Identifying multiple regimes

in the model of credit to households*

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Abstract

This research proposes a new method to identify the differing states of the market with respect to lending to households. We use an econometric multi-regime regression model where each regime is associated with a different economic state of the credit market (i.e. a normal regime or a boom regime). The credit market alternates between regimes when some specific variable increases above or falls below the estimated threshold level. A novel method for estimating multi-regime threshold regression models for dynamic panel data is also employed.

Keywords: credit boom, threshold regression, dynamic panel

JEL classification: E51, C23, C51

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1. Introduction

Credit booms and busts have been responsible for much of the macroeconomic turbulence in emerging and developed markets. Lending booms are also known to be good predictors of banking and other financial crises (Kaminsky and Reinhart, 1999; Gourinchas, Valdes, and Landerrechte, 2001; Tornell and Westerman, 2002; Laeven and Valencia, 2008; Roy and Kemme, 2012). Economists and policy makers often ask if credit grows too rapidly or too slowly given the actual state of the economy (Backé and Wójcik, 2008). Special attention is also paid to household loans that often initiate consumption, investment and production booms (Coricelli, Mucci, and Revoltella, 2006; Kiss, Nagy, Vonnák, 2006, Mendoza and Terrones, 2008).

Several studies aim to identify periods where credit was booming in different markets. For example, deviations from the long-run trend were used as a measure of the credit boom in some analyses (Mendoza and Terrones, 2008). Econometric error correction models were also employed to estimate the equilibrium level of credit and to assess possible divergence of credit levels from this equilibrium (Égert, Backé, and Zumer, 2006; Kiss, Nagy, and Vonnák, 2006, and references therein). However, the purely statistical methods used to calculate the long-run trend of credit (the Hodrick-Prescott (HP) filter) do not consider the link between credit and macroeconomic fundamentals and therefore may fail to distinguish booms from normal credit growth in many emerging (catching-up) economies (see also arguments in Coudert and Pouvelle, 2010; Geršl and Seidler, 2011).

Error correction models do in fact take into account the economic long-run relationship between lending to households as well as other macroeconomic factors. The situation where credit deviates from this relationship is often regarded as evidence of a credit boom. However, some divergence from the equilibrium may be caused by some specific economic condition, policy, regulatory or accounting reform. An observation of credit over

longer periods of time may reveal that although credit exceeds the sustainable level it follows the error correction mechanism and eventually returns to the equilibrium state (Kiss, Nagy, and Vonnák, 2006). The movement of credit to households toward the long-run equilibrium should not be treated as a boom. Standard calculations will tend to overstate the number of boom periods where such return processes are not discarded.

On the other hand, the estimation of error correction parameters will be downward biased in the presence of prolonged booms because many observations will constitute upward deviations from the error correction mechanism. These biases will tend to understate the true number of booms in favor of returns to the equilibrium.

A suitable procedure is clearly needed to distinguish true booms from incidental deviations, returns, and catching-up processes as well as to eliminate the biases in the selection of boom regimes. In this paper we propose a new method to identify possible boom and bust regimes in the credit to households market. This new method deals with the problem of imprecise identification of boom episodes encountered in earlier studies by accounting for changing regimes in the credit market during different periods. Our approach relies on the economic interpretation of these regimes rather than on using estimates of deviations from long-run trends to detect periods of credit boom.

We assume that potential normal, boom, and bust periods can be identified as separate economic regimes. In normal times credit moves along the equilibrium path and deviates only slightly after minor disturbances. In turn, a credit boom is identified as a period (or regime) where credit grows rapidly and departs from the long-run equilibrium. Booms may be associated with periods of economic expansion, rising asset prices, widening external deficits, or real appreciation. They can also result from competition between banks (possibly independent from economic cycles) and from financial liberalization (e.g. Cotarelli et al.,

2003; Gorton and He, 2008; Lorenzoni, 2008; Mendoza and Terrones, 2008). In the bust regime, credit falls back quickly to its equilibrium level.

We have constructed an econometric model where the impact of the explanatory variables on the growth rate of credit depends on the regime the model enters in a given period. This model is a multi-regime threshold regression where changes of regimes are governed by an exogenous threshold variable. When the threshold variable increases above or decreases below a predetermined level the model switches regimes. Statistical tests are then used to verify the number of regimes in the econometric model and each regime is identified as a normal state, state of boom, or a state of bust.

Our approach to identifying various credit regimes requires application of a novel econometric method. Given the short time-series data related to credit markets for individual countries and a limited number of countries with longer time-series data, we found it necessary to conduct estimation methods for panel data using a limited number of observations. The recently introduced methods for estimating dynamic threshold models for panel data rely on the instrumental variable approach (Caner and Hansen, 2004; Kremer, Bick, and Nautz, 2011). They are not explicitly designed for small samples and therefore may provide imprecise estimates of regression parameters.

We estimate the dynamic panel data models using the bootstrap-corrected LSDV (least squares dummy variable) method of Everaert and Pozzi (2007). This method produces more precise and less biased estimates in small samples than other estimation methods. Our analysis is one of the first applications of this method to dynamic threshold regressions for panel data.[1] Using this approach we are able to identify normal and boom regimes in the models of credit to households.

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[1] Shin and Kim (2011) analyzed a threshold model of Tobin's Q investment function with the same estimation technique. These authors also investigated the finite sample properties of this estimation method. However, their

In the next section we describe the method used to identify normal and boom regimes within the credit market. The data involved in this and selection of variables is described in Section 3. Empirical results are presented in Section 4 and the final section will share our conclusions.

2. Identification of multiple regimes for credit growth

Several studies analyze multiple states (or regimes) occurring within credit markets. The most common distinction that exists within the literature is between the credit-rationing regime and the "normal" (demand-driven) regime (Blinder, 1987; Azariadis and Smith, 1998; Balke, 2000). In the former regime the amount of loans distributed to firms and households depends on the supply-side which includes factors related to restrictive lending policies of banks, the interest rate spread, minimum loan to value ratios, and other measures of credit rationing. In the latter regime various demand factors including the lending interest rate, profits of companies, wages, and price of goods all affect the level of credit in the economy.

Another possible regime considered in economic studies is the state of boom. Markets for goods are vulnerable to booms that are driven by rapid and often prolonged growth in demand. Capital markets are afflicted by asset booms or bubbles when investor expectations move stock prices up and away from fundamentals. Similarly, boom periods in the credit market are observed when the demand for loans raises the level of credit beyond the sustainable equilibrium. Credit booms are modeled not only as deviations from that equilibrium but also as separate regimes that can last for some time (e.g., Backé and Wójcik, 2008; Lorenzoni, 2008; Martín, 2011). Such boom regimes end either with a bust or a soft landing after which credit returns to the long-run equilibrium.

model assumes only two regimes and does not explicitly control for changes in the constant term between regimes.

