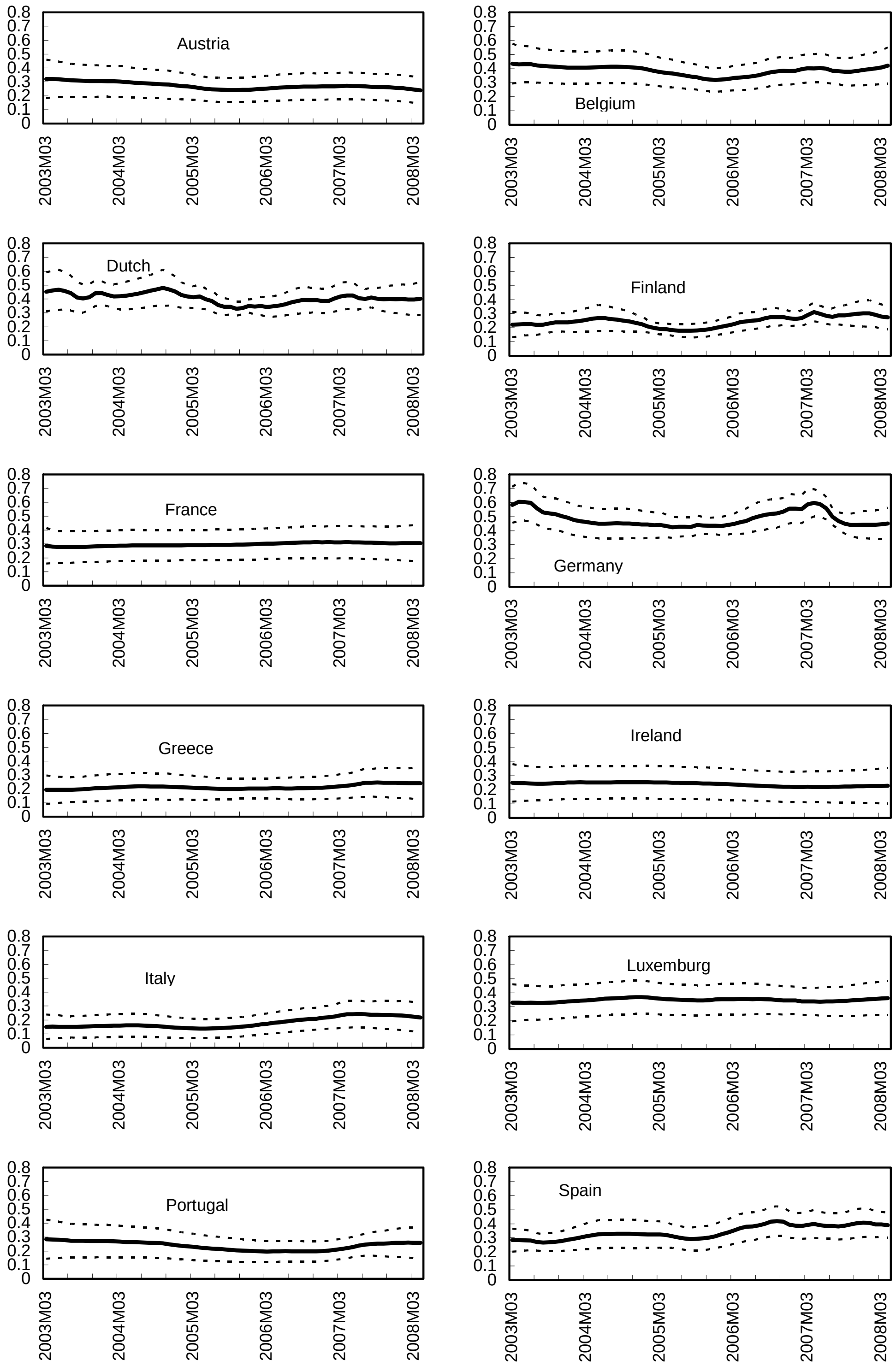

Figure 3: Calvo parameters for the long-term loans. Posterior means (solid) and one-standard-deviation bands (dashed).

