Lending Cycles in Estonia

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Working Papers of Eesti Pank
No 3, 2004

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May 2004
Revised in June 2004

The objective of this paper is to examine possible cyclical patterns in the lending behavior of Estonian commercial banks. Furthermore, the degree of cycle synchronization between the business cycle and the credit cycle and how much one cycle is behind the other in the case of Estonia is of particular interest. The paper uses data from between January 1994 and February 2004 to identify the Estonian business and credit cycles and compare their features. A Markov regime-switching technique was used in dating both business and credit cycles. Variables of interest in terms of the credit cycle include the total amount of loans provided by commercial banks, household loans, corporate loans, and the share of overdue loans in the total portfolio. Both, monthly and quarterly data was utilized to double-check the results and the business cycle was dated using the Industrial Production Index (IPI) and GDP, respectively. The share of overdue loans in the total portfolio appeared to be counter-cyclical as expected. Changes in the IPI seemed to cause changes in corporate loans with a two-quarter lag on average. Asymmetries between the credit and business cycles were found for Estonia. That is, it takes approximately five months from the beginning of an economic slowdown before corporate loans move into a contraction regime. However, it takes approximately eight months for corporate loans to recover their expansionary growth rate. Changes in household loans seemed to precede changes in economic activity by approximately one quarter.

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[*] Department of Economics, University of Aarhus, Denmark. This research was carried out during the three-month period the author spent in Eesti Pank as a visiting researcher. The author is grateful to Aurelijus Dabusinskas, Reimo Juks, Martti Randveer, Rasmus Kattai, John Lewis, Peeter Luikmel, Lenno Uusküla, Jana Kask, David Mayes as well as seminar participants in Eesti Pank for useful comments and suggestions. The author would also like to thank Kadri Männasoo for help with data.

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Introduction

According to economic theory and confirmed by large amounts of empirical evidence, financial cycles (credit developments and financial asset price trends) do indeed exist. It has been argued lately that financial cycles have a growing role in the pattern of the business cycle. However, the causal relationship between credit and business cycles is unclear and evidence differs across countries. Moreover, the question often arises of whether the credit cycle is indeed pro-cyclical (or counter-cyclical) compared to the business cycle. The question of bank lending being pro-cyclical is of great importance for monetary and financial authorities, as well as for policy makers. These institutions are in many respects concerned by the relative amplification that the credit cycle, in being pro-cyclical, may introduce to the macroeconomic sphere. In particular, pro-cyclical bank lending may initiate profound swings in the overall economy and lessen financial stability. Therefore, it is essential to know the cyclical features of the credit cycle and also the degree of synchronization between business and credit cycles when selecting the tools for policy implementation.

The general objective of the paper at hand is to examine possible cyclical patterns in the lending behavior of commercial banks. Dating the business cycle for Estonia and then dating the cycles for bank lending and overdue loans will deal with this issue. The question of pro-cyclicality of bank loans and the lag length between the business and credit cycles are of particular interest. In addition, an Autoregressive Distributed Lag (ARDL) model is used to describe commercial bank lending behavior.

The remainder of the paper is organized along the following lines. Section 1 handles the theoretical underpinnings of (business) cycle dating methods and briefly describes one particular parametric method to be used, namely, Markov regime-switching regressions. In addition, short overviews of bank lending channel theory and balance sheet channel theory are provided to generate theoretical linkages for modeling lending behavior. Section 2 provides results for preliminary data assessment. Moreover, co-movements in GDP and loans and leasing by commercial banks are considered. A brief analysis of changes in value added to GDP vs changes in loan and leasing portfolio by economic sector will be conducted. Section 3 provides a thorough analysis of cycle dating. The variables of interest are the Industrial Production Index (IPI), total loans granted by commercial banks, non-financial corporate loans, household loans, up to 30-day-overdue loans, and over 30-day-overdue loans. Furthermore, a descriptive model for the lending behavior of commercial banks is proposed. This model is a general version of that used in testing the bank lending channel theory. However, it is generalized in the sense that it is applied to aggregate commercial bank data. The information regarding the business cycle that is identified by Markov regime-switching models is incorporated. In particular, dummy variables are added for the periods of crisis in order to capture the asymmetry between business and credit cycles. Section 4 concludes.

1. Theoretical Underpinnings

1.1. Overview of Cycle Dating Methods

In order to analyze cycle synchronization between a particular set of variables, cycles should be dated. That is, the turning points in cycles, where an expansion in a variable changes into a contraction and a contraction changes into an expansion, should be found. There are several techniques for identifying cycles. Until recently, business cycles were mainly identified by the use of non-parametric methods – most famous among them being the Bry and Boschan (1971) procedure. More recently, the Markov regime-switching model proposed by Hamilton (1989) has been widely used to date business cycles. The main advantage of this fully parametric method is that it provides a probabilistic measure of the cyclical status for each time period. In addition, it is possible to apply the Markov regime-switching technique to any variable of interest to identify cycles in that variable, whereas this is usually not the case with non-parametric methods that are tailored to GDP data or other data indicating economic activity. Therefore, since one of the objectives of the paper at hand is also to identify cyclical patterns in the lending behavior of commercial banks, the Markov regime-switching approach is highly suitable.

As mentioned above, business cycles can be identified based on the periods of contraction and expansion in GDP (or some other variable indicating economic activity) by the use of Markov regime-switching regressions. Recent studies have shown that generally, both parametric and non-parametric methods end up with the same turning points for business cycles in the case of the US and the euro area (Harding and Pagan, 2003; Bruno and Otranto, 2004). Even though it is more time-consuming to test parametric models, especially in the form of Markov switching models, and robustness checks should be conducted (AR structure, sample period, sample size, etc), there is sounder economic reasoning behind this type of modeling than behind some non-parametric rules that are simply applied to the data (Hamilton, 2003). Furthermore, characteristics of the economic recession and expansion phases that can be identified by Markov models provide useful additional information for economists and policy makers. Second, exploiting the Markov regime-switching technique enables to identify cycles in any variable of interest and then compare the cycle synchronization between two cycles by calculating concordance indices, analyze lags between cycles, average the durations and probabilistic inference regarding the cycles.

Following mostly the notation of Hamilton (1990, 1994), only a short and general overview of the Markov regime-switching framework is provided here. The general idea is to model a time series of interest so that it is time invariant conditional on a latent regime variable (s_t). Thus, consider a stationary[1] time-series process $\boldsymbol{y} = (y_1, y_2, \ldots y_{T-1}, y_T)$ of sample size T. It is assumed that there might be occasional discrete shifts in the mean, variance or autoregressive dynamics of $\boldsymbol{y}$. For the sake of simplicity, assume that there are two possible regimes $s_t=1$ and $s_t=2$ from which a particular observation y_t might have been drawn. Let y_t be modeled as an AR process of order zero for the ease of tractability. Thus, y_t can be modeled as:

[1] The Markov regime-switching model was originally proposed to model non-stationary time-series, however, simple reparameterization leads to a regime-switching model for stationary time-series. The latter is more often presented in literature since the aim is usually to model the mean and variance of growth rates.

$$y_t = \begin{cases} \mu_1 + \varepsilon_{1t} & with \quad \varepsilon_{1t} \sim N\left(0, \sigma_1^2\right) \quad if \quad s_t = 1 \\ \\ \mu_2 + \varepsilon_{2t} & with \quad \varepsilon_{2t} \sim N\left(0, \sigma_2^2\right) \quad if \quad s_t = 2 \end{cases} \tag{1.1}$$

Thus, $\boldsymbol{y}$ is evaluated using no autoregressive dynamics where both, mean vector and variance-covariance matrix are functions of the state:

$$y_t \mid s_t \sim N\left(\mu_{s_t}, \Omega_{s_t}\right) \qquad s_t = 1,2 \tag{1.2}$$

Therefore, while under the non-linearity of the data generating process the general statistical model has time-varying parameters, parameters are constant conditional on the prevailing regime. To make the model operational, properties of the process s_t that govern the transition between states need to be specified. For that purpose, it is assumed that s_t follows a first-order ergodic Markov chain. By assuming a first-order process, the current regime s_t depends only on the regime one period ago, s_{t-1}. In addition, once the current regime is conditioned on s_{t-1}, s_t is independent of y_t and the lagged values of y_t. The transition between the regimes is governed by transition probabilities that define the Markov process. For the two-regime Markov model, transition probabilities are given as follows:

$$p\left(s_t = j \mid s_{t-1} = i\right) = p_{ij} \qquad with \quad \sum_{j=1}^{2} p_{ij} = 1 \qquad for \qquad i = 1,2 \tag{1.3}$$

When collecting all the transition probabilities into a matrix, transition matrix $\boldsymbol{P}$ of dimension two by two can be defined in the case of two possible states. Probabilities of main interest are p_{11} and p_{22}, that is, the probability that regime 1 will be followed by regime 1 and the probability that regime 2 will be followed by regime 2, respectively.

It should be mentioned that the state variable s_t is an unobserved variable yielding to maximizing the likelihood function of the observed data $f(y_T, y_{T-1}, \ldots, y_1; \boldsymbol{P}, \mu_1, \mu_2, \sigma_1^2, \sigma_2^2)$ by the choice of population parameters $\boldsymbol{\theta} \equiv (\boldsymbol{P}, \mu_1, \mu_2, \sigma_1^2, \sigma_2^2)$. Thus the density of y_t conditional on the random variable s_t taking the value j is:

$$f\left(y_t \mid s_t = j; \lambda\right) = \frac{1}{\sqrt{2\pi\sigma_j}} \exp\left[\frac{-\left(y_t - \mu_j\right)^2}{2\sigma_j^2}\right], \tag{1.4}$$

where $\boldsymbol{\lambda} \equiv (\mu_1, \mu_2, \sigma_1^2, \sigma_2^2)$. An unconditional probability that s_t takes the value one or two at any given time are given respectively by:

$$P\left(s_t = 1\right) = p_1 = \frac{1 - p_{22}}{2 - p_{11} - p_{22}} \text{ and } P\left(s_t = 2\right) = p_2 = \frac{1 - p_{11}}{2 - p_{11} - p_{22}} \tag{1.5}$$

These probabilities are often referred to as steady state probabilities. Then, a joint density-distribution function for y_t and s_t can be found by multiplying equation (1.4) by equation (1.5). The unconditional density of y_t can be found by summing the joint density functions over all possible values for *j*. The log-likelihood function is then constructed by summing the unconditional density of y_t over all time periods. Next, this log-likelihood function is then maximized by the use of the EM (Expectations Maximization) algorithm of Dempster *et al* (1977). According to Hamilton (1990), the EM algorithm is fairly robust with respect to poorly chosen starting values for parameter vector and quickly moves to a reasonable region of the likelihood surface. The EM algorithm is in itself an iterative procedure that, after specifying initial parameter values $\boldsymbol{\theta}^{(0)}$, consists of two steps:

1) Expectations step, and
2) Maximization step.

First, the expectations step is implemented by the use of filtering and smoothing functions. Using a recursive non-linear filter proposed by Kim (1994), it is possible to use the full data sample and draw inferences concerning the probabilistic structure of past regimes. Probabilities that provide this information are termed smoothed probabilities. Second, the outcome from the expectations step is then used in the maximization step. In general, to be able to exploit the EM algorithm, one should first find the set of updating equations for the parameters to be estimated. That includes taking derivatives of the log-likelihood function with respect to the parameter vector $\boldsymbol{\theta}$. The general way to proceed after one has derived updating equations is as follows:

1) Make an initial guess for parameter starting values ($\boldsymbol{\theta}^{(0)}$);
2) Calculate smoothed probabilities;
3) Re-weight the data with smoothed probabilities and calculate new mean values;
4) Calculate new variances using new mean values;
5) Calculate new transition probabilities and new steady state probabilities;
6) Calculate the value of the objective function;
7) Recalculate smoothed probabilities and repeat steps three to six until the log-likelihood function achieves its maximum according to some convergence criteria.

By modeling two univariate time series processes separately using Markov regime-switching regressions, it becomes possible to compare the probabilistic inference of the unobserved regimes of two variables. That embodies comparing two sets of smoothed probabilities and checking whether the regimes coincide across these two time series. To be more exact, the Markov regime-switching model permits testing for the degree of cycle synchronization. There are several non-parametric approaches available for defining co-movements of cycles and some of them will be used in further analysis. In particular, concordance coefficients (the percentage of time two variables of interest are in the same phase) in a form proposed by McDermott and Scott (1999) and Harding and Pagan (2004) will be calculated. It is also feasible to test for asymmetry in synchronization. That is, it has been shown for the US and euro area that downswings in the business cycle and credit cycle are generally simultaneous, while upswings in the business cycle precede those in the credit cycle. This lag is due to the fact that both corporate profitability and the supply of credit recover gradually after the phase of contraction (Banque de France Bulletin, 2001). One can determine this lag by looking at the smoothed probabilities and turning points implied by the former. In addition, it is possible to test for turning point asymmetry, namely sharpness. Sharpness refers to the fact that troughs are sharp while peaks are more rounded, and this can be tested using estimated transition probabilities (McAdam, 2003).

1.2. Linkages with Credit Channel Theory

General credit channel theory is concerned with the direct effects of monetary policy on interest rates and how this, in turn, affects the external finance premium (difference in cost between funds raised externally and funds generated internally) (Bernanke *et al*, 1995). On one side there is the bank lending channel theory that links the possible effects of monetary policy actions on the supply of loans by commercial banks. In this case, intuition suggests the following: a reduction in money supply by the Central Bank forces commercial banks to cut back on lending activities, which, in turn, affects businesses and even consumers so that economic activity slows down (Kashyap *et al*, 1994). The reason why commercial banks have to cut back on lending is that a tightening of monetary policy leads to a reduction in the volume of deposits. This, in turn, has an effect on bank lending. Thus, a change in money supply causes a change in lending activity, which causes a change in GDP.

On the other side, in a general credit channel framework, there is the balance sheet channel theory. It stresses the potential impact of changes in monetary policy on borrowers' balance sheets and income statements (including variables such as borrowers' net worth, cash flow, and liquid assets), representing the demand side of loans (Bernanke *et al*, 1995). Tight monetary policy directly weakens borrowers' balance sheets in at least two ways. First, rising interest rates directly increase interest expenses, reducing net cash flows and weakening the borrowers' financial position. Second, rising interest rates are also typically associated with declining asset prices, which among other things shrink the value of borrowers' collateral. Banks, as suppliers of credit, can therefore play an important role in the business cycle if during a cyclical downswing their lending policy becomes less liberal. This will reinforce trends in the real economy and therefore be pro-cyclical in effect (Bikker *et al*, 2003).

