Coping with unsustainable lending: early warning indicators and the use of macro-prudential instruments *

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Abstract

The paper investigates macro-prudential indicators and instruments that might be used for reaching a sound lending activity. We show that it is useful to complement the concept of excessive credit growth with the one of unsustainable lending, mainly to take on board a possible financial deepening process. Using micro data at bank level, we find that banks′ credit standards, competition and concentration in the banking sector are good early warning indicators for both excessive credit growth and unsustainable lending. We identify thresholds for the loan-to-value and debt-service-to-income caps that significantly decrease the probability of excessive credit growth or unsustainable lending, using as a case study the Romanian experience with such macro-prudential instruments.

Keywords: credit cycle, early warning indicators, macro-prudential instruments, debt-service-to-income (DSTI), loan-to-value (LTV)

JEL Classification: E32, G21, G28

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Non-technical summary

The international crisis that started in 2008 raised the awareness for monitoring and limiting the excessive credit growth. Moreover, preventing and curbing negative developments in lending activity has become a widely accepted intermediate objective for the macro-prudential policy. Currently, there is an effort intensification among academia and policy makers to find and operationalize appropriate instruments in order to prevent and mitigate excessive credit growth.

Our paper lays in the same avenue of assessing the relevant macro-prudential instruments and identifying early warning indicators needed for reaching a sound lending activity. In this respect we apply a three-step approach. In the first step, we investigate the differences between the two credit events of interest: excessive credit growth and unsustainable lending. More specifically, we are interested in assessing if the excessive credit growth indicator provides a fair signal relative to the level of risk accumulated in the banking sector and, therefore, can be used to calibrate the measures needed to reach a sound lending activity. In a second step, we set up a multivariate panel *logit* model, with fix effects, in order to assess what indicators are better suited to monitor excessive credit growth and/or unsustainable lending. In the third step, we look at suitable threshold values for some of the macro-prudential instruments (like *loan-to-value* and *debt-service-to-income* that would contribute to the prevention of a credit event. For the multivariate panel *logit* model we use bank level data, focusing on several categories of explanatory variables: banks′ lending standards (*debt-service-to-income*, *loan-to-value*, *loan-to-income*, and the share of new FX lending), competition and concentration indicators, prudential regulation, banks′ financial conditions (profitability, solvency and leverage, loan-to-deposit ratio and credit quality), and macroeconomic environment and monetary policy stance. We use the Romanian banking sector as a case study for two reasons: micro data availability and long (almost ten years) experience with macro-prudential instruments like DSTI and LTV.

One important conclusion is that excessive credit growth might not always tell the proper story about the unsoundness of the lending developments. Therefore, it is useful to complement the indicator for excessive credit growth with an indicator about unsustainable lending. Working with both concepts allows capturing the financial deepening process that might be roofed within a rapid lending activity. This issue is important especially for the emerging countries. For example, we find that financial deepening might have been a characteristic in the Romanian credit market, mainly during 2005/Q1-2006/Q4 and contributed to excessive credit growth.

Second, we find that concentration plays a significant role in building up excessive credit growth. Moreover, banks tend to lend more if they observe other banks engaging in more aggressive tactics to earn market share. Banks′ credit standard indicators are important for both excessive credit growth and unsustainable lending. In addition, we find evidence that the level of *debt-service-to-income* under regulatory requirements contributes to the reduction of the excessive credit growth, while overall macro-prudential regulation exerts a high impact on trimming down unsustainable lending.

Third, we identify thresholds for macroprudential instruments LTV, DSTI and LTI that might contribute significantly to the decrease of the probability of excessive credit growth or unsustainable lending. An LTI value higher than 3 enhances the probability of unsustainable lending between 4.5 to 8.6 percentage points, more than double the average marginal effects of lower LTI values. We observe that a DSTI value higher than 45% corresponds to a probability of unsustainable lending higher than 32% over the entire period (and over 62% during the upswing phase of the credit cycle). A value of LTV over 75% corresponds to a probability of excessive credit growth ranging from 60% to 80% in the building-up phase of risks, significantly higher than the probability measured for LTV values lower than 75%. These thresholds might be operationalized into macro-prudential instruments, as caps on DSTI, LTI and LTV.