The presence of credit-rationing, sustainable and unsustainable (boom and bust) states provides the rationale for using a multi-regime econometric model to explain the changes in credit to households. The statistical method to test for the presence of two, three or more states of the lending market is discussed below followed by a description of the procedure with which to identify each regime, including the boom regime.

2.1 Econometric modeling of multiple regimes for credit

A popular approach to explain the change in credit in relation to output, Δc, for country i at time t is to estimate the following error correction model

$$\Delta c_{i,t} = \alpha_i + \beta \cdot ECT_{i,t-1} + \sum_{k=1}^{m} \gamma_k \cdot x_{k,i,t} + \varepsilon_{i,t}, \tag{1}$$

where ECT is the error correction term from the long-run regression explaining the ratio of credit to output, c (e.g. Égert, Backé and Zumer, 2006; Kiss, Nagy and Vonnák, 2006; Coudert and Pouvelle, 2010, and references therein). The parameter β represents the rate at which credit nears the equilibrium after the occurrence of a shock that has shifted credit away from that established equilibrium, assuming that there are no other factors in play. A negative value of β is required for credit to persistently move towards the equilibrium. x_k is the kth explanatory variable affecting the credit growth in the short-run. The "fixed effect" parameters α_i serve as a control for possible differences in the average credit growth between countries.

The formula (1) was used to estimate the equilibrium level of credit and the short-term changes of credit depending on deviations from that equilibrium in some earlier studies. Any possible divergence of credit from theoretical values generated by this model would be considered a boom, a bust, or some other violation of the natural development of credit around the equilibrium such as the process of catching up or stagnation.

Due to the drawbacks of linear error correction models mentioned in the introduction, we propose another method to identify credit booms. Since a boom is defined as a divergence of credit from its equilibrium level, it may be possible to determine if the mechanism described by the error correction model does not function in some periods. There is the potential that there exists a state in the market when credit does not return to the equilibrium but instead it grows rapidly. This would be observable in model (1) if the parameter β took a nonnegative value.

We attempt to distinguish between periods of credit divergence from the long-run equilibrium using the following multi-regime threshold regression model

$$
\Delta c_{i,t} = \begin{cases}
\alpha_i + \beta^{(1)} \cdot ECT_{i,t-1} + \sum_{k=1}^{m} \gamma_k^{(1)} \cdot x_{k,i,t} + \varepsilon_{i,t} & when \quad z_{t-l} \leq \phi^{(1)} \\
\alpha_i + \beta^{(2)} \cdot ECT_{i,t-1} + \sum_{k=1}^{m} \gamma_k^{(2)} \cdot x_{k,i,t} + \delta^{(1)} + \varepsilon_{i,t} & when \quad \phi^{(1)} < z_{t-l} \leq \phi^{(2)} \\
\vdots & \vdots \\
\alpha_i + \beta^{(r)} \cdot ECT_{i,t-1} + \sum_{k=1}^{m} \gamma_k^{(r)} \cdot x_{k,i,t} + \delta^{(r-1)} + \varepsilon_{i,t} & when \quad \phi^{(r-1)} < z_{t-l}
\end{cases}
\tag{2}
$$

where the variable z_{t-l}, lagged by l periods determines the actual regime of the model in each period t. The threshold variable z_{t-l} may represent the trigger of a boom, as this is the variable that switches regimes of the model between the normal state and the states of boom and bust. The additional parameters $\delta^{(.)}$ serve as a control for possible differences in the average growth of credit between regimes (Bick 2010).

In one or more regimes it is noteworthy that credit follows macroeconomic fundamentals and returns to the equilibrium after possible shocks; however, in some regimes of the model (2) the regression parameters β, γ, and δ may become more characteristic of a boom. We discuss these issues in the subsection 2.3.

In our empirical analysis we use the estimation techniques developed for the dynamic panel data. Namely, we estimate different specifications of the models (1) and (2) using the

bootstrap corrected LSDV estimator developed by Everaert and Pozzi (2007). This estimation method provides precise estimates of regression parameters in small samples (see also Shin and Kim, 2011). A more detailed explanation of this estimation method is presented in Appendix 1.

The estimation procedure also helps to select the optimal threshold variable z_{t-l} and its lag l. When the number of candidate threshold variables and their lags is a finite integer, the best threshold variable is selected by estimating the threshold regression with each candidate variable separately. The optimal threshold variable is the one that minimizes the sum of the squared residuals in (2).

2.2 Selecting the number of regimes

The presence of multiple regimes is determined using the test developed by Hansen (1999) whereby the null hypothesis assumes no additional regimes in the model explaining changes of credit and there is at least one additional regime according to the alternative hypothesis. We start with the null hypothesis where the correct specification is the linear model (1) and the two-regime model is valid and in line with the alternative hypothesis:

$$H_0 : \beta^{(1)} = \beta^{(2)}, \gamma_k^{(1)} = \gamma_k^{(2)}, \delta^{(1)} = 0 \text{ and } H_1 : \beta^{(1)} \neq \beta^{(2)} \text{ or } \gamma_k^{(1)} \neq \gamma_k^{(2)}, \text{or } \delta^{(1)} \neq 0.$$

The parameter $\phi^{(1)}$ is not identified under the null hypothesis and therefore the Wald, Lagrange Multiplier, or Likelihood Ratio statistics do not have their standard distributions. As in Hansen (1999), we employ the $\sup F$ statistic and approximate its distribution under the null using the fixed-regressor bootstrap method.

In the first step we compute the F statistic using the following formula

$$F = \frac{SSR_0 - SSR_1}{SSR_1} \cdot n \cdot (T - 1) \tag{3}$$

where SSR_0 is the sum of squared residuals from the estimated linear model (1), SSR_1 is the sum of squared residuals from the estimated threshold model (2) with two regimes, n is the number of cross sections, and T is the number of time-series observations.

In the second step we apply a bootstrap procedure to calculate the p-values of the F statistic. We treat all explanatory variables including the threshold variable as given. We also construct the empirical distribution from residuals of the original estimated two-regime threshold model (2). We then draw (with replacement) elements from this distribution to create a bootstrap sample (bootstrapped values of $\Delta c_{i,t}$) under H_0. The bootstrapped sample is then used to estimate both linear and threshold models with which to calculate the F statistic (3). The bootstrap procedure is repeated a large number of times to construct the empirical distribution of F. Finally, we compare the original F statistic from the first step with the constructed empirical distribution and calculate the p-value for our test.