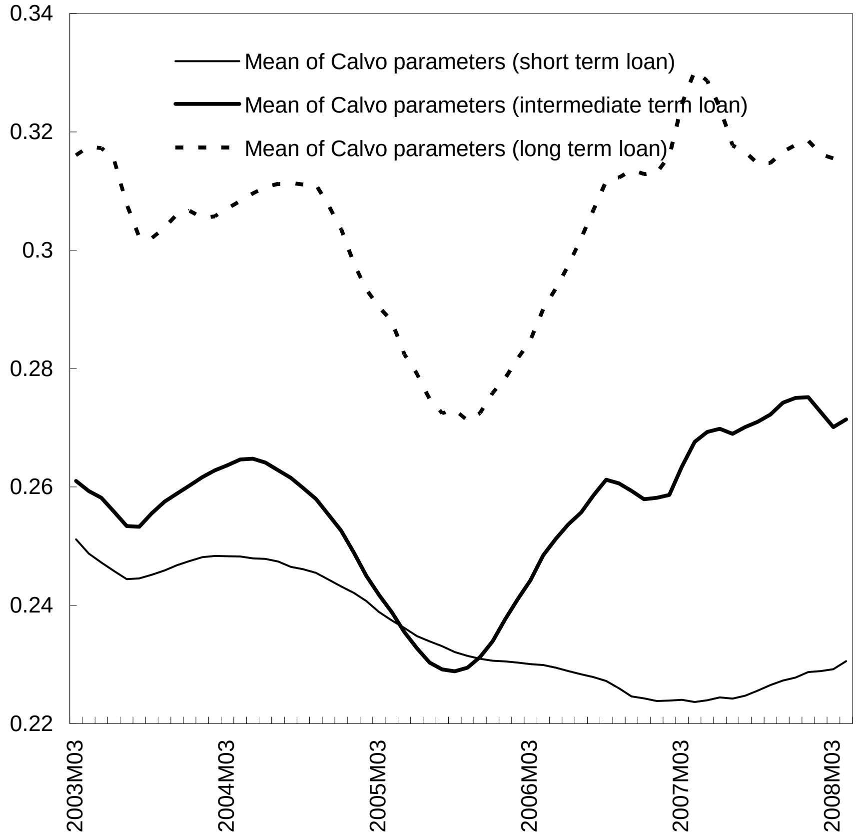

Figure 4: Transition of average of the posterior means of Calvo parameters across countries.