Forth, banks usually exhibit a high degree of herding behaviour when unsound lending manifests, supporting the use of macro-prudential instruments instead of micro-prudential measures. We reach this conclusion by building up concordance indicators between individual banks′ credit cycle and the overall credit cycle. This approach also allows grasping some flavour about the unintended consequences for banks, when macro-prudential instruments are implemented. The more-prudent banks would bear the same regulatory cost as the less-prudent banks. As such, the authorities might unintentionally encourage herding behaviour, because of penalties imposed on all banks through macro-prudential instruments. An alleviation of the micro-prudential burden applicable to the more-prudent banks might be a good counterbalance solution.

1 Introduction

The international crisis that started in 2008 raised the awareness for monitoring and limiting the excessive credit growth. Moreover, preventing and curbing negative developments in lending activity has become a widely accepted intermediate objective for the macro-prudential policy[1]. Some voices go further, considering that the main task for the macro-prudential policy should be smoothening the credit cycle (Constâncio, 2014). Currently, there is an effort intensification among academia and policy makers to find and operationalize appropriate instruments in order to prevent and mitigate excessive credit growth. Detken et al. (2014) represents such an example, focusing on the use of the countercyclical capital buffer.

Our paper lays in the same avenue of assessing the relevant macro-prudential instruments and early warning indicators needed for reaching a sound lending activity. We focus on answering the following three questions. (1) Does the excessive credit growth tells the proper story about the unsoundness of the lending developments? (2) Which indicators should be used by policy makers to monitor excessive credit growth and/or unsustainable lending? (3) Which should be the proper threshold values for debtor based instruments like debt-service-to-income (DSTI), loan-to-income (LTI) and loan-to-value (LTV) that would help prevent excessive credit growth or unsustainable lending? In order to answer these questions we use the Romanian banking sector as a case study for two reasons: micro data availability and long (almost ten years) experience of this country with macro-prudential instruments like DSTI and LTV.

The literature links excessive credit growth to an increase in financial crises occurrence (Kaminsky and Reinhart, 1999). Evidence is also found in the opposite direction, pointing to the fact that rapid credit growth can be a positive contributor to the economic activity (Rajan and Zingales (1996); Maechler et al. (2009)). Our first question is born on this background of eclectic views: Does the excessive credit growth tells the proper story about the unsoundness of the lending developments? We approach this question by analysing two indicators: one designed to capture excessive credit growth (constructed based on the annual credit growth dynamics) and the second one designed to assess unsustainable lending (i.e. the share of loans that migrate in the nonperforming state before loans reach their maturity). We find that periods of excessive credit growth may differ from periods of unsustainable lending, supporting the need to take on board the possibility that financial deepening[2] could characterize an excessive credit growth development. This result adds to the conclusion that from a macro-prudential perspective it is useful to complement the excessive credit growth approach with the one that captures unsustainable lending developments.

In order to identify the indicators that signal excessive credit growth and/or unsustainable lending (the second question of the paper), we set up an early warning approach by estimating a multivariate panel logit model. We use bank level data, focusing on credit institutions′ lending standards, competition and concentration within the financial system, while controlling for the financial soundness condition of the banking sector and for the macroeconomic stance (when is economically relevant). We find that concentration plays a significant role in building up excessive credit growth. Moreover, banks tend to lend more if they observe other banks engaging in

[1]The European Systemic Risk Board (ESRB) recommends, as an intermediate macro-prudential policy objective, the mitigation and prevention of excessive credit growth and leverage. To reach this objective, some macro-prudential instruments are suggested to be used by the responsible authorities: debt-service-to-income (DSTI) or loan-to-value (LTV) caps, countercyclical capital buffers (CCB), etc.

[2]We define *financial deepening* as the development of the credit market characterized by a permanent increase in the credit to GDP ratio. From a credit-risk perspective, *financial deepening* should be seen as the rapid increase of the stock of credit not followed by a significant accumulation of losses in the banks′ balance sheets (Figure A2.1, Annex 2).

more aggressive tactics to earn market share. Banks′ credit standard indicators are important for both excessive credit growth and unsustainable lending[3]. In addition, we find evidence that the level of *debt-service-to-income* under regulatory requirements contributes to the reduction of the excessive credit growth, while overall macro-prudential regulation exerts a high impact on trimming down unsustainable lending.