When the three-regime model is tested against the two regime threshold regression, the testing statistic is analogous to (3):

$$F_2 = \frac{SSR_1 - SSR_2}{SSR_2} \cdot n \cdot (T-1).$$ (4)

The value SSR_2 is the sum of squared residuals from the estimated threshold model (2) with three regimes.

The bootstrap procedure may also be used to approximate the distribution of the F_2 statistic where bootstrapped samples are constructed under the assumption that the two-regime model is the valid data generating process. A large number of bootstrapped samples are used to estimate the two-regime and three-regime models and to calculate the F_2 statistic for each sample. The approximate p-value can be found by comparing the F_2 statistic computed from the original data with the empirical distribution of the bootstrapped F_2 statistics. Analogously, a larger number of regimes can be examined by using the iterative

approach that starts with one regime and increases the number of regimes by one in each step until the null hypothesis is not rejected by the F test.

2.3 Identifying booms in the credit market

In our threshold error correction model the long-run relationship between credit and other macroeconomic variables does not change between regimes. This means that there exists only one long-term equilibrium state for credit. The short-run parameters and the error correction parameter are used to differentiate between different "transitional states" of the credit market. Some (at least one) of these transitional states should move credit towards the long-run equilibrium; the other states could potentially allow credit to deviate significantly from that equilibrium for some time.

We assume that each state of the credit market can be represented as a separate regime in the econometric model. The state at which credit moves along the long-run equilibrium would be called the "normal state" or the "sustainable state". It can be represented in the econometric model by the regime where the value of the error correction parameter $\beta^{(i)}$ belongs to the region $(-1; 0)$; in this case credit tends to return to the equilibrium after any disturbance. The parameters of the short-run regressors, $\gamma_k^{(i)}$, are expected to show signs consistent with the economic theory and as such relevant demand and supply factors should be accounted for.

The state of boom can be identified as the regime where $\beta^{(i)} \geq 0$; in this case credit tends to diverge or move independently from the long-run equilibrium. Additionally, when the lagged dependent variable is included among regressors, its (autoregressive) parameter is expected to be positive to account for the persistence of positive credit growth. The parameter $\delta^{(i)}$ should also be positive to allow credit to grow more rapidly during these booms than during normal times. The boom does not prohibit the parameters $\gamma_k^{(i)}$ to conform to the

demand and supply factors affecting changes in credit. For example, rising housing prices can significantly affect household credit during credit booms because rapid credit growth is often associated with a boom in a housing market. Additionally, we further limit the definition of booms in our empirical exercise in subsection 4.3 to situations where credit remains above the long-run equilibrium.

Credit busts are more difficult to identify; they are represented in the threshold error correction model by regimes where credit returns extremely quickly to the sustainable equilibrium. The error correction parameter would be close to -1 and the parameter $\delta^{(i)}$ could be negative in such cases. Both short-run supply and demand factors could also play a role here, especially if the busts were initiated by a decrease in the demand for goods, falling prices and more restrictive bank policies. However, some busts and soft landing incidents may be difficult to distinguish from the "normal states" where credit also tends to return to its equilibrium. One distinction rests on the fact that busts typically occur immediately after booms.

From a theoretical perspective the threshold error correction model has several advantages over the HP filter as a tool to identify credit booms. First, there are well-known problems with the HP filter concerning a precise measurement of the long-run trend at the end of the samples and when there are short time-series analyzed (e.g. less than 20 years of annual data; see e.g. IMF, 2004; Geršl and Seidler, 2011, p. 115). Second, selection of the parameter "lambda" in the HP filter impacts the duration and timing of credit booms (BCBS, 2010, p. 13; Geršl and Seidler, 2011, p. 115). Third, selecting the value of the threshold parameter when credit deviates from the long-run trend also impacts the length of booms (Coudert and Pouvelle, 2010). Fourth, the HP filter tends to recognize catching-up periods as credit booms. For example, a boom would be noted when credit grows rapidly in transition economies with low initial levels of credit to households (e.g. Égert et al., 2006; Coudert and Pouvelle, 2010).

Our identification method uses regime-switching models and does not rely on a precise estimation of the equilibrium level of credit (although it can use larger samples with panel data) or selection of the parameter values. Instead, this method estimates the threshold parameter to identify normal and boom regimes and recognizes catching-up periods with the use of explanatory variables (e.g. the initial levels of GDP per capita).

3. Data and selection of variables

We used annual data from 21 of the OECD or European Union countries for which the time series on credit to households, housing prices, and other important macroeconomic variables are available.[2] The sample used begins in 1995 and ends in 2009.

We investigated a number of macroeconomic variables in our empirical analysis and the selection of variables explaining the level of credit and its changes was based on the literature review. Earlier studies used both micro and macro data to estimate the levels and dynamics of household debt. For example, Perraudin and Sørensen (1992) use data from surveyed US households and find that the demographic characteristics of borrowers together with their income and job status influence lending decisions of banks. Alessie, Hochguertel, and Weber (2005) estimate the negative link between the interest rate on loans and the demand for loans using micro data from Italy. Similarly, Grant (2007) estimates the model of demand and supply of consumer debt of US households. His results suggest that both income and demographic factors significantly affect supply and demand for debt.

Chrystal and Mizen (2005) build a macro vector error correction model for the UK economy and find that consumer loans are driven by net labor income, net total wealth of

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[2] The investigated countries include: Australia, Austria, Belgium, Bulgaria, Canada, Denmark, France, Germany, Greece, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, South Korea, Spain, Sweden, Switzerland, the United Kingdom, and the United States of America.

households, interest rate spread on loans, and inflation in the long run. In the theoretical model of Iacoviello (2008), income inequality increases household debt. According to Iacoviello, this model can explain the endogenous dynamics of the aggregate household debt in the US remarkably well. Rubaszek and Serwa (2011) estimate cross sectional regressions and panel data regressions for a number of developed countries and find the significant link between household credit and interest rate spread, disposable income, a measure of household income persistence, and housing prices in the long run. Similar relationships have been considered in the empirical studies related to credit booms (Gourinchas, Valdes, and Landerrechte, 2001, Égert, Backé, Zumer, 2006, Kiss, Nagy, Vonnák, 2006, Mendoza and Terrones, 2008).

Typically, credit to households is measured in relation to the nominal GDP of each country and in each period. The explanatory variables usually considered in empirical studies of credit to households include the GDP per capita (or some other measure of disposable income), the market interest rates, the loan-deposit interest rate spread (as a measure of lending policies of the banks), the unemployment rate and the long-run unemployment rate (as measures of income uncertainty and persistence), and the housing price index (to account for the loan-to-value limits in housing loans).

After a careful robustness check, we chose only those variables that remained significant in different model specifications (i.e. they were significant in the dynamic linear models and in at least one regime of the threshold regression models). We found that the significant variables explaining the level of credit in relation to GDP were the interest rate spread, the level of GDP per capita, and the housing price index. All variables were computed in natural logarithms.