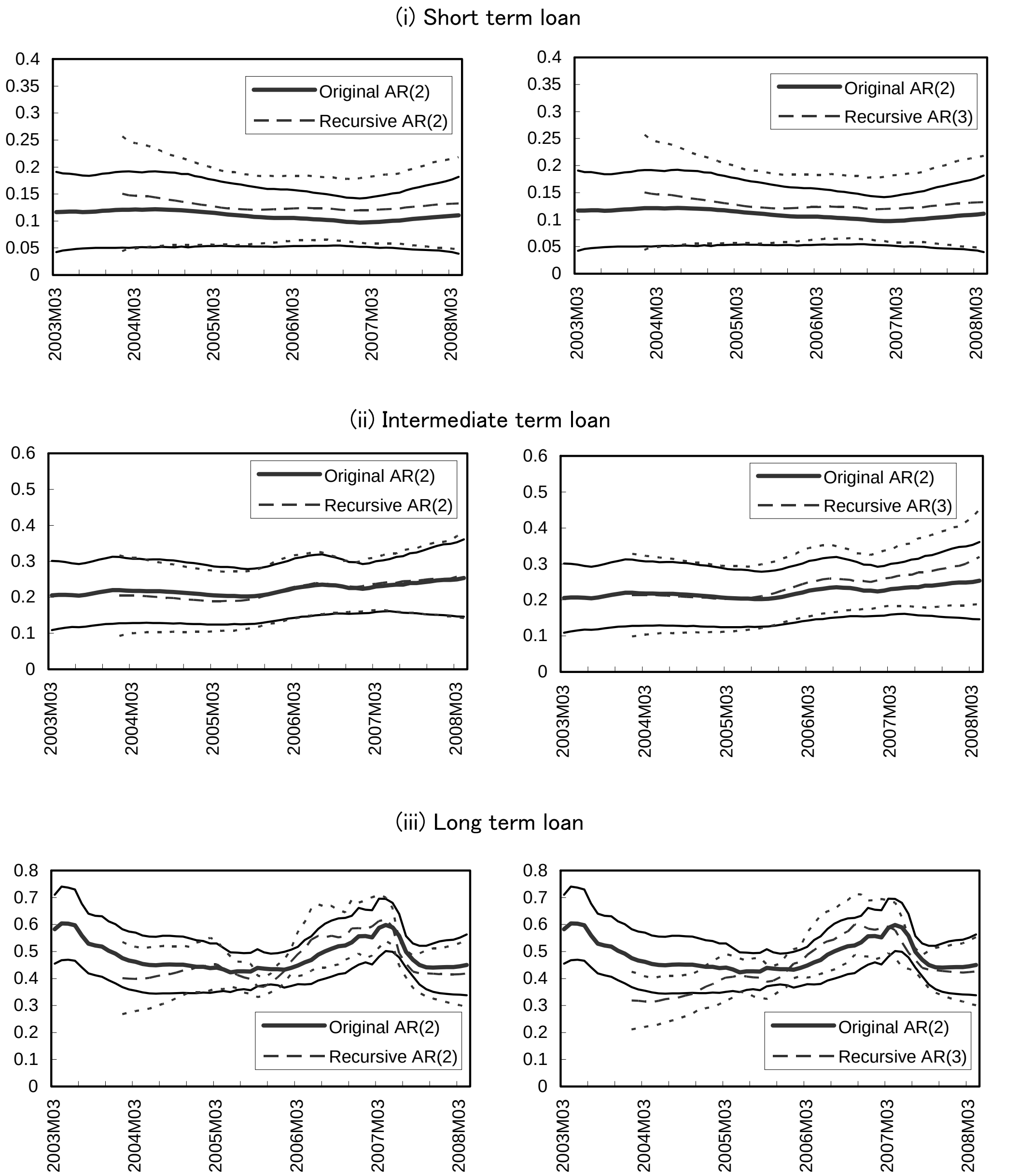

Figure 5: Posterior means and one-standard-deviation bands for Calvo parameters under difference expectation formations (Germany).