We also use the multivariate logit models to identify the thresholds for LTV, DSTI and LTI indicators that couls significantly decrease the probability of excessive credit growth or unsustainable lending (the third aim of the paper). The signal issued by these thresholds might be operationalized into macro-prudential instruments as caps on DSTI, LTI or/and LTV. Neagu et al. (2014) complements this approach by looking at the efficiency of such instruments in relation with other central bank measures (monetary policy and micro-prudential measures).

The remainder of the paper is structured as follows. Section two describes the data used and the variables constructed to conduct the researcht. It presents also the methodology of the research, providing details on the build-up of the concordance indicator and the multivariate panel logit model. The results are presented in section three, with an emphasis on disentangling between excessive credit growth and unsustainable lending developments. Section four concludes.

2 Data and Methodology

The paper aims at identifying the adequate measures that the macro-prudential authority could apply in order to prevent and mitigate excessive credit growth and/or unsustainable lending (a credit event [4]). In this respect we apply a three-step approach. In the first step, we investigate the definition of the credit event and the differences between excessive credit growth and unsustainable lending. More specifically, we examine whether excessive credit growth should be split into two distinct phases - financial deepening and exuberance or unsustainable phase (rapid credit growth that ends up in high losses). In a second step, we set up a multivariate panel logit model, with fix effects, in order to assess what indicators are better suited to monitor excessive credit growth and/or unsustainable lending. In the third step, we look at different threshold values for some macro-prudential instruments (like loan-to-value and debt-service-to-income) to assess what should be the optimal measures in order to prevent a credit event.

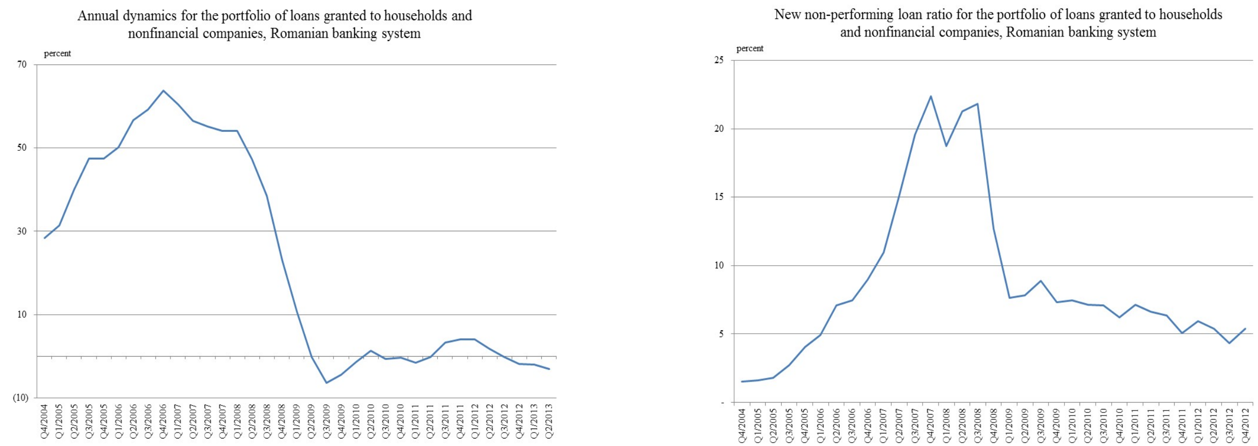
We use quarterly data at bank level that spans over the period 2005-2012. We select the banks based on their presence in the market during this period and on the relevance of their credit activity [5]. The selected banks account for over 70% of assets and over 80% of credit granted to households and firms.

[3] We follow the findings from Drehmann et al. (2013) which point to the fact that banks′ credit standard indicator such as DSTI captures very accurately the burden that debt imposes on borrowers and has a good performance in signaling banking crises at shorter horizons.

[4] For the purpose of this paper, we define as credit events the periods of excessive credit growth or unsustainable lending.

[5] We select the banks by putting a materiality threshold for their lending portfolio of 1% in total aggregate credit to household and firms, in total 14 banks.