There is, however, a more traditional channel for monetary policy transmission. Namely, the money channel alternatively denoted as the interest rate channel. The intuition of how the interest rate channel affects target variables goes along following lines. An increase in liquidity leads to lower interest rates and pushes people to transform their excess liquidity into assets to earn better returns (thereby increasing the demand for stocks and bonds). Then, with some imperfect adjustment in the aggregate price level, the target variables (for example output) are affected (Kashyap *et al*, 1994). Therefore, tightening of a monetary policy pushes interest rates up, which induces less investment, which, in turn, forces output to fall. Bank lending and balance sheet channels should not be considered as alternatives to the traditional monetary transmission mechanism. They are rather seen as complementary mechanisms possibly strengthening the direct interest rate effects (Bernanke *et al*, 1995).

The core explanatory variable in the bank loan model is an exogenous variable of monetary policy shocks. The literature makes two main suggestions about this variable. First, the change in short-term interest rates under the control of the Central Bank is widely used (Bernanke *et al*, 1992). Alternatively, residuals from a vector autoregression (VAR) representing the reaction function of the Central Bank are used (Bernanke *et al*, 1998). In the bank lending channel framework, bank loan behavior is usually modeled using autoregressive distributed lag (ARDL) models. It is common to include some business cycle indicators to account for the loan demand side. Thus, in general, the ARDL model for bank loans takes the following form:

$$\begin{aligned}\Delta Loan_t = c + \sum_{j=1}^{J}\gamma_j \Delta Loan_{t-j} + \sum_{j=0}^{J}\alpha_j \Delta InterestRate_{t-j} + \\ + \sum_{j=0}^{J}\beta_j \Delta GDP_{t-j} + \sum_{j=0}^{J}\delta_j \Delta CPI_{t-j} + u_t\end{aligned} \tag{1.6}$$

For panel data analysis, additional terms describing the characteristics of commercial banks (for example total assets, liquidity, capitalization) are usually included as well as several interactive terms. It is common also to incorporate dummy variables to control for seasonal variations or other factors. In addition, many studies operate with static models, where the effects of past loan realizations on current loan realizations and other dynamics are ignored. There are, however, several economic arguments suggesting the inclusion of lagged values of endogenous variables (bank lock-in effects making it costly for borrowers to change bank and, due to long term contractual commitments, policy will only impact lending behavior with a lag) (Westerlund, 2003).

In practice, it is difficult to determine whether the decrease in lending is a result of demand or supply factors. According to bank lending channel and balance sheet channel theories, the key issue in the cyclical behavior of bank lending is to what extent lending depends on either demand or supply variables. In general, demand for credit depends on the business cycle and the interest rate on loans. Credit supply, on the other hand, depends on the interest rate on loans and several bank-specific factors (capital and reserves, expected profits, etc).

Among others, Bikker and Hu (2003) suggested incorporating the bank lending channel and balance sheet channel theories into a single framework – that is, to define a simultaneous equation model (SEM) based on the relationships presented above. The reduced-form model for lending can be derived by solving the two equations above with the interest rate on loans as the equating price. Doing this enables one to analyze which factors really influence lending behavior and whether it is demand or supply side variables that have a major impact on bank lending behavior. The model proposed by Bikker and Hu (2003) has the following form:

$$\begin{aligned}\Delta Lending_t = \alpha_1 \Delta GDP_t + \alpha_2 Unemployment_t + \alpha_3 Inflation_t + \\ + \alpha_4 \Delta SharePrice_t + \alpha_5 \Delta M3_t + \alpha_6 InterestDifferential_t + \\ + \alpha_7 NonBankDeposits_t + \alpha_8 Capital\,\&\,Reserves_t + \alpha_9 Profits_t + u_t\end{aligned} \tag{1.7}$$

Results from a SEM of this form gave poor results in Bikker and Hu's (2003) panel data study incorporating 26 countries over the period 1979–1999. Not only were half of the estimated parameters statistically insignificant, but also it was difficult to come up with a reasonable interpretation. In addition, the modeling technique just described requires a relatively large dataset from the econometric point of view, which is hard to come up with in the case of Estonia.

Notice that in terms of modeling lending behavior, identifying periods of crisis and periods of non-crisis can also be considered as just a preliminary stage. In particular, identifying periods of crisis is necessary in order to build up an ARDL model for commercial bank loan behavior that can account for asymmetries between business and credit cycles. Thus, a dummy variable will be incorporated into the ARDL model for crisis periods to capture these asymmetries between the business and credit cycle. Therefore, the model to be used takes the following form:

$$\begin{aligned}\Delta Loan_t &= c + \sum_{j=1}^{J}\gamma_j \Delta Loan_{t-j} + \sum_{j=0}^{J}\alpha_j \Delta TALIBOR_{t-j} + \\ &+ \sum_{j=0}^{J}\beta_j \Delta IPI_{t-j} + \sum_{j=0}^{J}\delta_j \Delta IPI_{t-j} DUM_{t-j} + u_t\end{aligned}, \qquad (1.8)$$

where *Loan* denotes loans given out by commercial banks, *TALIBOR* denotes local money market rate, *IPI* denotes Industrial Production Index, and *DUM* stands for dummy variable taking a value of one in periods of crisis. Determining the lag structure to start the estimation is a separate subject of discussion, but the relatively small number of observations puts quite a strong restriction on the maximum number of lags that can be used. On the one hand, since the model will be applied to monthly data, the frequency of the data used suggests using up to 13 lags for loan variables and the IPI. Economic reasoning, however, suggests that not more than one or two lags should be used for interest rate and loan variables, but this is certainly not the case for the IPI. Since the changes in the interest rate and not the levels are incorporated into the model, it is intuitive that inclusion of one or two lags should be enough. On the other hand, one can determine the appropriate lag structure to be used in the ARDL model by estimating a number of autoregressive models of different order and pick the one with the smallest value of Schwartz Information Criteria (SIC). Both methods will be used in order to check the robustness of specified models.

The ARDL set-up proposed above enables to analyze transitory shocks to the error term that in turn affect changes in loans, that is, to evaluate the persistence of transitory shocks by looking at the sum of the AR parameters in the model (namely gammas). More importantly, it is now possible to evaluate permanent policy shocks in interest rates. Such shocks have contemporaneous effects on the growth of loans by a factor of α_0, the compounded loan sales response in the subsequent period is however $\alpha_1 + \gamma_1\alpha_0$. Thus, a long-run multiplier can be derived as $\sum_{j=1}^{J}\alpha_j \Big/ \left(1 - \sum_{j=1}^{J}\gamma_j\right)$. Calculation of long-run coefficients is necessary purely because of the fact that the model specified in equation (1.8) is dynamic (it incorporates lags of endogenous variable) and looking at the estimated α, β and δ coefficients separately does not provide one with adequate information.

2. Preliminary Data Assessment

2.1. Overview of the Data

Variables of interest include changes in the balance of private sector loans and leasing among Estonian commercial banks and changes in the ratio of overdue loans to the total loan portfolio. It is possible to differentiate between loans and leasing to non-financial corporations and households and that is also done during further analysis. The balance of up to 30-day-overdue and over 30-day-overdue loans at the end of every month is considered in calculating the ratios of overdue loans to total portfolio.

The sample period runs from January 1994 until February 2004. Both, data with monthly and quarterly frequency are used. The main reason for exploiting two frequencies is that when operating with quarterly data, it is possible to account for the leasing portfolio. When operating with monthly frequency, it is necessary to come up with some proxy for the traditional economic activity measure (GDP), since data for GDP is available only quarterly and using both monthly and quarterly data provides a good opportunity to double-check the results and conclusions. Data to be used regarding the Estonian financial sector has been collected by Eesti Pank (the central bank of Estonia). Data for the IPI (Industrial Production Index), CPI and GDP was retrieved from the website of the Statistical Office of Estonia and data concerning Estonian money market rates (3-month TALIBOR) was retrieved from the IMF International Financial Statistics (IFS) March 2004 CD-ROM. It should be noted that it is more reasonable to use the TALIBOR instead of the EURIBOR since the latter was not affected by the Russian crisis. The TALIBOR, on the other hand, exhibited a steep rise during the crisis as did average lending rates to the private sector.

It should be mentioned that the loan portfolio is adjusted for inflation (using the CPI) and, therefore, changes in real loans are of interest. Changes in variables are calculated on the basis of any change compared to the same period (month, quarter) in the previous year. The only exception is the TALIBOR, where changes are calculated as a change in the money market rate compared to the previous period's money market rate. Calculating the changes in variables in this way results in 110 observations for monthly data and 36 for quarterly data. Summary statistics for the differentiated variables of interest are presented in Table A.1 in the Appendix.

The optimal lag length for the autoregressive structure was found for every variable using the Schwartz Information Criteria (SIC) and these results are also presented in Table A.1. Maximum lag lengths considered were 15 for monthly and 6 for quarterly data. Unit root tests on the changes of variables under consideration were also conducted. In particular, the augmented Dickey-Fuller (ADF) unit root test was applied to monthly data. According to the ADF test, changes in loan variables still seem to be integrated by order one. On the one hand, this is surprising, because the effect of inflation has been eliminated from the beginning. One possible explanation why the ADF test failed to reject the unit root for first-differenced series is that it is widely known for its relatively poor power in small samples and this is indeed the case for the monthly dataset (110 observations less the lags to be included into the augmented Dickey-Fuller test). On the other hand, looking at the dynamics of the changes in total loans, household loans, and corporate loans indeed suggests the possibility of the series being I(1) (Figure 1).

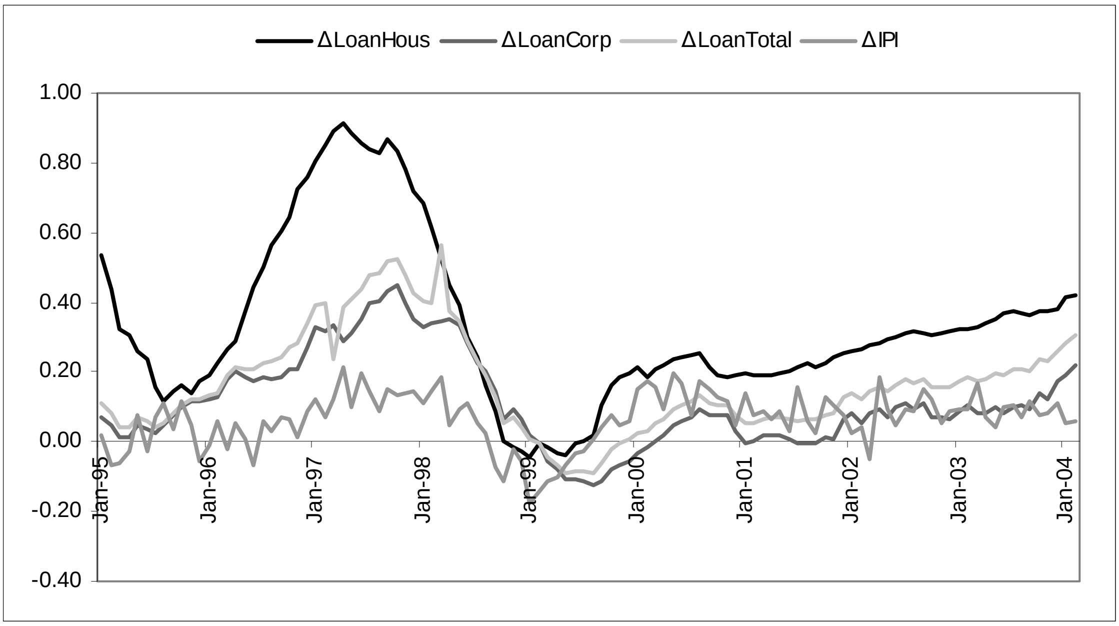

Figure 1. Dynamics of changes in total loans, household loans, corporate loans, and the IPI from January 1995 to February 2004

Hence, there are two possible ways to proceed. First, ignore the unit root test results and rely on the fact that the ADF test has relatively poor power in small samples.[2] Second, differentiate the loan variables twice to obtain stationary series. This, however, complicates the interpretation of the estimated coefficients considerably. Moreover, since the aim was to determine the lag structure, that is, whether changes in private sector loans lead the changes in economic activity or changes in economic activity are followed by changes in loans, differentiating loan variables twice changes the results available with respect to lag structure considerably. More specifically, running the regression with increase in the growth rate being an endogenous variable does not result in the same lag structure as running the regression of the growth rate being an endogenous variable, holding everything else the same across all models. Therefore, even though the ADF test suggests differentiating the series of changes in loans to private sector, households and corporations once more, adequate conclusions concerning the effect the IPI has on loans is, in this case, difficult to draw (especially in respect to lag lengths of this effect). Nevertheless, differentiating all loan variables once more yields a correct specification of the model in terms of stationarity (both sides of the regression equation are integrated by the same order) and should indeed provide adequate inference regarding the lending behavior of commercial banks.

[2] The author is aware of the consequences that disregarding the non-stationarity has on the parameter estimates in the ARDL set-up and also on the t-values of the estimated coefficients. However, the proposed ARDL model is still estimated in this case, but special care is taken when interpreting estimation results.

2.2. Graphical Analysis of Co-movements in Quarterly Data

First of all, switching from monthly to quarterly frequency has basically no effect on the dynamics of loan and overdue variables since Eesti Pank collects this data monthly. At the same time, an important advantage arises when using quarterly data. Namely, it is possible to incorporate data concerning leasing exposure. Thus, in this case, all possible funding opportunities provided by commercial banks to households and firms are included. Furthermore, it has been argued that monthly frequency is relatively noisy for macroeconomic data and using indicators with quarterly frequency to measure changes in economic activity is vastly preferred. This is well illustrated in Figure 2, which shows that changes in real GDP are considerably less volatile than changes in the IPI (see for example the dynamics of the IPI in Figure 1 and dynamics of GDP in Figure 2).