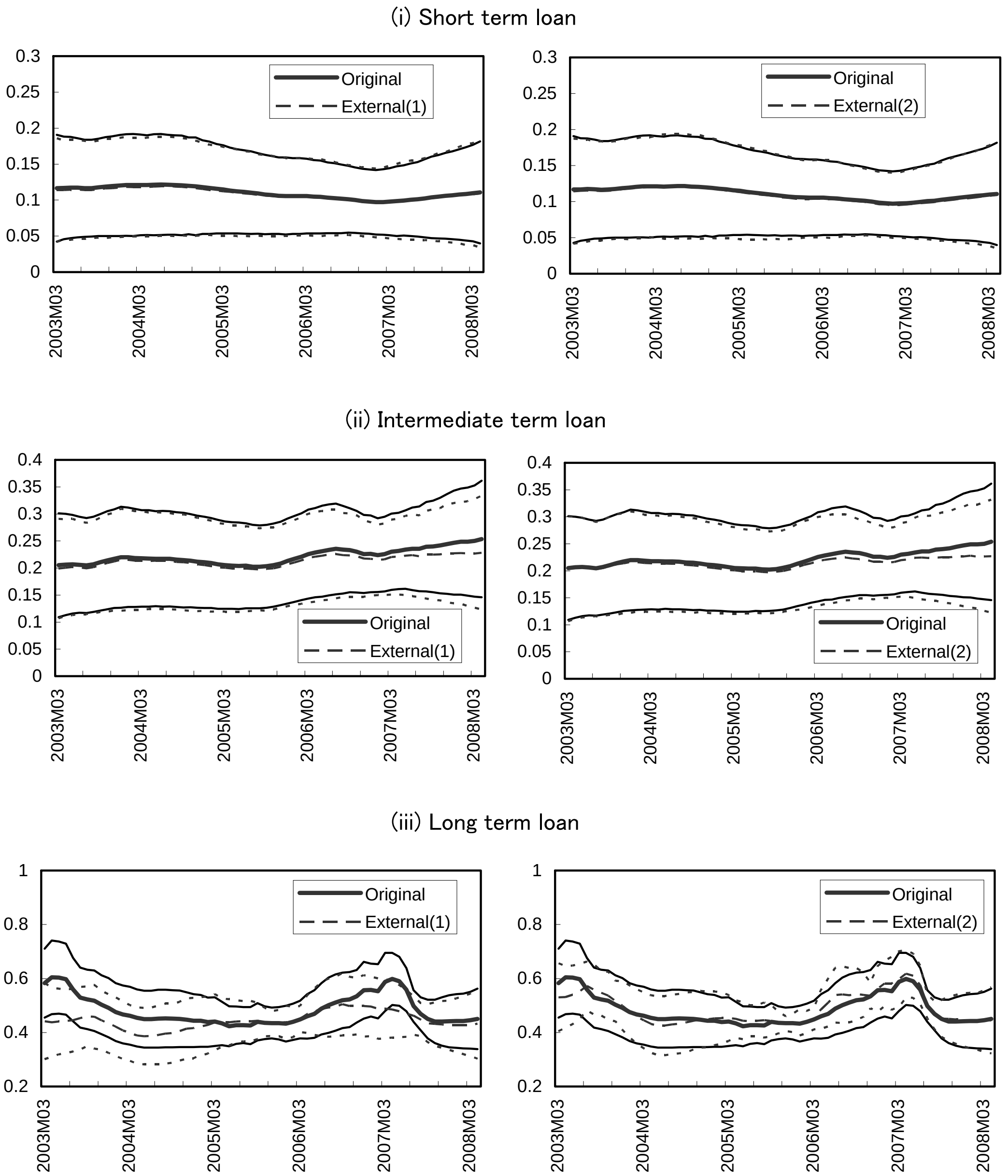

Figure 6: Posterior means and one-standard-deviation bands for Calvo parameters under different conditions of external finance (Germany). External (1) and (2) refer to the ratio of the external finance 0.5 and 0.75 respectively.

Appendix: MCMC algorithm for the TVR-SV model

Let $y = (y_1, \ldots, y_n)$, $h = (h_1, \ldots, h_n)$, $\lambda = (\tilde{\lambda}_1, \ldots, \tilde{\lambda}_n)$ and $\theta = (\sigma_u, \sigma_\eta)$. Under the prior $\pi(\theta)$, we obtain the posterior distribution as:

$$\pi(\lambda, h, \theta | y) \propto \pi(\theta) \times f(y|\lambda, h) \times \pi(\lambda|\sigma_u) \times \pi(h|\sigma_\eta),$$

where f is the conditional likelihood function of the observation equation. We draw samples from this posterior distribution by the MCMC method. There are several ways of sampling, while we propose the following algorithm, which is relatively simple:

1. Initialize θ, λ, h.
2. Sample $(\lambda, \sigma_u)|y, h$ by
   (a) sampling $\lambda|y, \sigma_u, h$,
   (b) sampling $\sigma_u|\lambda$.
3. Sample $(h, \sigma_\eta)|y, \lambda$ by
   (a) sampling $h|y, \sigma_\eta, \lambda$,
   (b) sampling $\sigma_\eta|h$.
4. Go to 2.

In step 2(a), we can sample λ using the Gaussian simulation smoother (de Jong and Shephard, 1995). In step 3(a), we implement the sampling with the help of a multi-move sampler for nonlinear Gaussian state space models (Shephard and Pitt, 1996, and Watanabe and Omori, 2004), which produces an efficient draw of the state variable (h in our case) relative to a single-move sampler. Steps 2(b) and 3(b) require only a draw from a gamma or Wishart distribution under a conjugate prior.