Given the limitation of the data, all variables (household loans) have been constructed to be consistent in time to a maximum extent; however, some differences in definitions

between countries are possible. The sources of data for variables used in our final models are as follows: the value of loans supplied to households was provided in nominal terms and the data came from the OECD, BIS Data Bank, ECB, international central bank databases, and Ecowin; the data for the nominal GDP and the GDP per capita at constant prices was taken from the World Bank WDI database; finally, the interest rate spread was determined as the approximate difference between the lending rate (usually the rate on housing loans or the rate for primer customers) and the deposit rate. The data for the lending and deposit rates came from the BIS Data Bank, ECB, and IMF IFS databases. The housing price indices (HPI) were constructed using data from the BIS Data Bank, national central banks and statistical offices, and from the Global Property Guide internet database.

4. Empirical results

4.1 Estimating the equilibrium credit/GDP ratio

We estimated the long-run relationship between the analyzed variables using the continuously-updated fully-modified (CupFM) estimator of Bai, Kao, and Ng (2009). This estimation method controls for possible common factors between cross-sections in the panel data, e.g. common trends or business cycles. The test provided by Bai, Kao, and Ng suggests that the correlation between cross-sections is indeed statistically significant.

[Table 1 about here]

The results presented in Table 1 suggest that the one percentage point increase in the loan-deposit interest rate spread lowers the equilibrium level of credit (in relation to GDP) by 4.5 percent. Similarly, a one percent increase in GDP per capita denotes a higher ratio of credit to GDP by 2.3 percent whereas a one percent increase in the housing price index causes

the credit to households (in relation to GDP) to increase by 0.5 percent. Such results are in line with those obtained by Chrystal and Mizon (2005), Égert et al. (2006), and Kiss et al. (2006) among others. We interpret the residual term from this long-run regression as a deviation of credit from the equilibrium level and employ this residual as an error correction term (ECT) in our dynamic panel data models.

4.2. Estimating multiple-regime models

In the next step, we estimate single and multi-regime error correction models. Given the limited number of observations we have restricted our specifications to account for up to three regimes. The estimated parameters for single and two-regime models are presented in Table 2.

[Table 2 about here]

In the single regime model the error correction term is a significant variable; however, its parameter denoting the estimated rate of return to the long-run equilibrium is relatively low (-0.1). This suggests that any shock that shifts credit away from the equilibrium may have a prolonged effect. The other variables affecting change in credit to households are the lagged changes in credit, changes in the housing price index and changes in the loan-deposit interest rate spread.[3]

The alternative specifications are the dynamic threshold models with the same explanatory variables but the different threshold variables. The value of the threshold variable

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[3] Changes in the interest rate spread can be an endogenous variable. Therefore, we also investigated other versions of the model where this variable was replaced by lagged changes in spread or by some proxies of income inequality. The fit of such models was worse, but the general conclusions regarding the identified boom periods remained unchanged in the best specifications.

identifies the current regime of the model at each period. In the analysis it is useful to employ such threshold variables that could act as potential triggers for credit booms. We used the growth rate of credit to GDP ratio lagged by one period, the growth rate of housing prices lagged by one period, the error correction term lagged by one period, and the level of credit to GDP ratio lagged by one period. The choice of threshold variables is motivated by the fact that credit booms are most typically associated with rapid credit growth (Δc_{t-1}), deviations of credit from the long-run equilibrium (ECT_{t-1}), booms in the housing market (Δhpi_{t-1}), or large and unsustainable levels of credit (c_{t-1}).[4]

In the model with the lagged credit growth rate acting as a threshold variable, the regimes change when the growth rate of credit increases above or falls below the rate of 9.4 percent of annual growth. This threshold level is rather high. If credit growth is extremely rapid in one period it will tend to follow the macroeconomic fundamentals and return slowly to the equilibrium in the next period. In the other regime, credit is not significantly affected by changes in the interest rate spread (approximating lending policies of banks) and returns to the equilibrium even more slowly. In both regimes changes in the housing price index are most strongly correlated to changes in credit; this suggests that housing loans constitute a significant portion of loans to households in the analyzed countries. There is no evidence of credit boom regimes in this specification.

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[4] Some threshold variables also appear as regressors in the threshold error correction models, which is not unusual for threshold regressions (e.g. the self-exciting threshold autoregressive models, see Hansen, 2011 and studies cited therein). However, the threshold variables must be exogenous and stationary. Therefore, results employing the threshold variable c_{t-1} should be treated with some caution. We have also experimented with (lagged) changes in the interest rate spread as a threshold variable indicative of the loose lending policies of banks during credit booms and found that this variable performed worse than changes in credit and changes in housing prices.

When the changes in HPI are used as the threshold variable, the following interpretation holds. In the first regime, corresponding to an annual rate of growth of HPI lower than 11.8 percent, credit returns very slowly to its equilibrium and does not react to short-run changes in the spread. The error correction parameter is statistically different from zero only at the 10% level of significance. In addition, there is some persistence in the growth rate of credit in the first regime since the autoregression parameter equals 0.2. These results may point to some weak evidence of a boom in the first regime. In the second regime, the credit returns to the equilibrium five times more quickly than in the first regime; moreover, it also reacts more strongly to short-run changes in the spread and in the HPI.

In the other two models where the error correction term and the level of credit act as the threshold variables, we find a slow adjustment of credit to the long-run equilibrium in most regimes. The strong impact of the error correction term on credit is present only in the first regime of the model with the ECT_{t-1} threshold variable.

This result can be interpreted in the following way: when credit falls too low (more than 13 percent) below the equilibrium level, there is a strong force pushing it back to that equilibrium. This force vanishes however when credit is close or above the equilibrium. Also, changes in the interest rate spread are insignificant in the second regime of both models suggesting that only demand factors affect credit in that state. Again, no boom regimes can be identified here.

All two-regime models are superior to the single-regime regression according to the measure of residual variance; this is in line with the results of Hansen's (1999) F test. The values of the respective F statistics are presented in Table 2. Interestingly, the optimal two-

regime model with a given set of explanatory variables is the one with the lagged ratio of credit to GDP acting as the threshold variable.[5]

[Table 3 about here]

We have presented the results from analogous three-regime models in Table 3. As expected, one additional regime decreases the value of the residual variance in each respective model. The F statistics also reject the null hypothesis of two regimes in favor of the alternative three regimes in all cases, except the model with the c_{t-1} threshold variable where the two-regime specification is not rejected. The optimal threshold variable in the three-regime model is represented by the lagged changes in credit to households Δc_{t-1}.