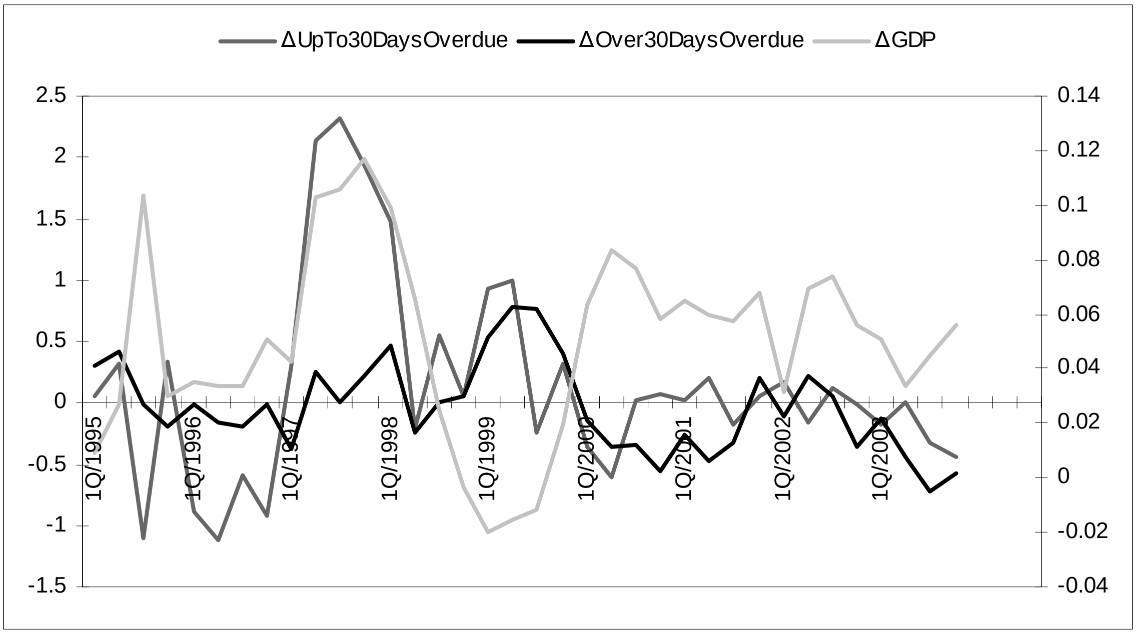

Figure 2. Dynamics of changes in GDP, ratio of up to 30-day-overdue loans to total loan portfolio and ratio of over 30-day-overdue loans to total loan portfolio over the period 1995 to 2003

Co-movements between changes in economic activity and changes in loan exposure at a more disaggregated level will be examined. In particular, the dynamics of value added to GDP vs changes in loan and leasing portfolio by economic sector are of particular interest. It should be mentioned that loan and leasing portfolios are considered in real terms. To make the analysis operational, data for value added to GDP by economic sector in constant prices was retrieved from the website of the Statistical Office of Estonia. As can also be seen from Figures A.1 through A.4 in the Appendix, relationships between these two variables by economic sector vary greatly. Yet, value added to GDP and loans to particular economic sectors do not seem to coincide closely with each other. This is confirmed when looking at the correlation coefficients between these variables (see Figure 3).

Notice that negative correlation coefficients were found for most of the sectors. In fact, this indicates that during the expansionary phase of the overall economy, firms in most of the sectors prefer to cut back on lending. However, this particular outcome is due to the fact that contemporaneous correlation coefficients were calculated, but lending activity is usually seen to either precede or follow the changes in economic activity. Thus, lagging one of the series and re-calculating correlation coefficients (r_{lag}) sheds more light on the causality issue.

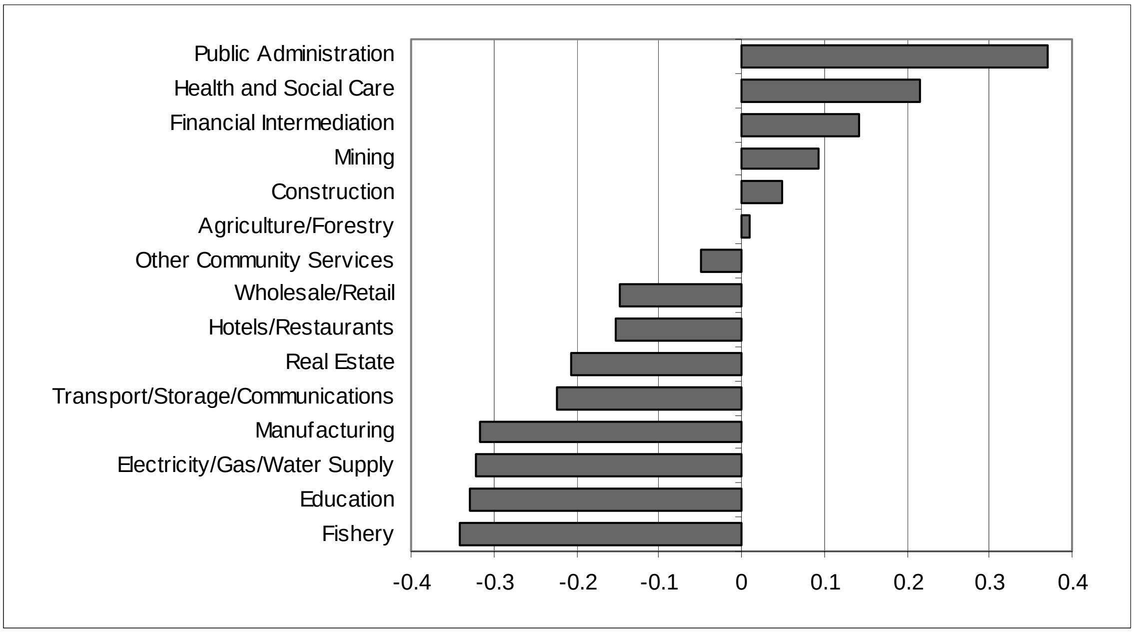

Figure 3. Correlation coefficients between changes in loan and leasing portfolios and changes in value added to GDP by economic sector over the period June 1998 to December 2003

Lags up to four quarters were considered when doing this kind of calculation and the following can be stated:

- Some weak evidence that changes in lending seem to precede changes in value added to GDP by two quarters for the mining sector (r_{-2} = 0.50) was found;
- There is weak evidence that changes in lending seem to follow changes in value added to GDP after three quarters in the real estate sector (r_3 = 0.50);
- Changes in lending seem to precede changes in value added to GDP by three quarters for the manufacturing sector (r_{-3} = -0.77), suggesting the lending activity to be counter-cyclical in the manufacturing sector;
- Changes in lending seem to precede changes in value added to GDP by two quarters for the construction sector (r_{-2} = 0.68);
- Changes in lending seem to follow changes in value added to GDP by two and four quarters for the education sector and public administration sector, respectively (r_2 = -0.61 and r_4 = -0.63), suggesting counter-cyclical lending behavior in the public sector.

Thus, there seem to be sectors where lending appears to be counter-cyclical. That is, for several sectors, lending activity slows down when overall economic activity increases. It is, however, unclear whether the demand for loans decreases in expansionary phases or the decrease is caused by supply-side factors. Moreover, it should be noticed that financing only by Estonian commercial banks is included in the above analysis and no alternative sources for financing are considered (lending from foreign banks, emission of bonds or shares, etc). Thus, the evidence based on calculated correlation coefficients should be taken as preliminary and further analysis is required concerning, for example, the counter-cyclical lending behavior in the manufacturing sector.

3. Estimations and Results

3.1. Identification of Cycles

3.1.1. Identification of Cycles Based on the Whole Sample Period

The Markov regime-switching regressions described in Section 1.1 were used when dating business and credit cycles for Estonia. The model in equation (1.1) was applied to six differentiated series:

- IPI;
- Total loans;
- Household loans;
- Non-financial corporate loans;
- Ratio of up to 30-day-overdue loans to total loan portfolio;
- Ratio of over 30-day-overdue loans to total loan portfolio.

It has been argued that cycle turning points do not depend on the autoregressive structure that is used to estimate a Markov regime-switching model (Harding and Pagan, 2003). Therefore, to begin with, the simplest structure with no autoregressive terms was considered. Since the main interest here is the cycle dating and not the forecasting power of the Markov model, this approach is highly justified. Estimation results from the Markov regime-switching models are presented in Table A.2 in the Appendix. As can be seen from the table, the hypothesis of equal variance across regimes cannot be rejected for three series.[3] Therefore, for household loans, corporate loans, and the IPI, the Markov regime-switching model with variances restricted to be the same across regimes was estimated. Table A.3 in the Appendix presents the results. As can be seen from Tables A.2 and A.3, the characteristics of the regimes remained more or less the same (mean growth rates, transition probabilities, durations of the regimes, number of switches, etc). In fact, the equality of the estimated parameters cannot be rejected at a 5% significance level for any of the series nor parameters in a restricted variance or unrestricted variance Markov model.[4] Moreover, it is a common

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[3] The standard testing procedure is valid in this case since the number of regimes is the same under both hypotheses, null and the alternative. The test used was the Wald test specifying the null hypothesis and the alternative as follows: $H_0: \sigma_1 = \sigma_2,\ \mu_1 \neq \mu_2$ *against* $H_A: \sigma_1 \neq \sigma_2,\ \mu_1 \neq \mu_2$

[4] The following t-test can be exploited and applied to any pair of estimated parameters (a^{model1} and a^{model2}):

$t = (a^{model1} - a^{model2}) / SQRT(Var(a^{model1}) + Var(a^{model2})) \sim N(0,1)$

result in business cycle dating literature that even though periods of expansion and recession have different mean growth rates, variance is the same in both regimes (Kim *et al*, 1999). Therefore, results concerning the IPI are in accordance with other empirical work on extracting business cycles using Markov regime-switching models.

Looking at the parameter estimates from the Markov regime-switching model presented in Tables A.2 and A.3 in the Appendix, one can see that for the IPI, specified regimes have growth rates with different signs. That is, periods of crisis with negative growth in the IPI and periods of non-crisis with positive growth in the IPI were identified. For loan variables, on the other hand, mean growth rates in both regimes are positive. That is, for private sector loans, household loans, and corporate loans, the Markov model ended up specifying regimes of moderate growth and high growth (boom), respectively. That is, no periods of negative growth in the respective loan portfolios were specified. That, in turn, complicates the comparison of cycle characteristics between business and credit cycles.[5] Looking at the parameter estimates of the ratio of up to 30-day-overdue loans to total loan portfolio and the ratio of over 30-day-overdue loans to total loan portfolio, it is clearly evident that for periods of crisis, the ratios mentioned above show a high positive average growth rate, while for periods of non-crisis, these ratios seem to decrease slightly. The specification testing was conducted following Hamilton (1996) and results from the specification tests are presented in Table A.4 in the Appendix. As can be seen, in most cases the assumption regarding the order of the Markov chain governing the transition between regimes is valid and that is of main importance here.[6] That is so because the estimates of main interest are the estimated smoothed probabilities and cycle turning points implied by these probabilities. It is worthwhile mentioning that estimates of smoothed probabilities, and thus cycle turning points, were quite robust in regard to the autoregressive structure used and also to slight changes in the sample size.[7] Figures A.5 through A.9 in the Appendix depict business cycle vs credit cycle and business cycle vs cycles in overdue loans. As argued above, a comparison of cycle synchronization between the IPI and loan variables is complicated and the model needs further refinements. However, it is possible to compare the dynamics and cycle synchronization between the IPI and overdue loan variables.

[5] The problem is that, supposedly, it is possible to compare the periods of expansion (recession) in economic activity with the periods of expansion (recession) in loan portfolios, but if the regimes for the different variables specified do not have similar characteristics, the comparison becomes meaningless. In particular, there is no point in comparing the synchronization between periods of recession in economic activity and periods of steady growth in lending activity, instead, periods of recession in lending activity should be considered.

[6] However, transition probabilities seem to depend on the mean values of the series of interest suggesting endogenous switching and that possibility should be considered when estimating a Markov regime-switching model for forecasting purposes.

[7] Markov regime-switching models with up to 4th order autoregressive terms were estimated in addition to AR(0) specification; tests for robustness of parameter estimates with respect to sample size were conducted by omitting up to five observations from the beginning of the series and up to 12 observations from the end of the series.

In terms of business cycle identification, it should be noticed that since the sample period only consists of monthly data for ten years, it is questionable whether the shifts in economic activity detected will be business cycles. It is more probable that in the case of Estonia and in the sample period under consideration, one is able to determine shifts that are caused by the contagious effects of crisis. What is meant here by contagion is the presence of shock transmission channels or change in the shock transmission channel between emerging market economies during a crisis. In other words, the term contagion is used to refer to the transmission of market disturbances – mostly on the downside from one market to another. Thus, strictly speaking, instead of identifying the Estonian business cycle as such, one is able to identify periods of crisis, when contagious effects appeared and triggered the recession in the Estonian economy. Determination of the Estonian business cycle is complicated purely because of the short sample period and the author would like to stress that even though the term business cycle will be used extensively hereinafter, results concerning mean growth rates, volatility, and durations of periods of expansion and recession should not be taken necessarily as those of the Estonian business cycle in the traditional sense.

As can be seen from Figure A.5 in the Appendix, the Markov regime-switching model identified three periods of crisis:

- 01/1995–06/1995;
- 02/1996–07/1996;
- 09/1998–08/1999.

However, the first two in the above list are not true crisis periods by nature, but rather periods with negative growth due to relatively high volatility in the Industrial Production Index during that period. This is confirmed by looking at the series of changes in GDP, where one can see that no negative growth occurred during the above-mentioned periods (see Figure 2). Therefore, the first two crisis periods can be excluded from the business cycle, since these were fluctuations in economic activity caused purely by the use of the IPI as a proxy for GDP. Thus, it can be concluded that from January 1995 to February 2004 there occurred only one period of crisis, that is, from September 1998 until August 1999.

Next consider Figures A.7 and A.8 in the Appendix. One can see that the ratio of up to 30-day-overdue loans to total loans entered into a crisis regime in May 1997 and stayed there until March 1998. Before that, at the beginning of 1997, TALSE, the market index for the Tallinn Stock Exchange, rose steeply and the amount of Estonian commercial bank repo loans grew rapidly. The first stock market slowdown, occurring in May 1997, gave the first setback for investors with considerable repo loan exposure. That resulted in agents ending up in difficulties with their repo loan (interest) payments and the ratio of up to 30-day-overdue loans to total loans increased sharply. Further, the stock market crash in October 1997 affected most agents with outstanding repo loan exposure, who in addition to losing money in the stock market had to come up with additional funds to cover their repo loan commitments. In addition, local money market interest rates skyrocketed right after the stock market crash in October 1997. This intense situation contributed even more to the domestic stock market crisis and resulted in a growing amount of overdue loan exposure. However, in February 1999 the ratio of up to 30-day-overdue loans to total loans started to increase considerably once again. The problem this time was the Russian crisis and rapidly rising interest rates. As can be seen from

Figure A.7 in the Appendix, it took five months from the economic slowdown in September 1998 until problems with up to 30-day-overdue loans started. However, this number should be treated with special care, since the up to 30-day-overdue loans variable seems to be relatively noisy. Thus, while the first period of increase in up to 30-day-overdue loans was purely due to financial market concerns, the second period was clearly caused by the economic slowdown due to the Russian crisis.