We check the convergence of the estimation result for the TVR-SV model. Figure 7 illustrates the MCMC sampling result; sample autocorrelations, sample paths and posterior densities of the parameters, σ_u, σ_η, $\tilde{\lambda}_{30}$ and h_{30}, which are obtained from the estimation using the Germany data for loans up to one year. The sample autocorrelations drop smoothly and the sample paths look stable, which indicates our sampling method efficiently produces uncorrelated samples. Table 4 reports the convergence diagnostics of Geweke (1992), which computes the CD statistics defined by:

$$\mathrm{CD} = \frac{\bar{x}_0 - \bar{x}_1}{\sqrt{\hat{\sigma}_0^2/n_0 + \hat{\sigma}_1^2/n_1}},$$

where $\bar{x}_j = \frac{1}{n_j}\sum_{i=m_j}^{m_j+n_j-1} x^{(i)}$, $\sqrt{\hat{\sigma}_j^2/n_j}$ is the standard error of $\bar{x}_j$ respectively for $j = 0, 1$, and $x^{(i)}$ is the i-th draw. If the sequence of the MCMC sampling is stationary, it converges in distribution to a standard normal. We set $m_0 = 1$, $n_0 = 1,000$, $m_1 = 5,001$ and $n_1 = 5,000$. The $\hat{\sigma}_j^2$ is computed using a Parzen window with bandwidth of 100. From the estimation result of the CD, the null hypothesis of the convergence to the posterior distribution is accepted for all parameters at the 5% significance level. From these results, we conclude that the MCMC sampling converges in our proposed method.

Table 4: CD statistics for the estimation result of MCMC sampling (Germany, Short-term loans).