The test results are important as they suggest that the three-regime model provide an overall better description of changes with credit to households than the two-regime model. Interpretation of the preferred three-regime models is essential for the identification of possible boom and/or bust periods within the credit markets.

In some specifications of the three-regime model it is possible to identify the states most likely resembling periods of a credit boom. The error correction term is insignificant in these regimes and credit does not return to the equilibrium. One such regime is present in the superior model with the lowest residual variance where Δc_{t-1} is the threshold variable. This model enters the boom regime when the credit-output ratio grew at the rate between 1.2 and 9.4 percent one period earlier. Interestingly enough, this regime is also characterized by the strong persistence of credit growth and no immediate reaction to changes in the interest rate spread. A similar boom regime is present in the second model (presented in the second

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[5] According to Hansen (1999) the optimal model is the one with the lowest residual variance or equivalently with the largest value of the F statistic.

column of Table 3) in periods when the threshold variable ECT_{t-1} indicates only small deviations of credit from the equilibrium, between -13 and $+12$ percent.

Another interesting result is that there is a stronger tendency for credit to return to the equilibrium when credit grows at the rate greater than 9.4 percent or the deviation of credit from the equilibrium is larger than 12 percent.

In the third model, where the threshold variable is Δhpi_{t-1}, the tendency for the credit to return to the long-run trend is the weakest in the first regime and is the strongest in the third regime when house prices grow slowly ($\Delta hpi_{t-1} < 0.045$) and rapidly ($\Delta hpi_{t-1} \geq 0.118$), respectively, just one year earlier. At the same time there is a strong correlation between credit change and the housing price index. Therefore, a credit bust is possible in this regime but it requires a simultaneous decline in the price of houses.

The fourth three-regime model, where the threshold variable is c_{t-1}, does not explain credit to households significantly better than the two-regime model that is presented in Table 2. Additionally, the three-regime model with the threshold variable c_{t-1} has a larger residual variance than the model with the stationary threshold variable Δc_{t-1}.

4.3. Identifying credit booms around the recent global financial crisis

In this section we analyzed changes in credit to households in six developed countries around the 2008-2009 financial crisis.[6] Credit to households was expanding quite rapidly (above 5% annually) in Spain, Canada, and in the US prior to this crisis but was growing only moderately in the Netherlands, Germany, and in Switzerland (although it reached the annual rate of 17% in the latter country in 2006). While credit growth halted in Germany, Spain, the

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[6] We thank the anonymous reviewer for suggesting us this examination.

US, and in Netherlands between 2008 and 2009, it only slowed to 2% in Switzerland and the rate of growth was still above 7% in Canada.[7]

We compared the results from our method to identify credit booms with the standard HP filter approach for the six countries mentioned above. Table 4 provides the empirical results from this analysis. The first column contains boom periods identified with the best performing threshold error correction model. The second column presents booms identified as periods when credit-to-GDP ratio increases above the long-term trend estimated using the HP filter. The third column identifies booms where credit-to-GDP ratio grows beyond some threshold value above the HP trend. The threshold value is equal 1.5 standard deviations of credit over the HP trend (e.g. Mendoza and Terrones, 2008).

[Table 4 about here]

It is clear that boom periods detected with the HP filter strongly depend on the threshold value: longer boom periods are identified for lower threshold values.[8] For example, the third method in Table 4 does not identify any boom in the US credit market prior to the financial crisis. In turn, the second method identifies a boom in the stagnating German market in 2009 although deviation from the long-run trend is very small.

The threshold model indicates a Canadian boom in 2002 but credit is below the long-run equilibrium in later periods (although the model remains in the second regime between 2002 and 2009). A calm in the credit market does not show any boom in Germany using the

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[7] It must be noted that credit to households behaved in a much different way than credit to non-financial companies during the crisis. Corporate loans were more strongly affected by the crisis than loans to households in most of the analyzed countries.

[8] Larger "lambda" values in the HP filter also extend the boom periods for Spain, Switzerland, and the US. However, they reduce boom periods for the Netherlands and Germany.

threshold error correction model. Credit booms in the Netherlands are present between 2004 and 2006. In contrast, the HP filter method suggested different periods or no booms at all for the Netherlands.

The Spanish boom was estimated to take place in 2008; however, credit also rapidly increases throughout 2002-2003, which can be interpreted as a "catching-up" period (i.e. credit remains below the equilibrium level). Throughout 2004-2007 the model enters the third regime where short-term changes in both spread and housing prices have a strong impact on household credit. Again, the HP method suggests different periods of credit booms.

The Swiss boom lasted throughout 2002-2006 according to results of the threshold model (similar to the first HP method results). Finally, the rapid credit growth in the US is associated with a boom throughout 2002-2004 and also in 2008; these years saw slower GDP growth and rapid credit growth in the US.

The global financial crisis caused the end of credit booms in many developed countries. Results from our boom identification exercise confirm this finding for all countries except Canada, where credit growth was relatively high even in the throughout 2008 and 2009. Moreover, the boom regimes preceding the financial crisis, as presented in Table 4, closely match the expansionary credit regimes found in the work of Martín (2012). Both Hume and Sentance (2009) and Mendoza and Terrones (2012) also identify boom periods in Spain, Switzerland, and the US prior the global crisis, but no booms in Canada, Germany, or the Netherlands.

The threshold regression approach generally matches booms more closely to the deviation of credit to households based on macroeconomic fundamentals whereas the HP filter methods rely on the deviation of credit from its long-run trend. Our empirical exercise confirms the theoretical difference between both types of boom identification methods discussed in subsection 2.3.

5. Conclusions

The results of our empirical analysis provide important information about the possible triggers of a credit boom. We found that the growth rate of credit to households above the rate of economic growth can be a sign of a future boom. Extremely rapid growth of house prices or credit may lead to a regime where credit quickly returns to its equilibrium. Booms also often follow periods where credit does not deviate too strongly from the long-run trend.

The method proposed by this study may be useful in identifying other types of booms (housing booms, asset bubbles) or to detect periods where some economic variables deviate from their long-run trends or equilibria. While the time-series methods to identify multiple regimes require a large number of consecutive observations, our panel data approach utilizes a limited number of time-series observations from several countries or other cross-sectional units.

Possible extensions of our model include: (1) enabling regime changes affected by a set of variables instead of a single variable in order to enrich the economic interpretation of the model, (2) specifying threshold vector error correction models to account for possible bilateral links between macroeconomic variables, (3) applying Markov chains to explain the changing regimes of the models – in order to calculate the probability of regime changes. A similar approach may also be used to identify regimes for credit supplied to firms or for other types of loans.

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References

Alessie R., Hochguertel S., & Weber G. (2005). Consumer Credit: Evidence from Italian Micro Data. Journal of the European Economic Association 3, 144 – 178.