Looking at the estimated probability that the crisis regime would prevail for the ratio of over 30-day-overdue loans to total loan portfolio, it can be seen that four periods of crisis can be identified in that variable (Figure A.9 in the Appendix). The first increase in over 30-day-overdue loans occurred in April 1995 and this was probably due to the instability of the financial market at that time.[8] As for up to 30-day-overdue loans, over 30-day-overdue loans entered a crisis regime in May 1997 due to the first slowdown in the Estonian stock market. Unlike the ratio of up to 30-day-overdue loans, the ratio of over 30-day-overdue loans recovered somewhat after the first stock market slowdown, but entered a crisis regime again right after the stock market crash in October 1997. In the period of the Russian crisis, it took only three months (one quarter) for the shock to the overall economy to be transmitted to the loan market in terms of over 30-day-overdue loans. Coming out of the crisis, however, took more time for the overdue loan variable since the lag now is five instead of three. In addition, inspection of Figure A.9 in the Appendix sheds some light on the duration of crisis periods. In particular, it seems that the longer the crisis, the more time it takes for the ratio of overdue loans to achieve its usual level (around 2–4% of the total loan portfolio in 1995–2003). Therefore, this suggests that the recovery of the quality of the loan portfolio depends proportionally on the duration of the crisis. Yet, this is weak evidence, firstly because of the relatively small sample size and second, because the "crisis" period for the ratio of over 30-day-overdue loans from April to August 1995 was more of an instability issue than a true crisis.

3.1.2. Identification of Cycles Based on a Shortened Sample

As argued before, it is difficult to conduct a comparison of cycle synchronization and such when the regimes that were identified for loan variables were in boom and moderate growth. Inspection of the series of total loans, household loans, and corporate loans suggest shortening the sample period to exclude the quick growth era in the loan market. That is, to consider the sample period from July 1998 to February 2004. Doing so results in the parameter estimates presented in Table A.5 in the Appendix. To double-check the conclusion regarding the business cycle, the IPI was also estimated based on a shortened sample. It would be interesting to test for business cycle asymmetries. It has been documented that expansions last more than contractions. This is also clearly the case for Estonia because the average duration of a crisis regime was estimated at approximately 13 months, while the average duration of a non-crisis regime was estimated as close to 61 months (see Table A.5 for estimated durations).

[8] Instability of financial markets at a particular period was apparent mainly because of the fact that Estonian economy as well as financial markets were in the early development stage and over-reacting in financial markets was not rare. This, in turn, intensified the volatility of the market even more.

In addition, testing for turning point asymmetry results in failing to reject the null hypothesis of non-sharpness.[9] Thus, it cannot be said that troughs in the Estonian business cycle are sharp and peaks more rounded, as it is often found for US and euro area business cycles (McAdam, 2003).

As can be seen from Table A.5 in the Appendix, the Markov model was able to detect the credit cycle regimes with negative and positive mean growth rates for household loans and corporate loans. Figures A.10 and A.11 in the Appendix present changes in household loans and changes in corporate loans with a respective probability of being in a crisis regime. Based on the estimated smoothed probabilities it is now possible to compare cycle synchronization between the IPI and household and corporate loans. Figure 4 depicts the probability of all these three variables being in a crisis regime.

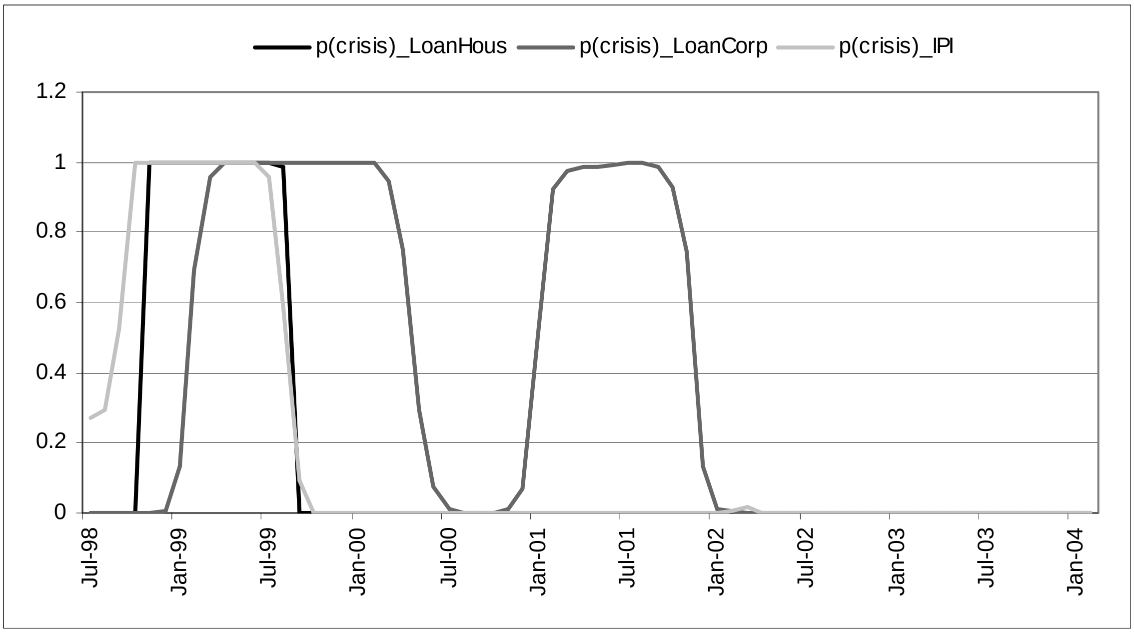

Figure 4. Probability of being in a crisis regime for household loans, corporate loans, and the IPI over the period July 1998 to February 2004

As can be seen from Figure 4, business cycle turning points exactly match those found based on the whole sample period. The growth rate of household loans slowed down during the Russian crisis, but picked up an average monthly growth rate of 30% right after overall economic activity had started to increase again. The story was somewhat different for corporate loans. It took five months for the growth of corporate loans to start to decrease after the economy had entered into a recession regime in September 1998. However, it took eight months for the growth of corporate loans to start to increase once again after the recession period was over. Thus, it took more time for lending activity to recover from periods of recession than for economic activity itself. Consequently, there is evidence that the often-reported asymmetry between business and credit cycles also holds for Estonia.

[9] The null of non-sharpness (H_0: $p_{12} = p_{21}$) against the alternative of sharpness (H_A: $p_{12} > p_{21}$) was tested for based on estimated transition probabilities. Sharpness implies that the probability of moving from the contraction regime to an expansion regime exceeds the reverse probability.

Yet, there is another period of crisis for corporate loans lasting from January to November 2001. There seemed to be stagnation in the growth of the loan portfolio of commercial banks and not a crisis as such during that period. In particular, the average growth rate of real corporate loans was 0.6% between January and November 2001. The main reason why the Markov regime-switching model identified this period as an episode of crisis is due to the fact that the growth of real corporate loans was negative in January and February 2001 and also from July to September 2001 (see Figure A.11 in the Appendix). This stagnation is also present when looking at the quarterly data with leasing and loan data added together. Even though corporate leasing increased during that period, growth was considerably lower than the average growth rate before and afterwards. Thus, such stagnation is definitely not caused by the substitution effect of leasing being preferred over loans at that particular time. Moreover, such stagnation was neither caused by the change in capital adequacy requirements nor the effects from income tax reform, because these events took place two and a half year and one year, respectively, before the stagnation started. As a result, the reasons for the slowdown in lending activity in Estonian commercial banks from January to September 2001 are probably connected to non-financial corporations entering into capital markets themselves. That is, Estonian companies probably emitted new shares or bonds or took loans from foreign commercial banks as alternatives to taking loans offered by domestic commercial banks. This shift in preferences might arise from the fact that the EURIBOR was peaking during that period. Even though this explanation seems reasonable, it requires more in-depth analysis.

Since regimes for both loan variables and the IPI have similar properties now, it is also possible to test for cycle synchronization by the use of formal tests. Concordance coefficients between household loans vs the IPI and corporate loans vs the IPI were calculated.[10] Concordance coefficients were calculated following Harding and Pagan (2004), using estimated smoothed probabilities. It is possible to lag one of the cycles and re-calculate the concordance coefficient in order to determine the lag length between cycles and that was also done. The concordance coefficients calculated are presented in Table 1.

Results from Table 1 suggest that changes in household loans move closely together with changes in the IPI. However, concordance coefficients for lags zero, one, and two differ from each other only marginally, yielding ambiguous conclusions regarding the lag length. For the changes in corporate loans, the concordance coefficients clearly suggest that changes in the IPI precede changes in corporate loans by approximately two quarters.

[10] The concordance coefficient illustrates the fraction of time two cycles are in the same phase (regime). Thus, the concordance coefficient basically shows the correlation between estimated smoothed probabilities.

Table 1. Concordance coefficients between the business and credit cycles

Lag	LoanHous vs IPI	LoanCorp vs IPI
0	0.9706	0.6471
1	0.9701	0.6716
2	0.9697	0.6970
3	0.9385	0.7231
4	0.9063	0.7500
5	0.8889	0.7778
6		0.7742
7		0.7705
8		0.7833
9		0.7627
10		0.7414

Notes: Lag denotes how many months the business cycle was shifted to precede the credit cycle; shaded cells indicate the largest coefficient for a particular pair of variables.

The shortcoming of this type of analysis, however, is that asymmetries between business and credit cycles were detected, but the concordance index is unable to capture this phenomenon.

3.1.3. Correlation Analysis Based on the Whole Sample Period

In addition to using a Markov regime-switching approach to determine causal relationships between different loan variables and the IPI, one can simply calculate correlation coefficients between these variables. Moreover, lagging one of the variables and then calculating correlations should give more insights into the lag structure of causal relationships between the selected pair of variables. Correlation coefficients in the way just described were calculated for both, monthly and quarterly data and the results are presented in Table 2 and Table 3, respectively.

As can be seen from Table 2, the calculated correlation coefficients suggest that changes in the IPI precede changes in the total real loans by 3 months and precede changes in real corporate loans by five months. Changes in household loans, however, seem to precede the IPI by two months. The latter result should be treated with caution since the IPI is not a particularly good proxy to use for economic activity, when analyzing the dynamics in household loans.

Table 2. Correlation coefficients between changes in loan variables and changes in the IPI

Lag	LoanTotal vs IPI	LoanHous vs IPI	LoanCorp vs IPI
12	0.041	-0.137	0.046
11	0.131	-0.083	0.135
10	0.184	-0.022	0.197
9	0.270	0.034	0.254
8	0.307	0.095	0.311
7	0.362	0.168	0.357
6	0.428	0.231	0.415
5	0.475	0.293	0.452
4	0.493	0.349	0.440
3	0.503	0.396	0.446
2	0.495	0.432	0.434
1	0.488	0.457	0.397
0	0.460	0.466	0.356
-1	0.375	0.472	0.287
-2	0.342	0.476	0.216
-3	0.284	0.470	0.165
-4	0.214	0.450	0.089
-5	0.134	0.389	0.003
-6	0.027	0.331	-0.073

Notes: Lag denotes the number of months by which changes in the IPI preceded changes in particular loan variables; shaded cells indicate the largest correlation coefficient for a particular pair of variables.

Table 3. Correlation coefficients between changes in loan variables and changes in GDP

Lag	LoanTotal vs GDP	LoanHous vs GDP	LoanCorp vs GDP	LoanLeasing Total vs GDP	LoanLeasing Hous vs GDP	LoanLeasing Corp vs GDP
4	-0.068	-0.194	-0.024	-0.054	-0.133	-0.042
3	0.149	-0.058	0.207	0.155	0.012	0.175
2	0.397	0.133	0.452	0.399	0.192	0.428
1	0.583	0.355	0.605	0.601	0.409	0.614
0	0.675	0.528	0.651	0.661	0.553	0.645
-1	0.611	0.681	0.524	0.616	0.700	0.560
-2	0.383	0.653	0.261	0.395	0.649	0.315
-3	0.142	0.449	0.014	0.161	0.442	0.077
-4	-0.207	0.132	-0.305	-0.200	0.120	-0.272

Notes: Lag denotes the number of quarters by which changes in GDP preceded changes in particular loan variables; shaded cells indicate the largest correlation coefficient for a particular pair of variables.

Still, the evidence is somewhat mixed for two reasons. Firstly, the calculated correlation coefficients based on quarterly data indicate that even though household loans and also household loans and leasing seem to lead changes in GDP, changes in total loans and aggregated loan and leasing portfolios, as well as corporate loans and leasing, do not lead or follow changes in GDP, but move together with no significant time difference (see for Table 3).

Second, a major drawback of this type of analysis is that it ignores the asymmetries between business and credit cycles, as does the analysis based on concordance coefficients. Thus, even though it may take five months until loan growth goes negative, it will probably take more than five months for loan growth to become positive again once the recession is over.

Furthermore, one can argue that concerning macroeconomic data, monthly frequency is too noisy and the main conclusions should indeed be drawn from the results based on quarterly frequency. Therefore, quarterly data was also used to model the Markov regime-switching regression for loan variables.[11] Results were, in general, similar to those presented above. In the case of corporate loans and leasing, when entering into a recession regime, GDP seemed to precede changes in loan and aggregated loan and leasing portfolios by one quarter. On the other hand, when entering an expansion regime, GDP led changes in corporate loans by one quarter, while leading changes in loan and leasing portfolios by two quarters. Evidence regarding household loans was mixed. On the one hand, changes in household loans seemed to precede changes in GDP by one quarter. On the other hand, there were cases, where regime switches took place simultaneously. Thus, this issue requires more analysis; particularly in regard to the direction of the causal relationship between changes in economic activity and changes in household loans.

All in all, based on the Markov regime-switching technique and also on the calculated correlation coefficients, it is safe to say that while changes in household loans seem to precede changes in the IPI, changes in corporate loans appear to follow changes in the IPI. In fact, both household and corporate loans are pro-cyclical, but seem to differ in terms of causal relationships with the IPI. The time interval between business and credit cycles is still somewhat unclear and it is difficult to give a single valid answer. This is mainly because of the asymmetries that were also detected between the business and credit cycles in the case of Estonia. Yet, it can be said that changes in corporate loans appear to follow changes in the IPI with an approximate 2-quarter lag. Household loans seem to precede changes in the IPI by a quarter.