Parameter:	σ_u	σ_η	$\tilde{\lambda}_{30}$	h_{30}
P value	0.594	0.222	0.409	0.101

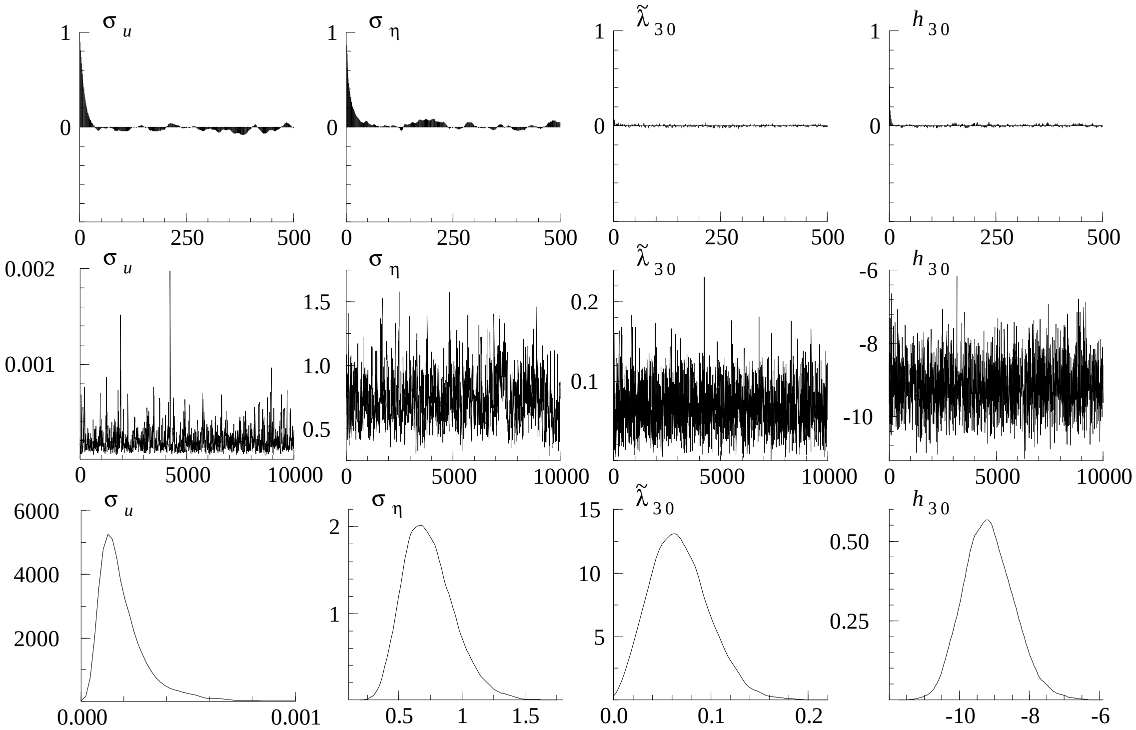

Figure 7: Estimation result of MCMC sampling (Germany, short-term loan). Sample autocorrelations (top), sample paths (middle) and posterior densities (bottom).

We state one of the advantages to use a Bayesian inference and the MCMC method as follows. The structural model of the loan rate curve forms a nonlinear equation with respect to the Calvo parameter. To obtain the posterior distribution of the Calvo parameter, we sample the parameters and only need to compute the Calvo parameter from the draw of $\tilde{\lambda}_t$ for every iteration of MCMC sampling. Figure 8 draws the posterior densities of the Calvo parameter on June of each year for Austria for short-term loans.

We analyze the dynamics of the Calvo parameter by plotting the time series of posterior means in this paper. Figure 9 draws the posterior mean, median and one-standard-deviation band of the Calvo parameter for Austria for short-term loans. Although the density of the Calvo parameter is slightly asymmetric as shown in Figure 8, the posterior mean and median are moving together over time.

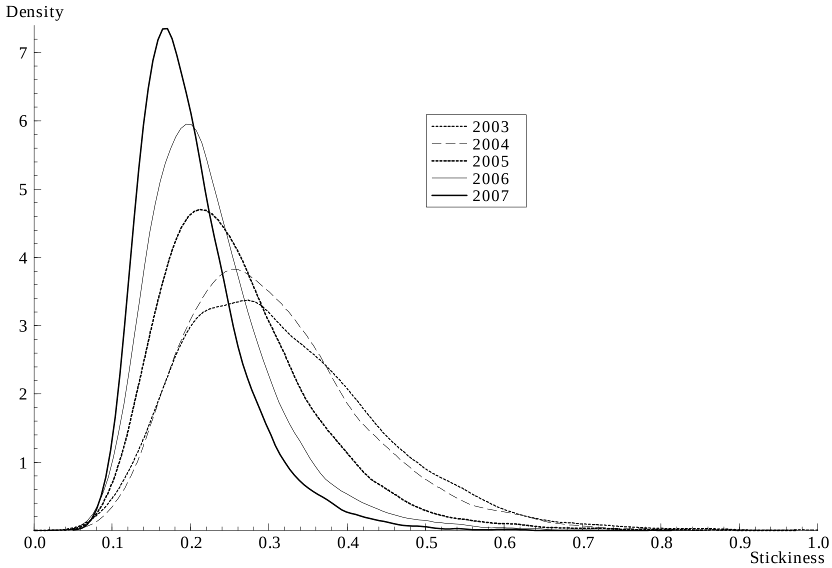

Figure 8: Posterior densities of the Calvo parameter in June in different years (Austria, short-term loans).

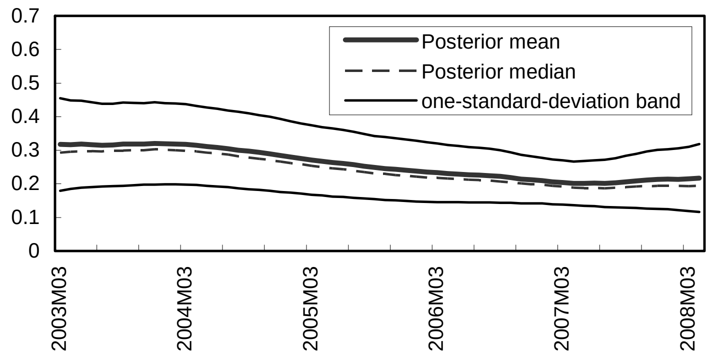

Figure 9: Posterior mean, median and one-standard-deviation bands for the Calvo parameter (Austria, short- term loans).