Azariadis C., & Smith B. (1998). Financial Intermediation and Regime Switching in Business Cycles. American Economic Review 88, 516 – 536.

Backé P., & Wójcik C. (2008). Credit booms, monetary integration and the new neoclassical synthesis. Journal of Banking and Finance 32, 458 – 470.

Basel Committee on Banking Supervision (BCBS) (2010). Guidance for national authorities operating the countercyclical capital buffer, Bank for International Settlements.

Bai J., Kao Ch., & Ng S. (2009). Panel cointegration with global stochastic trends. Journal of Econometrics 149, 82 – 99.

Balke N. (2000). Credit and Economic Activity: Credit Regimes and Nonlinear Propagation of Shocks. Review of Economics and Statistics 82, 344 – 349.

Bick A. (2010). Threshold Effects of Inflation on Economic Growth in Developing Countries. Economics Letters 108, 126 – 129.

Blinder A. (1987). Credit Rationing and Effective Supply Failures. Economic Journal 97, 327 – 352.

Caner M., & Hansen B. (2004) Instrumental variable estimation of a threshold model. Econometric Theory 20, 813 – 843.

Chrystal K. A., & Mizen P. (2005). A Dynamic Model of Money, Credit, and Consumption: A Joint Model for the UK Household Sector. Journal of Money, Credit and Banking 37, 119 – 143.

Coricelli F., Mucci F., & Revoltella D. (2006). Household Credit in the New Europe: Lending Boom or Sustainable Growth?, CEPR Discussion Paper 5520.

Coudert V., & Pouvelle C. (2010). Assessing the Sustainability of Credit Growth: The case of Central and Eastern European Countries. European Journal of Comparative Economics 7, 87 – 120.

Égert B., Backé P., & Zumer T. (2006). Credit growth in Central and Eastern Europe - new (over)shooting stars?, European Central Bank Working Paper 687.

Everaert G., & Pozzi L. (2007). Bootstrap-based bias correction for dynamic panels. Journal of Economic Dynamics & Control 31, 1160 – 1184.

Geršl A., & Seidler J. (2011). Excessive credit growth as an indicator of financial (in)stability and its use in macroprudential policy. In: Czech National Bank, Financial Stability Report (pp. 112 – 122).

Gourinchas P., Valdés R., & Landerrechte O. (2001). Lending booms: Latin America and the world, NBER Working Paper 8249.

Grant Ch. (2007). Estimating credit constraints among US households. Oxford Economic Papers 59, 583–605

Hansen B. (1999). Threshold effects in non-dynamic panels: Estimation, testing, and inference. Journal of Econometrics 93, 345 – 368.

Hansen B. (2011). Threshold autoregression in economics. Statistics and Its Interface 4, 123 – 127.

Hume M., & Sentance A. (2009). The global credit boom: Challenges for macroeconomics and policy. Journal of International Money and Finance 28, 1426 – 1461.

Iacoviello M. (2008). Household Debt and Income Inequality, 1963–2003. Journal of Money, Credit and Banking 40, 929 – 965.

International Monetary Fund (IMF) (2004). Are credit booms in emerging markets a concern?, World Economic Outlook, April.

Kaminsky G., & Reinhart C. (1999). The Twin Crises: The Causes of Banking and Balance-of-Payments Problems. American Economic Review 89, 473 – 500.

Kiss G., Nagy M., & Vonnák B. (2006). Credit Growth In Central and Ekstern Europe: Trend, Cycle or Boom?, National Bank of Hungary Working Paper.

Kremer S., Bick A., & Nautz D. (2011). Inflation and Growth: New Evidence From a Dynamic Panel Threshold Analysis, mimeo, Humboldt University, Berlin, Germany.

Laeven L., & Valencia F. (2008). Systemic Banking Crises: A New Database, IMF Working Papers 08/224, International Monetary Fund.

Lorenzoni G. (2008). Inefficient Credit Booms, Review of Economic Studies 75, 809 – 833.

Martín R. (2011). Credit cycles: Evidence based on a non linear model for developed countries, Bank of Spain Working Papers 1113.

Mendoza E., & Terrones M. (2008). An anatomy of credit booms: evidence from macro aggregates and micro data, NBER Working Paper 14049.

Mendoza E., & Terrones M. (2012). An Anatomy of Credit Booms and their Demise, Working Papers Central Bank of Chile 670.

Perraudin W., & Sørensen B. (1992). The Credit-Constrained Consumer: An Empirical Study of Demand and Supply in the Loan Market. Journal of Business & Economic Statistics 10, 179 – 192.

Roy S., & Kemme D. (2012). Causes of banking crises: Deregulation, credit booms and asset bubbles, then and now. International Review of Economics and Finance 24 (2012) 270–294.

Rubaszek M., & Serwa D. (2011). Determinants of credit to households in a life-cycle model, National Bank of Poland Working Paper 92.

Shin Y., & Kim M. (2011). Bootrstrap-based Bias Corrected Within Estimation of Threshold Regression Models in Dynamic Panels, mimeo.

Tornell A., & Westermann F. (2002). Boom-Bust Cycles in Middle Income Countries: Facts and Explanation. IMF Staff Papers 49, 111 – 155.

Appendix 1: The bootstrap-based bias correction method for estimating threshold error correction models for panel data.

We begin by describing the procedure to estimate the following linear error correction model

$$\Delta y_{i,t} = \alpha_i + \beta \cdot (y_{i,t-1} - \mathbf{x}_{i,t-1}\mathbf{b} - \lambda_i) + \mathbf{w}_{i,t}\boldsymbol{\gamma} + e_{i,t} \tag{A.1}$$

where $\Delta y_{i,t} \equiv y_{i,t} - y_{i,t-1}$, $\mathbf{x}$ is the vector of explanatory variables in the long-run relationship and $\mathbf{w}$ is the vector of variables including $\Delta y_{i,t-1}$ explaining the short-run changes in y. The error term $e_{i,t}$ is independent and identically distributed with mean zero and finite variance σ_e^2. The parameters β, $\mathbf{b}$, and $\boldsymbol{\gamma}$ take on common values for different cross sections whereas α_i and λ_i are the fixed-effects parameters in the short-run and long-run relationships, respectively.

In the first step we estimate the cointegration relationship between the dependent variable y and the vector $\mathbf{x}$. In our case, we employed the method of Bai, Kao, and Ng (2009) to control for potential cross-sectional correlation (i.e. common global stochastic trends) in the panel data.