3.2. Modeling Lending Behavior

Firstly, the model in equation (1.8) was estimated without an interactive term between a dummy variable and the IPI using monthly data. Estimation results clearly indicated problems with the stationarity of an endogenous variable for all the three loan variables considered. The main indicator of the non-stationarity problem was that the t-value for the lagged endogenous variable was comparatively high (even exceeding 30 in some cases) and the estimated slope coefficient for the lagged endogenous term was very close to one. This clearly suggests that the endogenous variable follows a random walk and the model has to be re-specified. Therefore, changes in total loans, household loans, and corporate loans were once more differentiated. This resulted in a series of increases in loan growth rates and these were considered endogenous variables in subsequent analysis. Augmented Dickey-Fuller tests were conducted on these series and the tests resulted in rejecting the null of non-stationarity in all three cases. Thus, the model

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[11] The author is aware of the consequences that arise when estimating a Markov regime-switching model with very few observations and that is why no defined estimation results are presented. The aim of this exercise was only to double-check the conclusions drawn based on results from monthly data and thus only turning points implied by smoothed probabilities were of interest.

presented in equation (1.8) is now balanced in terms of both sides of the equation being integrated to the same order. No reasonable specification was found for total loans. All lags for the IPI were both individually and jointly insignificant at the 5% significance level and the only statistically significant term seemed to be changes in the current Industrial Production Index. Still, the estimation results are presented in Table A.6 in the Appendix. Poor results may arise from any model with changes in the growth rate of total loans as an endogenous variable because of the fact that corporate and household loans behave considerably differently. As also mentioned in the previous section, household loans seem to either move concurrently with changes in economic activity or even lead changes in the IPI (or GDP). Thus, regressing the aggregated loan portfolio on changes in the IPI is not consistent. Therefore, separate models for household loans and corporate loans should be specified.

Next, the ARDL model for changes in the growth rates of household loans was estimated. However, as with the regression specified for total loans, all the explanatory variables, except the lagged endogenous one, were found to be both individually and jointly insignificant at the 5% level. Taking into account the reasoning and discussion regarding causal relationships between household loans and changes in economic activity in sections 2.2 and 3.1, it is possible to argue that the reason behind the failure to specify a sound model for corporate loans might be due to the fact that changes in household loans seem to precede changes in economic activity. Yet, looking at the estimation results presented in Table A.7 in the Appendix, one can see that the t-value for the lagged endogenous variable is relatively high. That is clearly an indication of a non-stationarity problem. Plotting the changes in the growth rates of household loans results in patterns similar to a random walk. Thus, even though the ADF test rejected the null of a unit root in the twice-differentiated series, both estimation results and graphical inspection of the series still suggest the series to be non-stationary. Thus, no reliable results from the ARDL framework are available for household loans either.

Estimation results for corporate loans are presented in Table 4. An interactive term between the IPI and a dummy variable (one for periods of crisis and zero otherwise) with several lags was also included, but it turned out to be jointly insignificant at the 5% level and was thus omitted from the model in further testing. In addition, an Instrumental Variables (IV) estimation was used to handle probable endogeneity issues between contemporaneous changes in the growth rate of corporate loans and changes in the IPI and TALIBOR. Both changes in the IPI and TALIBOR were instrumented by lagged values of themselves. As can be seen from Table 5, the longest lag of the IPI that was found to be statistically significant at the 5% level was lag six. However, the sign of the coefficient in front of this variable is in contradiction with economic reasoning. A negative sign thus indicates that changes in the growth rate of corporate loans seem to decrease whenever changes in the IPI increase. Still, looking at the long-run coefficients, one can see that the effect of changes in the IPI has a positive sign and the effect of changes in the TALIBOR has a negative sign.[12] This is in accordance with sound reasoning regarding the dynamics of the variables of interest.

[12] For detailed test results regarding the joint significance of each lag and variable see Table A.7 in the Appendix.

Table 4. Estimation results from the ARDL model for changes in the growth rates of corporate loans using monthly data

	Instrumented	Coefficient	Std. error	t-value	p-value
dIPI	Yes	0.19902	0.146	1.37	0.175
dTALIBOR	Yes	-0.00807	0.004	-1.95	0.054
ddLoanCorp_1		0.19705	0.141	1.40	0.164
dIPI_2		0.03249	0.058	0.56	0.577
dIPI_3		-0.04975	0.082	-0.61	0.544
dIPI_4		-0.05577	0.049	-1.13	0.260
dIPI_5		0.09239	0.057	1.62	0.109
dIPI_6		-0.11067	0.051	-2.15	0.034
Constant		-0.00658	0.005	-1.24	0.219

AR 1–12 test: F(12,81) = 0.6790 [0.7667]
ARCH 1–12 test: F(12,69) = 0.3068 [0.9861]
Normality test: Chi^2(2) = 1.6020 [0.4489]
hetero test: F(16,76) = 1.8833 [0.0352]*
hetero-X test: F(44,48) = 1.3284 [0.1681]
Additional instruments: [0] = dIPI_1 [1] = dIR_1
Testing beta = 0: Chi^2(8) = 31.676 [0.0001]**

Solved static long run equation for ddLoanCorp:

	Coefficient	Std. error	t-value	p-value
dIPI	0.13415	0.076	1.77	0.08
dTALIBOR	-0.01006	0.005	-1.90	0.06
Constant	-0.00819	0.006	-1.34	0.18

Wald test: Chi^2(2) = 4.74393 [0.0933]

Notes: Dependent variable was changes in the growth rates of corporate loans (ddLoanCorp), explanatory variables included were changes in the IPI (dIPI) and changes in 3-month money market rate (dTALIBOR).

It is possible to test for the null that all of the long-run coefficients are zero (except for the constant term). As indicated by the Wald test in Table 4, the null hypothesis can be rejected at the 10% significance level. In addition, it can be seen from Table 4 that there is no remaining autocorrelation or ARCH effects in the regression residuals and the residuals also seem to be normally distributed.[13] Even though the model presented above describes the dynamics of changes in the growth rates of corporate loans relatively well according to specification tests, it has yet nothing to do with the correctness of describing the lag structure of causal relationships between changes in corporate loans and changes in economic activity. Moreover, it is practically impossible to determine by how many months changes in the IPI precede changes in corporate loans since the endogenous variable was differentiated once more due to non-stationarity problems. Doing so results in having to regress the increase in the growth rate (acceleration) in corporate loans on the growth rate of the IPI. Since negative acceleration does not instantly mean negative growth, the lag structure cannot be carried over to the analysis of growth rates. The only thing that can be said about the lag length between changes in corporate loans and changes in the IPI is that it should be longer than indicated by the model above.

[13] Because estimation was conducted using data of monthly frequency, lags up to 12 were considered when testing for possible remaining autocorrelation and heteroskedasticity in regression residuals.

The model in equation (1.8) was also estimated using quarterly data. However, the same problems occurred as with monthly data when considering changes in total loans, household loans, and corporate loans. In particular, the coefficient of a lagged endogenous variable was found to be highly significant and close to one in value. Additionally, whenever robustness checks in terms of sample size and sample period were conducted, the signs of the estimated coefficients changed randomly. All that indicated that the problem of non-stationarity was still present and that the regression equation used in estimation was not balanced in terms of the integration order of the series of interest. Therefore, no estimation results are presented for quarterly data.

In addition to the above analysis, as with the method used in section 3.1, a shortened sample period was considered and an ARDL model, as presented in equation (1.8), was estimated using the series differentiated only once. For monthly frequency, there was no improvement concerning the non-stationarity issue. Thus, no reasonable specification was found and no results are presented. For the quarterly data, however, starting the sample period from the 2nd half of 1998 results in changes in total loans, household and corporate loans being stationary.[14] Even though the number of observations was relatively small, namely 22, estimation was still conducted and some results are presented. Table 5 presents the estimation results for the changes in corporate loans as an endogenous variable.

Table 5. Estimation results from the ARDL model for changes in corporate loans using quarterly data

	Instrumented	Coefficient	Std. error	t-value	p-value
dGDP	Yes	1.15784	0.254	4.55	0.000
dLoanCorp_1		0.56654	0.072	7.85	0.000
Constant		-0.02032	0.014	-1.49	0.153

AR 1–4 test:	F(4,15)	=	0.79019 [0.5494]
ARCH 1–4 test:	F(4,11)	=	0.24035 [0.9096]
Normality test:	Chi^2(2)	=	4.0979 [0.1289]
hetero test:	F(4,14)	=	0.55890 [0.6962]
hetero-X test:	F(5,13)	=	0.45112 [0.8052]
Additional instruments: [0]		=	dGDP_1
Testing beta = 0: Chi^2(2)		=	90.466 [0.0000]**

It should be mentioned that an Instrumental Variable (IV) estimation was used in order to avoid possible problems with endogeneity. In addition, contemporaneous and lagged effects of changes in the TALIBOR proved to be both individually and jointly statistically insignificant at the 5% level and were thus omitted in further testing of the model. As can be seen from Table 5, changes in GDP seem to have a contemporaneous effect on changes in corporate loans in terms of quarterly data. Moreover, an increase in GDP by 1% seems to cause corporate loans to increase by 1.16%. Therefore, according to estimation results in Table 5, corporate loans seem to be pro-cyclical in nature and changes in corporate loans seem to occur within the same quarter as changes in economic activity. However, changes in aggregated corporate loan and leasing

[14] Due to the relatively small number of observations, no formal unit root tests were conducted, but a visual inspection of the series and further estimation results support this belief.

portfolios were also considered an endogenous variable and the subsequent estimation results are presented in Table 6.

Table 6. Estimation results from the ARDL model for changes in corporate loans and leasing using quarterly data

	Instrumented	Coefficient	Std. error	t-value	p-value
dGDP	Yes	1.59829	0.241	6.62	0.000
dLoanLeasingCorp_1		0.55409	0.056	9.91	0.000
Constant		-0.02060	0.013	-1.53	0.142

AR 1–4 test:	F(4,15)	=	1.2611 [0.3283]
ARCH 1–4 test:	F(4,11)	=	1.1346 [0.3899]
Normality test:	Chi^2(2)	=	1.2599 [0.5326]
hetero test:	F(4,14)	=	2.1661 [0.1261]
hetero-X test:	F(5,13)	=	1.6091 [0.2261]
Additional instruments: [0]		=	dGDP_1
Testing beta = 0:	Chi^2(2)	=	164.90 [0.0000]**

As can be seen from Table 6, changes in loan and leasing portfolios added together seem to respond more strongly to changes in GDP as the coefficient of interest is somewhat larger, namely 1.6. This is reasonable because the leasing portfolio has shown considerably higher growth rates compared to the loan portfolio throughout the sample period. It should be mentioned that changes in the 3-month money market rate appeared to be once again statistically insignificant. In conclusion, more proof regarding pro-cyclical behavior in the dynamics of corporate loans (and leasing) was found.

In terms of household loans, both changes in loans and changes in loan and leasing portfolios were considered endogenous variables. However, estimating and testing with both models yielded that all variables were individually and jointly statistically insignificant at the 5% level except for once lagged endogenous variables. Such estimation results obviously suggest that changes in household loans may instead precede changes in GDP and not follow them (as was specified by the models). This is to a great extent in accordance with results from previous analysis. The correlation coefficients calculated in Table 2, as well as in Table 3, clearly indicate that changes in household loans seem to precede changes in economic activity. In addition, such a pattern is also evident in Figure A.6 in the Appendix, where business and credit cycles are presented. Changes in household loans preceding changes in economic activity appear to be the case especially when moving from an expansionary phase into a depression phase.

Based on the analysis so far, the evidence regarding causal relationships between changes in different loan variables and changes in economic activity seems to be relatively distinct. Still, no formal causality tests have yet been conducted. This has been left to last intentionally in order to once more check the validity of conclusions drawn until now. In terms of causality tests, the standard test for Granger causality cannot be applied to the series of interest here due to non-stationarity issues. Therefore, non-standard tests for causality were conducted. Furthermore, three different tests were considered to double-check the conclusions being drawn regarding causal relationships. The tests used were:

- Standard Wald test augmented with "surplus" lags to account for integrated and cointegratedness (Toda and Yamamoto, 1995; Dolado and Lütkepohl, 1996);
- Model selection type causality procedures (Swanson *et al*, 2001).

Swanson, Ozyildirim and Pisu (2001) provide a detailed Monte Carlo analysis concerning the performance of the above-mentioned and several other causality tests, and the three best-performing tests according to their findings are used for this paper. Table 7 presents test results and also conclusions regarding the direction of causal relationships. Notice that causality is tested in both directions: firstly, testing the null that changes in some loan variable or interest rate do not Granger cause changes in economic activity and second, testing the null that changes in economic activity do not Granger cause changes in some loan variable or interest rate. This enables to finally determine the direction of the causal relationship between pairs of variables of interest using formal causality tests.

Table 7. Results from pair-wise causality tests

	Augmented Wald Test		**SIC-based Test**		**AIC-based Test**		
H_0 (var$_1$ does not Granger cause var$_2$)	**Value of the F-test**	**p-value**	**SIC for the best AR model**	**SIC for the best ARDL model**	**AIC for the best AR model**	**AIC for the best ARDL model**	**Conclusion**
dLoanTotal vs dIPI	0.88	[0.4169]	-5.798	-5.801	-6.100	-6.066	Accept H_0
dLoanHous vs dIPI	4.00	[0.0025]**	-5.798	-5.866	-6.100	-6.140	Reject H_0
dLoanCorp vs dIPI	0.63	[0.5992]	-5.798	-5.780	-6.100	-6.081	Accept H_0
dLoanTotal vs dTALIBOR	8.83	[0.0003]**	0.241	0.268	0.109	-0.298	Ambiguous
dLoanHous vs dTALIBOR	2.45	[0.0304]*	0.241	0.263	0.109	0.007	Ambiguous
dLoanCorp vs dTALIBOR	4.98	[0.0030]**	0.241	0.252	0.109	0.053	Ambiguous
dIPI vs dLoanTotal	1.98	[0.0662]	-6.254	-6.361	-6.602	-6.616	Reject H_0
dIPI vs dLoanHous	0.81	[0.5815]	-7.502	-7.486	-7.771	-7.868	Accept H_0
dIPI vs. dLoanCorp	3.19	[0.0046]**	-7.166	-7.199	-7.433	-7.479	Reject H_0
dTALIBOR vs dLoanTotal	0.28	[0.5965]	-6.254	-6.211	-6.602	-6.737	Accept H_0
dTALIBOR vs dLoanHous	1.92	[0.1140]	-7.502	-7.459	-7.771	-7.922	Accept H_0
dTALIBOR vs dLoanCorp	6.02	[0.0162]*	-7.166	-7.145	-7.433	-7.473	Reject H_0

Notes: Pair-wise causality tests were conducted as presented in the first column. In the case of the augmented Wald test, the value of standard F-test with a subsequent p-value is presented. For the SIC and AIC-based tests, on the other hand, values of relevant information criteria are presented for the best-performed autoregressive (AR) and autoregressive distributed lag (ARDL) models. Whenever the information criterion of the best AR model is smaller than that of the best ARDL model, the null hypothesis of no Granger causality cannot be rejected. Ambiguous results in three cases arose because there were some specification problems with both AR and ARDL models when considering changes in the TALIBOR as a possible explanatory variable.