Figure 1: Annual credit growth for total portfolio (left panel) and non-performing loan ratio (right panel)



Note: The data reflects the developments for the aggregate credit portfolio (households and firms) regarding both credit growth and non-performing loan ratio. The data for credit is adjusted for inflation and exchange rate effects.
Source: Central Credit Register, Ministry of Public Finance, National Bank of Romania, own calculations.

Figure 1 shows the credit developments for the Romanian banking sector, both in terms of credit dynamics (left panel) and unsoundness of lending (non-performing loans ratio, right panel). We embark in the first part of the analysis, by defining the credit events (excessive credit growth and unsustainable lending). The analysis of financial cycles have been recently a lot in the attention of academia and policy makers (Detken et al., 2014). The flow of research was conducted both in the direction of accurately identify excessive or unsustainable credit developments, and in the direction of signalling variables. In our analysis for the Romanian banking system, we use a common indicator for excessive credit growth: the annual credit growth dynamics. The data is expressed in real terms and adjusted for the currency effects in order to take on board the euroization phenomenon[6]. For the assessment of unsustainable lending, we construct an indicator based as follows: the share of quarterly new lending that migrates to a non-performing state during the observation period (Q4/2004-Q2/2013)[7].

[6] We also tested credit-to-GDP gap as indicator for excessive credit growth, based on the findings from Drehmann et al. (2010), but the results are not reliable due to short data history.

[7] The non-performing state is characterized by overdue payments of 90-days or more. A loan is considered nonperforming, if it had the 90-days past due flag at least once during the observation period, even if it recovered afterwards. Pesola (2005) defines the credit distress cycle in a similar way, considering that an increase in indebtedness (after the financial deepening stage) is followed by a deterioration of debtors′ capacity to repay their debts.

Both credit event indicators (excessive and unsustainable) are constructed as binary variables on bank level data:

$$Y_{it} = \begin{cases} 1, & if\, x_{it} \geq E(x_{i,t}) + k * std(x_{it}) \\ 0, & otherwise \end{cases} \tag{1}$$

where x_{it} represents the annual credit growth or the rate of new non-performing loans, as described above, for bank i (capturing excessive credit growth or unsustainable lending), $E(x_{it})$ is the average value of the credit indicator, and k is a multiplying parameter[8] (details on the indicators′ set up are presented in Annex 1). Both types of indicators are subject to limitations[9].

Further on, we analyse the distributions of the indicators constructed for the credit events (excessive credit growth and the unsustainable lending developments) and the concordance index of the two cycles. We apply the concordance indicator (CI) following Claessens et al. (2011a, 2011b)[10]. We define two phases for the credit cycle: excessive and non-excessive, unsustainable and sustainable, respectively:

$$CI = T^{-1} \sum_{t=1}^{T} [S_t^i * S_t^j + (1 - S_t^i)(1 - S_t^j)] \tag{2}$$

where:

$$S = \begin{cases} 1, & excessive/unsustainable\ period \\ 0, & otherwise \end{cases} \tag{3}$$

and T is the number of periods observed.

The CI counts the periods when two cycles are synchronized. In the first place we analyse the differences between individual bank′s credit cycle and the system credit cycle. This information contributes to the assessment of the suitability of macro-prudential instruments versus micro-prudential measures in dealing with credit development challenges. If there is a large synchronization between the cycles, macro-prudential instruments would be the first option, due to the common behaviour that is taking place in the market.

In the second step, we investigate the indicators that contribute to an increase of the probability of a credit event (excessive credit growth and/or unsustainable lending). The variables considered

[8]This approach is extensively used in the literature. Mendoza and Terrones (1999) propose a multiplying factor of 1.75, Elekdag and Wu (2011) propose a baseline threshold of 1.55 (corresponding the the 6^{th} percentile), while Barajas et al. (2007) use two methods in the identification of credit booms: first imposing a numerical threshold for the growth of credit to GDP of 10%, and second, based on a specific multiplying factor.