The error correction term for the country i and the period t is estimated as a residual from cointegration relation

$$ect_{it} = y_{it} - \hat{\mathbf{b}} \cdot \mathbf{x}_{it} - \hat{\lambda}_i. \tag{A.2}$$

In the second step we estimate the vector of parameters $\theta \equiv (\beta, \boldsymbol{\gamma}')'$ of the error correction model using the method described by Everaert and Pozzi (2007). This method corrects bias in parameters estimated with the least squares dummy variable (LSDV) method, $\hat{\theta}_{LSDV} \equiv (\hat{\beta}_{LSDV}, \hat{\boldsymbol{\gamma}}'_{LSDV})'$. The bootstrap procedure simulates the distribution of the LSDV

estimator by sampling from (A.1) as well as some vector of parameters $\tilde{\theta} \equiv (\tilde{\beta}, \tilde{\gamma}')'$ and

returns the mean bootstrap estimate $\hat{\theta}_b \equiv (\hat{\beta}_b, \hat{\gamma}'_b)'$ as explained in detail by Everaert and

Pozzi (2007). A simple iteration procedure is used to find such a vector $\tilde{\theta}$ that generates the

mean bootstrap estimate $\hat{\theta}_b$ equal to the original biased LSDV estimate $\hat{\theta}_{LSDV}$. The final

estimate of θ is $\tilde{\theta}$ for which $\hat{\theta}_b = \hat{\theta}_{LSDV}$.

The same procedure can be used to estimate the threshold error correction model with

R regimes:

$$\Delta y_{i,t} = \begin{cases} \alpha_i + \beta^{(1)} \cdot (y_{i,t-1} - \mathbf{x}_{i,t-1}\mathbf{b} - \lambda_i) + \mathbf{w}_{i,t}\boldsymbol{\gamma}^{(1)} + \varepsilon_{i,t} & when \quad z_t \leq \phi^{(1)} \\ \alpha_i + \beta^{(2)} \cdot (y_{i,t-1} - \mathbf{x}_{i,t-1}\mathbf{b} - \lambda_i) + \mathbf{w}_{i,t}\boldsymbol{\gamma}^{(2)} + \delta^{(1)} + \varepsilon_{i,t} & when \quad \phi^{(1)} < z_t \leq \phi^{(2)} \\ \vdots & \vdots \\ \alpha_i + \beta^{(R)} \cdot (y_{i,t-1} - \mathbf{x}_{i,t-1}\mathbf{b} - \lambda_i) + \mathbf{w}_{i,t}\boldsymbol{\gamma}^{(R)} + \delta^{(R-1)} + \varepsilon_{i,t} & when \quad \phi^{(R-1)} < z_t \end{cases}$$

$$(A.3)$$

where the vector of short-run parameters $\theta^{(r)} \equiv (\beta^{(r)}, (\boldsymbol{\gamma}^{(r)})')'$ alternate their values between

regimes, but the long-run parameters $\mathbf{b}$ and the fixed effects α_i and λ_i remain constant

throughout all regimes. The term $\varepsilon_{i,t}$ is assumed to be independent and identically distributed

with zero mean and finite variance σ_ε^2.

When the values of the threshold parameters $\phi^{(1)}$, $\phi^{(2)}$, ..., $\phi^{(R)}$ are known, the

threshold regression (A.3) can be easily transformed into the linear model

$$\Delta y_{i,t} = v_{i,t}^{(1)}\theta^{(1)} + v_{i,t}^{(2)}\theta^{(2)} + ... + v_{i,t}^{(R)}\theta^{(R)} + \sum_{r=1}^{R}\alpha_i^{(r)}I^{(r)} + \sum_{r=2}^{R}\delta^{(r-1)}I^{(r)} + \varepsilon_{i,t} \qquad (A.4)$$

where $I^{(r)} \equiv I(\phi^{(r-1)} \leq z_t < \phi^{(r)})$ is the indicator variable taking on 1 in the regime r (i.e.

when $\phi^{(r-1)} \leq z_t < \phi^{(r)}$, and 0 otherwise; $v_{i,t}^{(r)} \equiv v_{i,t} \cdot I^{(r)}$ and $v_{i,t} \equiv (ect_{i,t}, w_{i,t})$). The formula

(A.4) is a dynamic linear regression model and can be estimated with the bias-corrected

LSDV method of Everaert and Pozzi (2007).

Our method of estimating threshold regressions with unknown values of the threshold parameters $\phi^{(1)}$, $\phi^{(2)}$, ..., $\phi^{(R)}$ is similar to the method proposed by Hansen (1999) for non-dynamic panel threshold regressions. We start with a two-regime model and estimate its parameters by guessing the value of $\phi^{(1)}$, transforming the parameters into the linear model (A.4) and using the method of Everaert and Pozzi (2007) to obtain parameters $\theta^{(r)} \equiv (\beta^{(r)}, (\gamma^{(r)})')'$ from each regime. The estimate of $\phi^{(1)}$ is found using a grid search over the set G. G is the set of all observation values of the threshold variable z_t in the sample constrained by 15% of the highest and 15% of the lowest observation values. For each guess of the $\phi^{(1)}$ value we estimate the parameters $\theta^{(1)}$ and $\theta^{(2)}$ of the threshold model and compute the residual variance $\mathrm{var}(\varepsilon)$. The estimates of $\phi^{(1)}$, $\theta^{(1)}$, $\theta^{(2)}$ are those that minimize the value of $\mathrm{var}(\varepsilon)$.

For the three-regime model we use the estimate of $\phi^{(1)}$ from the two-regime model and determine the estimate of $\phi^{(2)}$ using the grid search method described above. The minimum allowed distance between the estimated values of $\phi^{(1)}$ and $\phi^{(2)}$ is imposed in such a way that none of the regimes consists of less than 15% of the observations in the sample. The estimates of $\phi^{(1)}$, $\phi^{(2)}$, $\theta^{(1)}$, $\theta^{(2)}$, $\theta^{(3)}$ are those that minimize the value of $\mathrm{var}(\varepsilon)$. An analogous iterative procedure can be used to estimate threshold models with a larger number of regimes.

Table 1: Long-run dependence between credit and other macroeconomic variables

	Parameter value	t-statistic	p-value
Spread	-4.49	-3.61	0.000
GDP per capita	2.29	6.65	0.000
hpi	0.54	7.66	0.000
F statistic	124.44		0.000

Note: The F statistic verifies the null hypothesis which is that the correlation between cross sectional panels is equal to zero against the alternative of significant cross-sectional interdependence.