As can be seen from Table 7, changes in household loans seem to precede changes in the IPI, while changes in total loans and corporate loans seem to follow changes in the IPI. In terms of causality between changes in loans and changes in the TALIBOR, only changes in corporate loans seem to be Granger caused by changes in the TALIBOR.

4. Conclusions

Understanding the linkages between business and credit cycles and the features of these cycles is essential for policy makers. Documenting these features indeed helps institutions that deal with analytical forecasting, model selection, and policy analysis. Furthermore, it enables to compare the characteristics of Estonian business and credit cycles with those of euro area countries and also neighboring countries. The paper at hand has dealt with identifying the business and credit cycle for Estonia and comparing cycle synchronization and causal relationships between variables indicating economic activity and variables describing the loan portfolios of Estonian commercial banks. However, it should be emphasized that conclusions drawn regarding both the business cycle and the credit cycle are based on a relatively short sample period and with only one period of recession in economic activity.

The main conclusions of this paper are the following. There is some weak evidence that changes in economic activity (namely in real GDP) and changes in total loan and leasing portfolios are negatively correlated for the manufacturing, construction, education, and public administration sectors. Thus, lending activity seems to be counter-cyclical in the above-mentioned sectors. More specifically, while for the manufacturing and construction sectors changes in loan and leasing portfolios seem to precede changes in real GDP, changes in lending activity seem to follow changes in real GDP for the education and public administration sectors. However, evidence is only one-sided because no alternatives for domestic bank lending (lending directly from foreign banks, issuing bonds or shares) were considered. This fact should be kept in mind especially in the case of the manufacturing sector since evidence from other EU countries suggests that lending in the manufacturing sector is rather pro-cyclical than counter-cyclical. On the other hand, there is evidence, albeit weak, that lending activity is pro-cyclical in the mining and real estate sectors. More specifically, changes in lending precede changes in economic activity for the mining sector, but follow changes in real GDP for the real estate sector.

Only one period of recession was identified during the period from January 1995 to February 2004 for the business cycle, namely starting from September 1998 and lasting until August 1999. Tests for business cycle asymmetry indicated that in accordance with empirical evidence in business cycle literature, expansionary periods in economic activity lasted longer than recessions (average estimated durations were 61 and 13 months, respectively) and variances in economic activity did not differ across crisis and non-crisis periods. On the other hand, the often-reported turning point asymmetry seemed not to be present in Estonia. That is, in the case of Estonia, it cannot be said that troughs are sharp and peaks more rounded.

Two things can be said about the dynamics of the ratio of over 30-day-overdue loans to total loan portfolio. Firstly, it took only three months for the ratio of over 30-day-overdue loans to total portfolio to enter a crisis regime (with average growth of this ratio during the crisis regime being 55% on an annual basis) after the economy entered the recession phase, but it took five months for the ratio of interest to enter a non-crisis regime after the recession was over. Second, there is evidence, albeit weak due to the short sample period, that the longer a recession lasts, the more time it takes for the ratio under consideration to achieve its usual level (around 2–4% of total loan portfolio during 1995 to 2003). That is, there seems to be duration dependence in the recovery of the ratio of overdue loans to total loan portfolio.

When looking at the dynamics of household loans, it is safe to say that changes in household loans are pro-cyclical in nature and seem to precede changes in economic activity by approximately one quarter. This conclusion is based on a simple analysis of correlation coefficients, results from causality tests, estimation results from Markov regime-switching models, and calculated concordance coefficients. It should be emphasized that the result did not depend much on the frequency of the data used. That is, the IPI seemed to proxy GDP reasonably well even when analyzing household loans.

Corporate loans also seem to be pro-cyclical in nature and results from causality tests indicate that changes in the Industrial Production Index (that is, changes in economic activity) Granger cause changes in corporate loans. Furthermore, important asymmetries between credit and business cycles arose when analyzing corporate loans. In particular, in terms of the Markov regime-switching framework, changes in corporate loans entered a crisis regime (negative real loan growth compared to the same period in the previous year) five months after the general economy entered the recession phase. On the other hand, it took eight months for the corporate loans to enter a positive growth regime (with 10% average annual growth of the real loan portfolio) after expansion in economic activity started. Additionally, estimation results from ARDL models using quarterly data indicate that changes in corporate loans are affected by contemporaneous changes in real GDP, while results from the models operating with monthly frequency suggest a time lag around six months (probably more due to model specification issues). Thus, generalizing all the above, one can say that changes in corporate loans seem to follow changes in economic activity by approximately a one-to two-quarter lag and the latter indeed Granger causes changes in corporate loans.

Still, notice once more that all the above conclusions are drawn based on only 10 years of data and one period of recession that appeared during the period from January 1995 to February 2004.

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Appendix

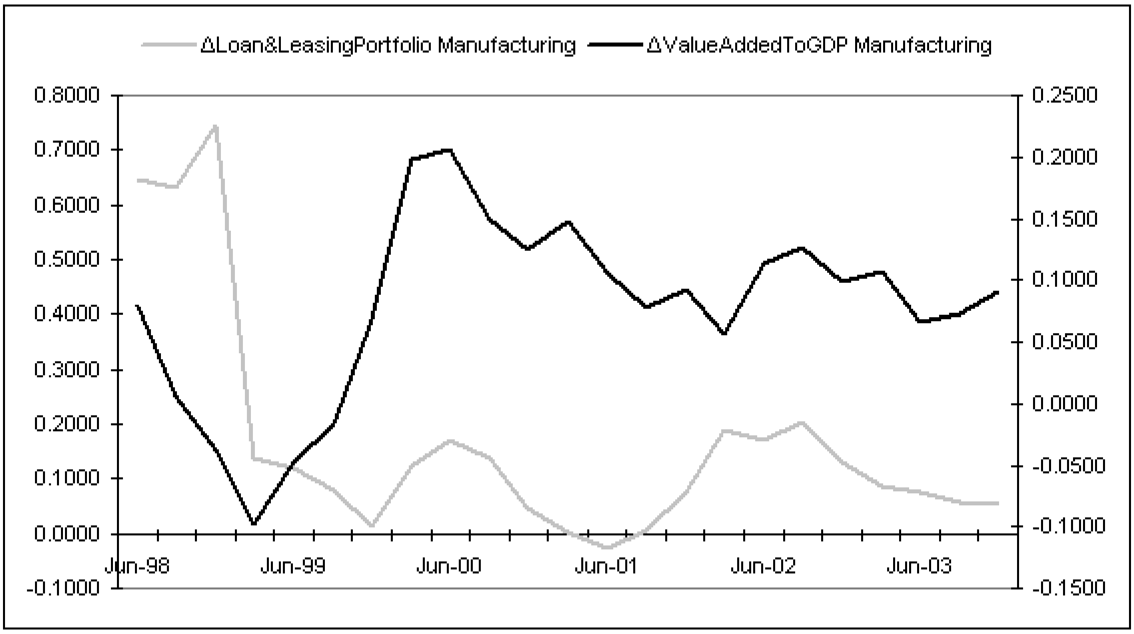

Figure A.1. Dynamics of changes in loan and leasing portfolios and value added to GDP in the manufacturing sector over the period June 1998 to December 2003

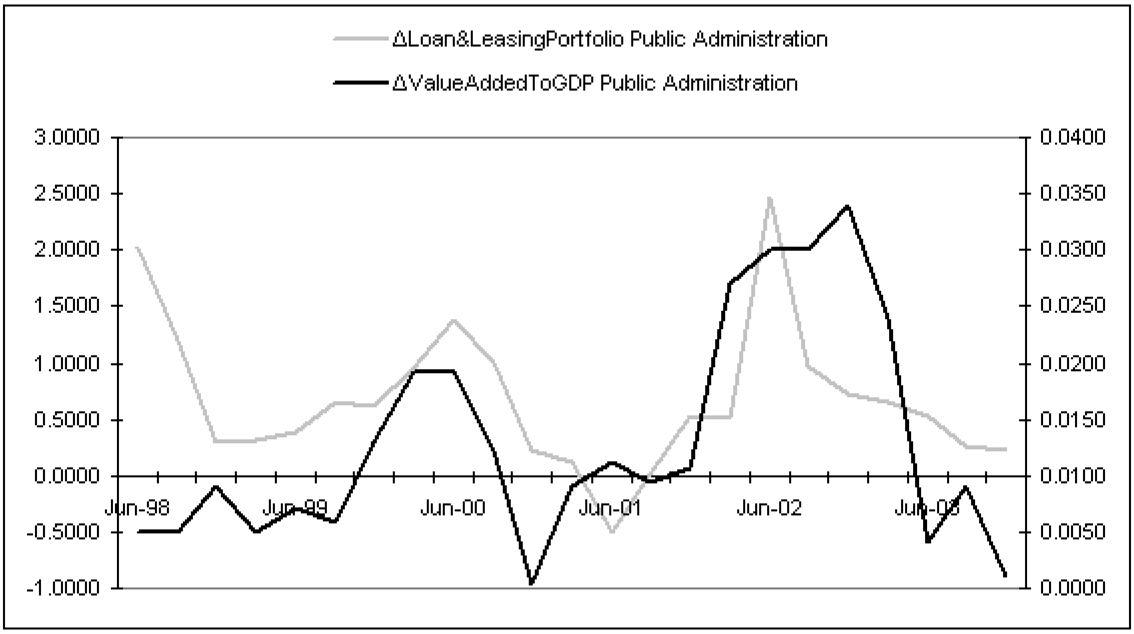

Figure A.2. Dynamics of changes in loan and leasing portfolios and value added to GDP in the public administration sector over the period June 1998 to December 2003

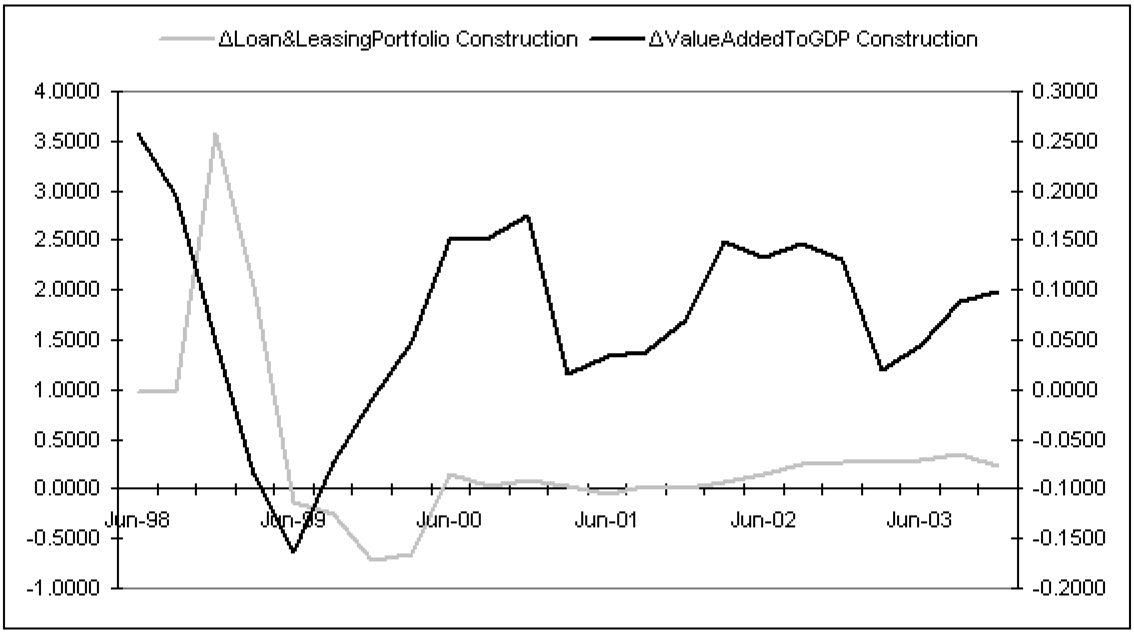

Figure A.3. Dynamics of changes in loan and leasing portfolios and value added to GDP in the construction sector over the period June 1998 to December 2003

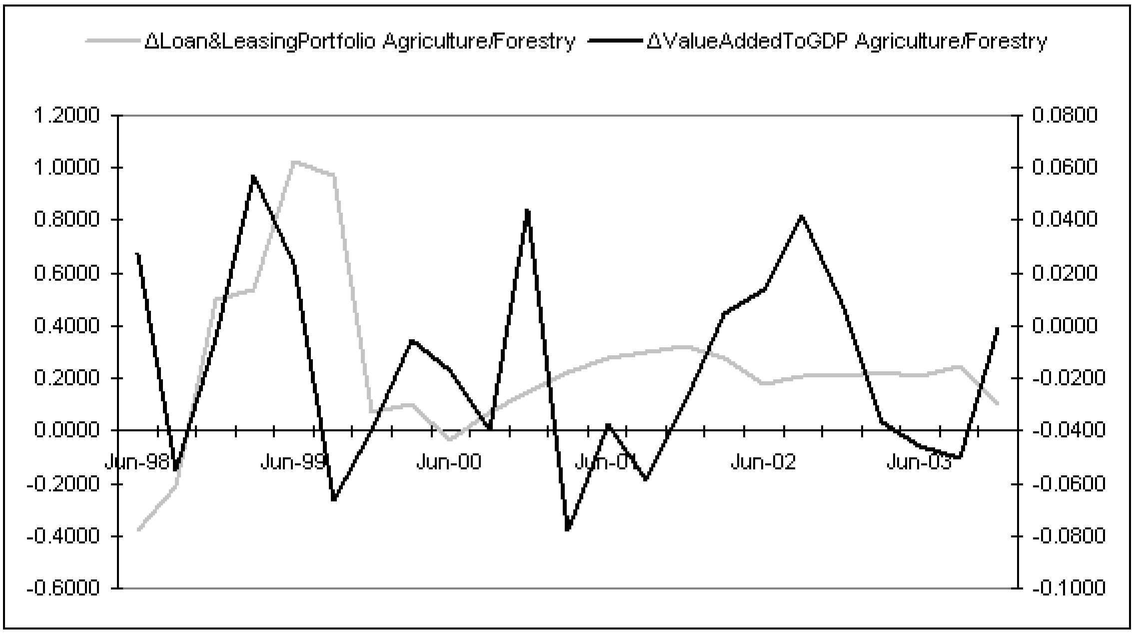

Figure A.4. Dynamics of changes in loan and leasing portfolios and value added to GDP in the agriculture and forestry sector over the period June 1998 to December 2003