[9]In case of excessive credit growth, using only domestic credit dynamics to compute excessive credit growth, we underestimate the true indebtedness in the system. According to the BNR (2013), a material lending activity is provided by the non-residents (banks and parent companies), by the non-bank financial institutions or is not captured by the domestic monetary aggregates due to securitization. On the unsustainable lending front, the non-performing loan indicators might be affected by the possible banks′ ever-greening policies. Banks can avoid recording a loan as non-performing by implementing different techniques like rescheduling or restructuring before the loan reaches the non-performing state. We correct the data for rescheduling by excluding the new loans that are reported as such in the Central Credit Register database. In this manner, we avoid the double counting of previously granted loans and rescheduled afterwards.

[10]The authors apply the concordance indicator calculated by Harding and Pagan (2002), using an approach for the business cycles.

to signal a credit event are derived from the literature on financial cycles, for example Gorton and He (2008), Dell'Ariccia and Marquez (2006). Nevertheless, we concentrate on two main channels through which imbalances are built-up into the financial system. The first refers to the financial accelerator mechanism (cyclical fluctuations of collateral′ value amplify the credit cycle, Almeida et al. (2000)) and the second to the fluctuations in banks′ credit policies as a result of (i) banks trading the quality of loans for market share (Dell'Ariccia and Marquez, 2006) and of (ii) competition between banks (Gorton and He, 2008). In this respect, we analyse the market concentration and banks′ competition from the banks′ lending strategies perspective.

The variables that we use in our estimations are split in the following five categories (A-E)[11] and are defined as follows:

(A) Banks′ lending standards: LTV, DSTI, LTI and indicators on the credit flow.

The LTV is computed at the origination of the loan, using the following formula:

$$LTV_{loan} = 100 * \frac{Outstanding\ loan\ amount}{Adjusted\ collateral\ value} \tag{4}$$

In the regressions, the LTV_{it} indicator is computed as the median value of all individual LTV_{loan} for bank i at time t.

Due to data limitations[12], we use the S1/2012 collateral values, which we consider to represent the original values. We assume that figures from S1/2012 onwards represent the market value[13] .

The DSTI for the indebted households is constructed by using the constant annuities hypothesis:

$$DSTI_{loan} = 100 * \frac{\frac{\frac{r}{12} * P}{1-(1+\frac{r}{12})^{-n}}}{I} \tag{5}$$

where r is the annual interest rate; P it the credit value at origination; n is the original maturity of the loan (number of months), I is the average of monthly net income for debtor for credit. In the regression we use $DSTI_{it}$ indicator, computed as the median value of all individual $DSTI_{loan}$ for bank i at time t.

The LTI is calculated for loans granted to firms as:

$$LTI_{it} = 100 * \frac{\sum_j Outstanding\ loan\ amount}{\sum_j Operational\ income} \tag{6}$$

where j refers to all new credit granted by bank i at time t.

To capture the structural developments in lending, we consider the credit split by currency (i.e. the percentage of foreign denominated loans in total outstanding loans).

[11]Tables A2.1 and A2.2 from Annex 2 present the main indicators used in the paper, their data sources and the calculation methodology.The data is checked for abnormal values and the outliers are eliminated using a winsorization technique.

[12]The collateral data is available starting 2012 in the Central Credit Register.

[13]According to BNR (2013), external auditors of banks were asked twice by the supervision authority (after the first half of 2012 and 2013) to reevaluate the real estate collateral from banks portfolio. Such reevaluation brought important downward adjustments in the real estate collateral value.

(B) Concentration and competition indicators: for concentration, we use Herfindahl−Hirschman Index (defined on banks′ credit portfolios); for competition, we implement two indicators inspired from Gorton and He (2008). For these indicators we apply a refinement in order to capture the macro perspective regarding banks′ lending decisions: we look at the individual bank′s reaction (in terms of leading or following the market) to the whole sector (and not at the bilateral answers):

(B1) credit as a percentage of total assets relative to the system:

$$Competion\_ca_{it} = \frac{1}{n-1}\sum_{j\neq i}^{n}\frac{Credit_{jt}}{Assets_{jt}} - \frac{Credit_{it}}{Assets_{it}} \tag{7}$$

The rationale behind this indicator refers to banks′ decision to change their lending strategy based on the observation of their competitors′ lending behaviour. A higher value for $Competition\_ca_{it}$ indicates a lower position for $bank_i$ in terms of outstanding credit to total assets compared to its competitors, which might translate into a larger probability for this bank to push for higher credit growth rates.