Table 2: Estimates of the one-regime and two-regime models of credit growth

	two-regime models										
Threshold variable	Δc_{t-1}			ECT_{t-1}			Δhpi_{t-1}			c_{t-1}	
variables	param.	Std		param.	Std		param.	Std		param.	Std
1. regime											
Δc_{t-1}	-0.007	(0.048)		-0.053	(0.053)		0.216	(0.062) ***		0.091	(0.044) **
ECT_{t-1}	-0.08	(0.029) ***		-0.427	(0.108) ***		-0.045	(0.025) *		-0.075	(0.030) ***
$\Delta spread_t$	0.044	(0.339)		-2.026	(0.563) ***		0.202	(0.411)		-2.72	(0.564) ***
Δhpi_t	0.255	(0.048) ***		0.274	(0.094) ***		0.333	(0.059) ***		0.618	(0.066) ***
2. regime											
Δc_{t-1}	-0.137	(0.102)		0.326	(0.067) ***		0.146	(0.083) *		0.268	(0.106) **
ECT_{t-1}	-0.108	(0.034) ***		-0.097	(0.032) ***		-0.243	(0.065) ***		-0.065	(0.033) **
$\Delta spread_t$	-3.046	(0.597) ***		-0.352	(0.417)		-1.628	(0.782) **		0.057	(0.421)
Δhpi_t	0.663	(0.074) ***		0.257	(0.049) ***		0.531	(0.085) ***		0.182	(0.055) ***
δ_1	0.011	(0.018)		0.051	(0.024) *		-0.042	(0.017) **		-0.017	(0.016)
Threshold ϕ_1	0.094			-0.132			0.118			-0.823	
95%-confidence region for ϕ_1	[0.078 : 0.099]			[-0.132 : -0.132]			[0.042 : 0.118]			[-1.062 : -0.509]	
$\mathrm{var}(\varepsilon)$	1.701			1.753			1.790			1.674	
F statistic	50.75	***		40.67	***		34.32	***		55.66	***
single-regime model											
Δc_{t-1}	0.129	(0.046) **									
ECT_{t-1}	-0.104	(0.022) ***									
$\Delta spread_t$	-0.768	(0.355) **									
Δhpi_t	0.357	(0.043) ***									
$\mathrm{var}(\varepsilon)$	2.007										

Note: the explained variable is the growth rate of credit in relation to GDP and the names of the explanatory variables are given in the first column. The columns denoted "param." consist of parameter estimates and the columns denoted "Std" contain the standard deviations of estimated parameters computed using the bootstrap method. The standard deviation cannot be computed for ϕ_1, therefore we present the 95%-confidence region for ϕ_1 under its point estimate. The rows denoted "$\mathrm{var}(\varepsilon)$" contain estimated residual variances for each model multiplied by one thousand. The asterisks "*", "**" and "***" denote the statistical significance of variables at the 10%, 5% and 1% levels, respectively. The F statistic is from the Hansen (1999) test of the null hypothesis assuming no threshold effects, thus the single-regime model is valid. The alternative hypothesis assumes that the two-regime threshold model is valid. The asterisks "***" denote rejection of the null hypothesis at the 1% level of significance.

Table 3: Estimates of the three-regime models of credit growth

Threshold variable	Δc_{t-1}			ECT_{t-1}			Δhpi_{t-1}			c_{t-1}		
variables	param.	Std		param.	Std		param.	Std		param.	Std	
1. regime												
Δc_{t-1}	-0.146	(0.052)	**	-0.046	(0.049)		0.484	(0.055)	***	0.085	(0.045)	*
ECT_{t-1}	-0.105	(0.044)	**	-0.392	(0.111)	***	-0.053	(0.033)		-0.075	(0.028)	***
$\Delta spread_t$	0.687	(0.782)		-1.835	(0.555)	***	-0.049	(0.572)		-2.703	(0.550)	***
Δhpi_t	0.384	(0.091)	***	0.284	(0.094)	***	0.435	(0.090)	***	0.620	(0.062)	***
2. regime												
Δc_{t-1}	0.640	(0.213)	***	0.441	(0.087)	***	-0.087	(0.089)		-0.042	(0.184)	
ECT_{t-1}	-0.030	(0.031)		-0.052	(0.056)		-0.065	(0.037)	*	-0.120	(0.067)	**
$\Delta spread_t$	-0.271	(0.446)		0.240	(0.497)		0.259	(0.555)		-0.425	(0.894)	
Δhpi_t	0.107	(0.056)	**	0.217	(0.058)	***	0.284	(0.075)	***	0.247	(0.133)	*
δ_1	-0.004	(0.012)		0.044	(0.024)	*	0.013	(0.010)		0.007	(0.019)	
3. regime												
Δc_{t-1}	-0.077	(0.095)		0.144	(0.102)		0.133	(0.070)	*	0.352	(0.129)	***
ECT_{t-1}	-0.102	(0.035)	***	-0.237	(0.112)	**	-0.237	(0.055)	***	-0.061	(0.036)	*
$\Delta spread_t$	-3.027	(0.583)	***	-1.853	(0.859)	**	-1.913	(0.675)	**	0.124	(0.430)	
Δhpi_t	0.655	(0.074)	***	0.433	(0.093)	***	0.565	(0.083)	***	0.157	(0.063)	**
δ_2	0.029	(0.017)		0.078	(0.035)	**	-0.040	(0.017)	**	-0.027	(0.018)	*
Threshold ϕ_1	0.012			-0.132			0.045			-0.823		
95%-confidence region for ϕ_1	[-0.001 : 0.037]			[-0.132 : -0.132]			[-0.004 : 0.051]			[-1.062 : -0.509]		
Threshold ϕ_2	0.094			0.116			0.118			-0.526		
95%-confidence region for ϕ_2	[0.078 : 0.099]			[0.037 : 0.126]			[0.042 : 0.118]			[-0.526 : -0.103]		
$var(\varepsilon)$	1.501			1.631			1.614			1.623		
F statistic	36.57		***	20.80		*	29.86		**	8.52		

Note: see Table 2. In the last row, the Hansen (1999) F test assumes that two regimes are valid under the null hypothesis and that three regimes are suitable under the alternative. The asterisks "*", "**" and "***" denote rejection of the null hypothesis at the 10%, 5% and 1% levels, respectively.

Table 4: Identification of boom periods between 2002 and 2009

	Threshold ECM	HP filter	HP filter with a 1.5σ threshold
Canada	2002 (2002-2009)	2002-2009	2009
Germany	---	2009	---
Netherlands	2004-2006 (2002-2007)	2003-2005, 2008	---
Spain	2008 (2002-2003, 2008)	2002-2007	2005-2006
Switzerland	2002-2006 (2002-2006)	2002-2007	2006
The United States	2002-2004, 2008 (2002-2008)	2002-2006	---

Note: Threshold ECM is the model presented in the first column of Table 3. Boom periods are defined as years when the model enters the second (boom) regime and credit is above its long-run equilibrium (e.g. Égert et al., 2006; Kiss et al., 2006). Periods presented in parentheses are indicative of years when the threshold model enters the second (boom) regime.