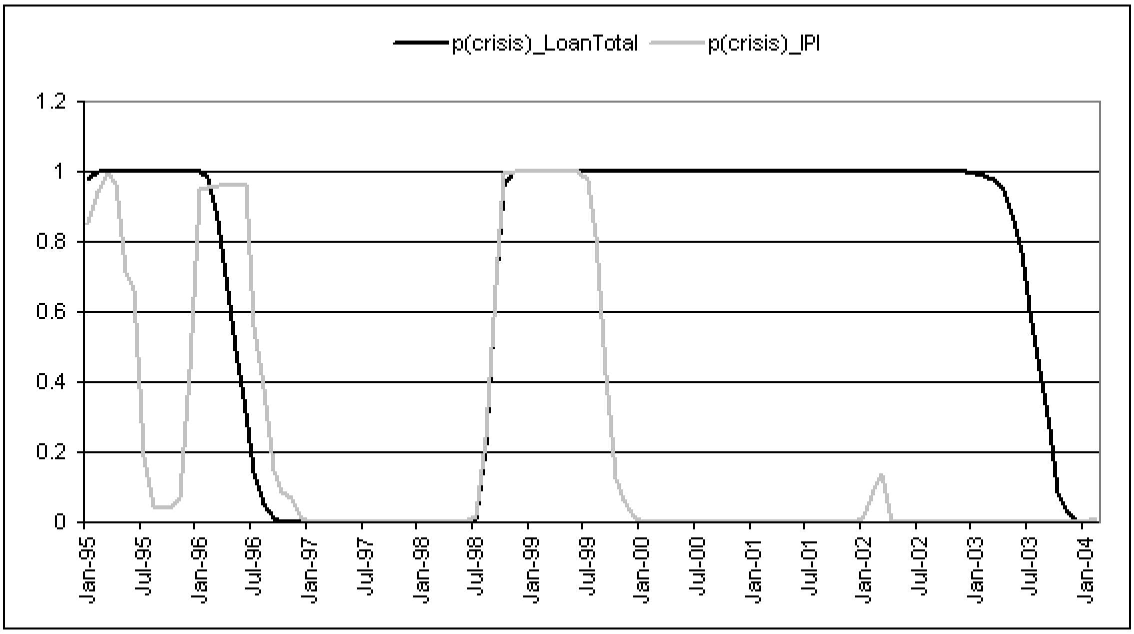

Figure A.5. Probability of being in a crisis regime for the IPI and total private sector loans variables from January 1995 to February 2004

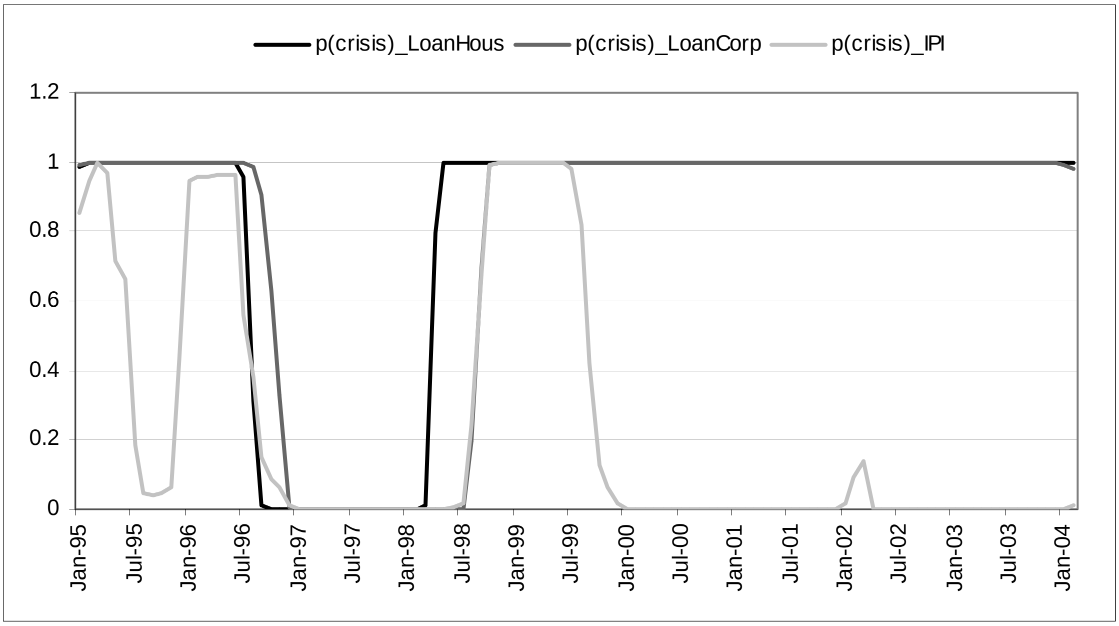

Figure A.6. Probability of being in a crisis regime for the IPI, household loans, and corporate loans from January 1995 to February 2004

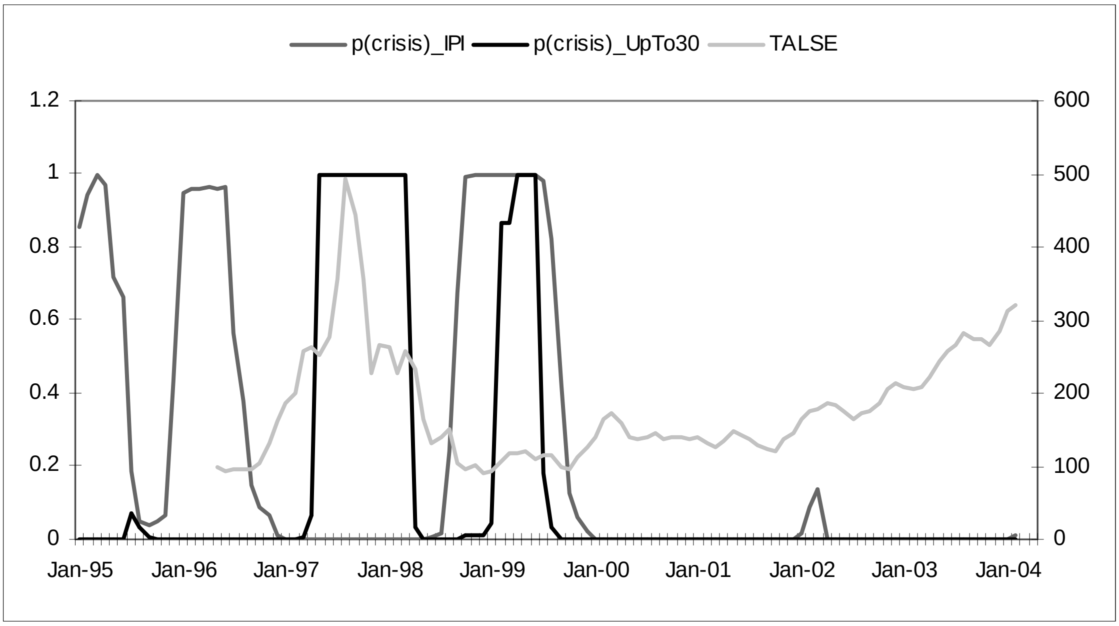

Figure A.7. Probability of being in a crisis regime for the IPI, the ratio of up to 30-day-overdue loans to total loans, and the dynamics of TALSE from January 1995 to February 2004

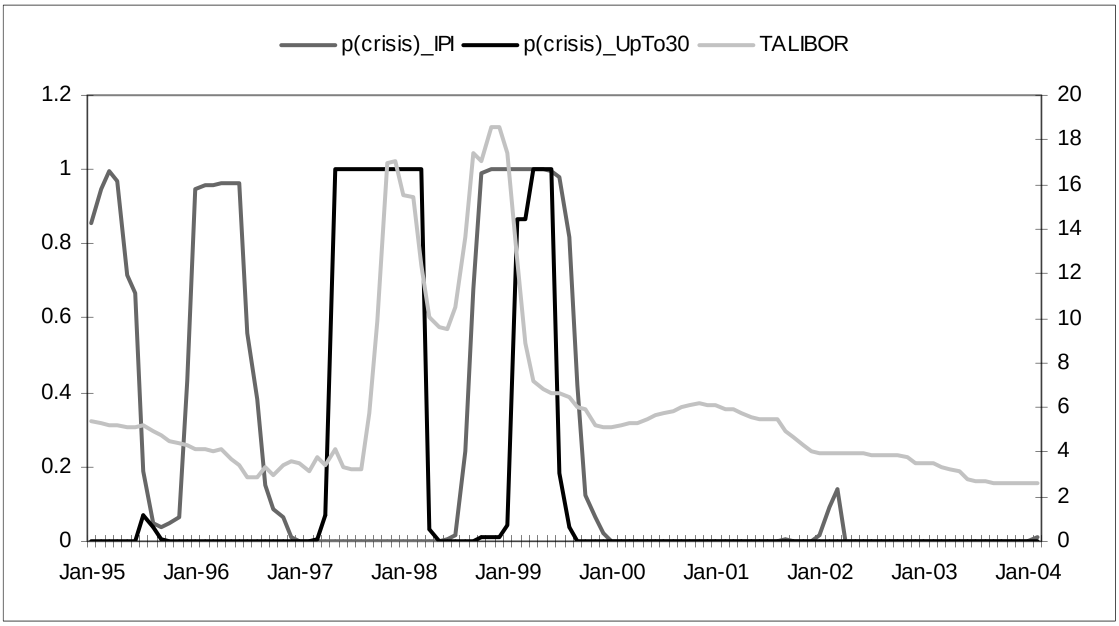

Figure A.8. Probability of being in a crisis regime for the IPI, the ratio of up to 30-day-overdue loans to total loans, and the dynamics of TALIBOR from January 1995 to February 2004

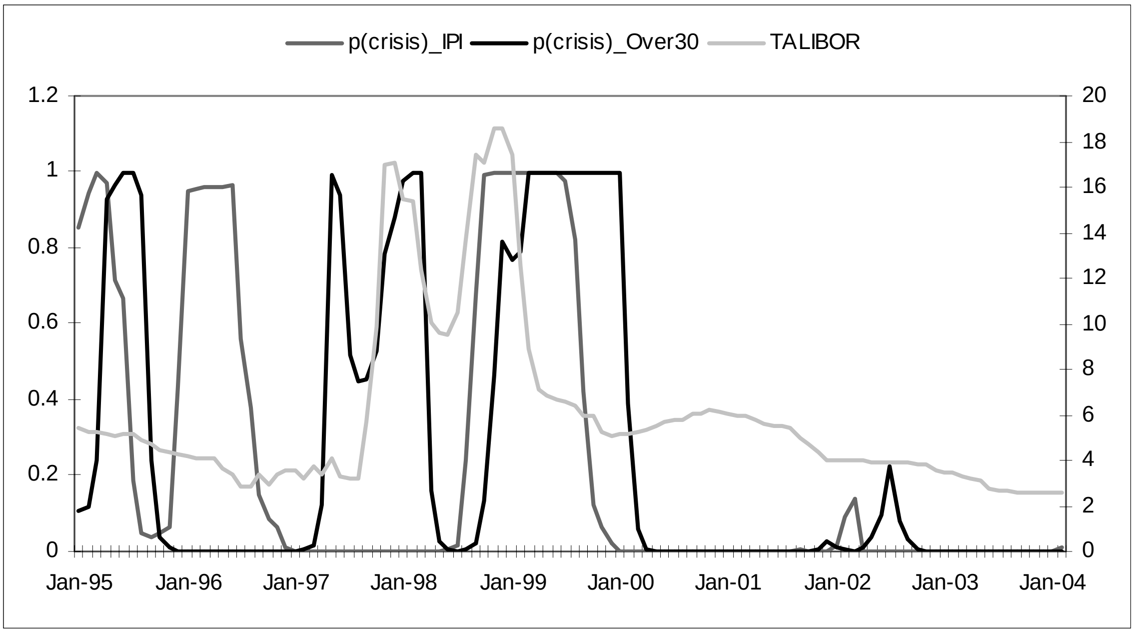

Figure A.9. Probability of being in a crisis regime for the IPI, the ratio of over 30-day-overdue loans to total loans, and the dynamics of TALIBOR from January 1995 to February 2004

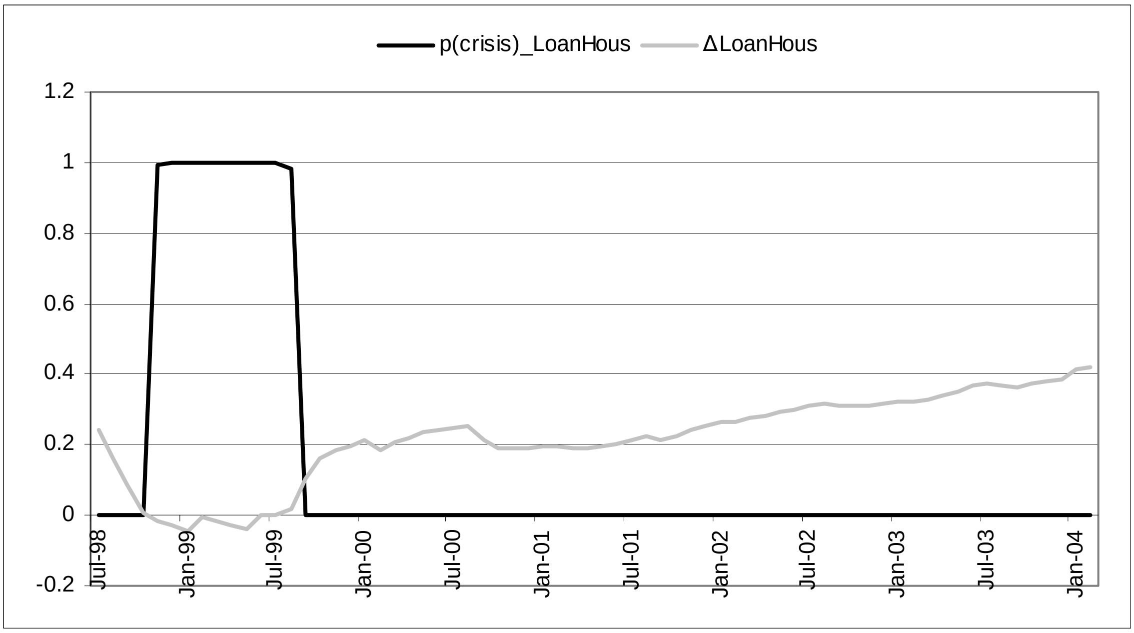

Figure A.10. Probability of being in a crisis regime for the household loans variable and the dynamics of changes in household loans over the period July 1998 to February 2004

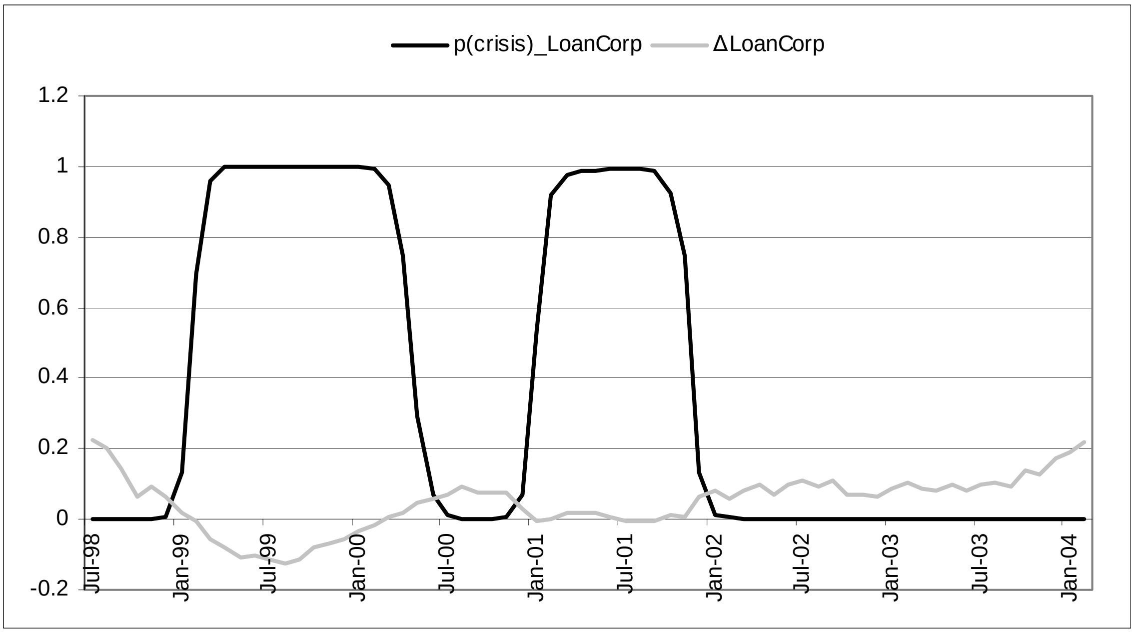

Figure A.11. Probability of being in a crisis regime for the corporate loans variable and the dynamics of changes in corporate loans over the period July 1998 to February 2004

Table A.1. Descriptive statistics for the variables of interest

	Mean	Std. deviation	Skewness	Excess Kurtosis	Normality test	AR order according to SIC
Monthly:						
LoanTotal	0.1918	0.1824	1.0610	0.7264	35.191 [0.0000]**	1
LoanHousehold	0.4352	0.3812	1.3534	0.9503	89.139 [0.0000]**	4
LoanCorporate	0.1305	0.1560	0.9329	0.2056	32.870 [0.0000]**	2
IPI	0.0701	0.0810	-0.4670	0.0376	4.6526 [0.0977]	7
UpTo30	0.9616	2.9950	3.2786	10.9410	530.21 [0.0000]**	2
Over30	0.0332	0.5061	2.5878	9.5997	126.85 [0.0000]**	1
TALIBOR	-0.0256	1.2241	1.5941	13.3830	96.084 [0.0000]**	1
Quarterly:						
LoanTotal	0.2515	0.1743	0.4358	-0.5166	2.1017 [0.3496]	2
LoanHousehold	0.4187	0.2635	0.7274	-0.3357	6.7790 [0.0337]*	2
LoanCorporate	0.2005	0.1722	0.4119	-0.8671	3.9148 [0.1412]	2
LoanLeasingTotal	0.29747	0.20888	0.85169	0.4616	5.3452 [0.0691]	2
LoanLeasingHousehold	0.4456	0.2708	0.7612	-0.0379	5.5250 [0.0631]	2
LoanLeasingCorporate	0.2591	0.2082	0.8570	0.2776	6.1544 [0.0461]*	2
GDP	0.0499	0.0338	-0.1199	-0.3753	0.13436 [0.9350]	1
TALIBOR	-0.084167	2.5817	1.6749	7.3748	21.820 [0.0000]**	0

Notes: Descriptive statistics are presented for the changes of variables of interest; UpTo30 and Over30 refer to changes in ratio of up to 30-day-overdue loans to total loan portfolio and to changes in ratio of over 30-day-overdue loans to total loan portfolio, respectively; for normality tests, the value of the test statistic with subsequent p-value in brackets is presented.

Table A.2. Estimation results from the Markov regime-switching model for the whole sample period

	LoanTotal	LoanHous	LoanCorp	IPI	UpTo30	Over30
μ_1	0.0949363	0.271273	0.0646579	-0.0257402	5.82288	0.553512
	[6.51]	[15.45]	[5.67]	[-1.51]	[5.37]	[4.21]
μ_2	0.411647	1.11986	0.393179	0.105637	-0.0817961	-0.195497
	[9.41]	[16.37]	[10.56]	[14.55]	[-2.12]	[-7.17]
σ_1^2	0.00679454	0.0241967	0.00680714	0.00382899	21.4478	0.373093
	[4.63]	[6.01]	[5.13]	[3.24]	[3.11]	[3.97]
σ_2^2	0.0237246	0.0703615	0.00801322	0.00291358	0.131692	0.0334574
	[3.86]	[2.72]	[1.68]	[5.64]	[6.65]	[4.61]
p_{11}	0.977993	0.98924	0.989896	0.899684	0.828908	0.869501
	[60.73]	[90.25]	[95.91]	[14.39]	[9.48]	[12.01]
p_{22}	0.958605	0.945299	0.947459	0.958556	0.966147	0.947319
	[28.74]	[20.04]	[20.59]	[38.73]	[49.88]	[31.71]
p_1	0.65	0.84	0.84	0.29	0.17	0.29
p_2	0.35	0.16	0.16	0.71	0.83	0.71
Log-likelihood	189.614	130.63	210.569	247.365	-13.1555	72.543
SIC	-2.9347	-1.8623	-3.3157	-3.9848	0.7520	-0.8062
Wald for μ_1=μ_2	74.13	158.15	102.61	67.49	29.68	35.48
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Wald for σ_1^2= σ_2^2	6.61	2.92	0.04	0.49	9.55	13.24
	[0.0101]	[0.0873]	[0.8290]	[0.4835]	[0.0019]	[0.0002]
Duration of state 1	45.44	92.93	98.97	9.96	5.84	7.66
Duration of state 2	24.15	18.28	19.03	24.12	29.53	18.98
# of switches	3	2	2	5	4	8

Notes: Markov switching model was applied to differentiated series, thus estimated means represent the average growth rates in different regimes. Rows 1–6 present the estimated coefficients from the Markov regime-switching model with subsequent t-values in brackets, rows 7–8 present estimated steady state probabilities, log-likelihood in row 9 represents the value of the log-likelihood function, and SIC in row 10 denotes the value of Schwartz Information Criteria. Values of the Wald test statistics with subsequent p-values in brackets are given in rows 11–12. Both Wald statistics are distributed as $\chi^2(1)$ with the critical value being 3.841. Durations for regimes 1 and 2 are calculated as $1/(1-p_{11})$ and $1/(1-p_{22})$, respectively. Finally, the number of regime switches was also calculated based on smoothed probabilities.

Table A.3. Estimation results from the Markov regime-switching model with restricted variance for the whole sample period

	LoanHous	LoanCorp	IPI
μ_1	0.281181 [15.79]	0.0659964 [7.04]	-0.0284695 [-1.74]
μ_2	1.17664 [27.51]	0.399082 [17.83]	0.103933 [13.62]
σ^2	0.0274279 [8.29]	0.00696498 [7.42]	0.00379245 [5.53]
p_{11}	0.990374 [101.8]	0.99009 [98.51]	0.903324 [14.56]
p_{22}	0.940223 [18.02]	0.945999 [20.17]	0.9625 [43.04]
p_1	0.86	0.84	0.28
p_2	0.14	0.16	0.72
Log-likelihood	127.169	210.539	246.276
SIC	-1.7994	-3.3152	-3.9650
Duration of state 1	103.88	100.90	10.34
Duration of state 2	16.72	18.51	26.66
# of switches	2	2	5

Table A.4. Specification testing results from the specified Markov regime-switching models

	LoanTotal	LoanHous	LoanCorp	IPI	UpTo30	Over30
White's test for autocorrelation	95.93 [0.0000]	106.08 [0.0000]	106.23 [0.0000]	12.79 [0.0123]	16.14 [0.0028]	45.56 [0.0000]
White's test for ARCH effects	43.74 [0.0000]	55.02 [0.0000]	57.78 [0.0000]	6.21 [0.1845]	9.09 [0.0587]	15.91 [0.0031]
White's test for Markov specification	86.51 [0.0000]	21.46 [0.0000]	134.71 [0.0000]	43.21 [0.0000]	48.82 [0.0000]	16.91 [0.0020]
White's test for order of Markov chain	34.04 [0.0000]	1.72 [0.4216]	4.11 [0.1284]	0.08 [0.9587]	0.71 [0.7005]	7.58 [0.0225]
LM test for autocorrelation in regime 1	78.91 [0.0000]	80.72 [0.0000]	82.81 [0.0000]	8.15 [0.0042]	4.29 [0.0381]	12.99 [0.0003]
LM test for autocorrelation in regime 2	29.61 [0.0000]	16.84 [0.0000]	21.72 [0.0000]	3.19 [0.0736]	10.36 [0.0012]	39.31 [0.0000]
LM test for autocorrelation across regimes	90.82 [0.0000]	87.09 [0.0000]	96.21 [0.0000]	8.17 [0.0042]	1.93 [0.1637]	46.01 [0.0000]
LM test for ARCH effects	35.76 [0.0000]	24.64 [0.0000]	54.42 [0.0000]	0.02 [0.8789]	2.82 [0.0929]	5.57 [0.0182]

Notes: Table presents calculated test statistics with subsequent p-values in brackets. All White's tests are distributed asymptotically as $\chi^2(4)$ except White's test for order of Markov chain, which is distributed as $\chi^2(2)$, while all LM tests are distributed asymptotically as $\chi^2(1)$.

Table A.5. Estimation results from the Markov regime-switching model for the period July 1998 through February 2004

	LoanHous	**LoanCorp**	**LoanCorp (restricted variance)**	**IPI**	**IPI (restricted variance)**
μ_1	-0.0136419 [-2.47]	-0.0270102 [-2.61]	-0.0265942 [-2.61]	-0.0670694 [-2.03]	-0.0668283 [-3.26]
μ_2	0.3035 [22.84]	0.105182 [11.88]	0.105673 [12.81]	0.0980169 [11.78]	0.0980601 [13.06]
σ_1^2	0.000333145 [2.33]	0.00234958 [3.47]	0.0023533 [5.96]	0.00284609 [1.11]	0.00286308 [5.43]
σ_2^2	0.0100307 [5.31]	0.0026654 [4.29]	-	0.00289292 [5.09]	-
p_{11}	0.898106 [10.28]	0.915344 [17.81]	0.916079 [18.01]	0.923158 [6.92]	0.923774 [9.93]
p_{22}	0.984473 [63.01]	0.956838 [30.81]	0.956715 [30.72]	0.983692 [57.51]	0.983672 [57.98]
p_1	0.13	0.34	0.34	0.18	0.18
p_2	0.87	0.66	0.66	0.82	0.82
Log-likelihood	132.748	158.338	158.19	158.959	158.958
SIC	-3.1597	-3.9124	-3.9080	-3.9306	-3.9306
Wald for μ_1=μ_2	487.36 [0.0000]	111.08 [0.0000]	-	29.78 [0.0000]	-
Wald for σ_1^2= σ_2^2	26.23 [0.0000]	0.12 [0.7319]	-	0.00 [0.9861]	-
Duration of state 1	9.81	11.81	11.91	13.01	13.11
Duration of state 2	64.40	23.16	23.10	61.31	61.24
# of switches	2	4	4	2	2

Table A.6. Estimation results from the ARDL model for changes in the growth rates of total loans

	Coefficient	**Std. error**	**t-value**	**p-value**
dIPI	0.15527	0.051	3.03	0.003
Constant	-0.00827	0.005	-1.56	0.122

AR 1–6 test:	F(6,94)	=	1.5557 [0.1688]
ARCH 1–6 test:	F(6,88)	=	4.1334 [0.0011]**
Normality test:	Chi^2(2)	=	71.791 [0.0000]**
hetero test:	F(2,97)	=	1.3241 [0.2708]
hetero-X test:	F(2,97)	=	1.3241 [0.2708]
RESET test:	F(1,99)	=	0.49784 [0.4821]

Table A.7. Estimation results from the ARDL model for changes in the growth rates of household loans

	Coefficient	Std. error	t-value	p-value
ddLoanHous_1	0.75021	0.065	11.50	0.000
Constant	0.00107	0.002	0.45	0.651
AR 1–6 test: F(6,94) = 1.3094 [0.2606]				
ARCH 1–6 test: F(6,88) = 2.9088 [0.0124]*				
Normality test: Chi^2(2) = 7.7868 [0.0204]*				
hetero test: F(2,97) = 0.30932 [0.7347]				
hetero-X test: F(2,97) = 0.30932 [0.7347]				
RESET test: F(1,99) = 2.1172 [0.1488]				

Table A.8. Lag structure analysis from the model of corporate loans

Variable	F-test		Value	[Prob]
Tests on the significance of each variable:				
ddLoanCorp	F(1,93)	=	1.9658	[0.1642]
dIPI	F(6,93)	=	2.9861	[0.0103]*
dTALIBOR	F(1,93)	=	3.8208	[0.0536]
Constant	F(1,93)	=	1.5313	[0.2190]
Tests on the significance of each lag:				
Lag 1	F(1,93)	=	1.9658	[0.1642]
Lag 2	F(1,93)	=	0.31371	[0.5768]
Lag 3	F(1,93)	=	0.37075	[0.5441]
Lag 4	F(1,93)	=	1.2858	[0.2597]
Lag 5	F(1,93)	=	2.6214	[0.1088]
Lag 6	F(1,93)	=	4.6438	[0.0337]*
Tests on the significance of all lags up to 6:				
Lag 1–6	F(6,93)	=	2.8380	[0.0139]*
Lag 2–6	F(5,93)	=	2.5742	[0.0316]*
Lag 3–6	F(4,93)	=	3.0733	[0.0200]*
Lag 4–6	F(3,93)	=	2.3770	[0.0749]
Lag 5–6	F(2,93)	=	2.6573	[0.0755]
Lag 6–6	F(1,93)	=	4.6438	[0.0337]*