(B2) loan loss provisions as percentage of credit portfolio relative to the system (information producing intensity):

$$Competion\_pv_{it} = \frac{1}{n-1}\sum_{j\neq i}^{n}\frac{Provisions_{jt}}{Credit_{jt}} - \frac{Provisions_{it}}{Credit_{it}} \tag{8}$$

For this indicator, a higher value might trigger a lower probability of future excessive credit growth or unsustainable lending. The reasoning is that a bank would act more prudent when it sees an increase in the costs of its competitors (through higher provisions).

(C) Macro-prudential regulation: we construct a regulatory dummy variable that accounts for the prudential measures applied during the analysed period: 2005 - 2012 (see Table A2.3, Annex 2). The dummy variable is set to 1 in the quarter when the measure is officially approved and zero for the rest of the period. We consider only prudential measures that explicitly target diminishing credit risks and risks stemming from the rapid growth of FX lending. The results should be interpreted with care, because various other prudential regulations were implemented in the same time, leading to difficulties in disentangling the individual effects[14].

(D) Banks′ financial stance: we evaluate banks′ profitability (return on equity and return on assets), solvency and leverage, loan-to-deposit ratio and credit quality (non-performing loan ratio and loan loss provision ratio). The analysis of financial soundness indicators of the banking sector reveals high heterogeneity, mainly linked to early developments of the credit market (during 2004-2006 period) and to different strategies applied by banks during the downturn phase of the credit cycle (in terms of profit and credit quality, the 2009-2012 period)[15].

(E) Macroeconomic environment and monetary policy stance: we exploit the variables used in the literature (GDP growth, unemployment, disposable income).

[14] One such example is the regulation on limiting the foreign denominated exposures resulted from credit activity that entered into force in 2005 and was kept until end-2006.

[15] These findings are in line with the empirical literature underling that larger banks are usually better suited to cope with possible shortage of funding or have better risk management systems that help them weather more easily a rapid deterioration of credit portfolio.

The general specification for the probability of a credit event (excessive credit growth and unsustainable lending) is given by the following regression (see Table A1.1, Annex 1 for details on the dependent variables):

$$ln\frac{P(Y_{it}=1)}{1-P(Y_{it}=1)} = \beta_1\ X_{it-k}+\beta_2\ M_{it-k}+\beta_3\ Z_{it-k}+\beta_4\ W_{t-k}+M_{it-k}*R_{t-k}+R_{t-k}+\eta_i+\epsilon_{it} \quad (9)$$

where:
Y_{it} : the binary variable for the credit event (excessive or unsustainable) at bank level;
X_{it} : the banks$'$ financial soundness indicators (profitability, solvency, liquidity, ratio of loans the loss category, loan-loss provisioning, loan-to-deposits ratio, etc.);
M_{it} : the banks$'$ lending standards (DSTI, LTI, LTV and the share of new Fx loans);
Z_{it} : the banks$'$ competition indicators;
W_t : the macroeconomic variables (unemployment rate, economic growth, disposable income growth rate, etc.);
M_{it}*R_t : the interaction factor between the banks$'$ lending standards and the regulation dummy variable;
R_t : the regulation dummy variable[16];
k : the number of lags (we test for a number of quarters from 0 to 4).

In order to tackle a potential endogeneity problem in the estimation of excessive credit growth, we make the following decisions: i) while the decision to introduce a new regulation or change an existing one is based on current credit dynamics (generally a tightening regulation aims at diminishing credit growth) we introduce the regulation dummy variable enters the regression with a lag of one quarter; ii) banks$'$ lending standards indicators and the concentration index are introduced with a lag of four quarters, considering that most banks are setting their credit policy once a year; iii) competition variables are tested with a four quarters lag, as banks can usually observe their competitors with a lag and it is incorporated into annual credit strategy. In case of unsustainable lending, we do not identify exactly the moment of default, we consider a contemporaneus signal stemming from banks$'$ lending standards and regulation.

3 Results

3.1 Excessive credit growth and unsustainable lending

In order to answer the first question, we examine the credit dynamics over the period 2004/Q4 2013/Q2 from both a macro and micro perspective (at bank level). We are interested in evaluating whether the excessive credit growth indicator provides a fair signal relative to the level of risk accumulated in the banking sector and, therefore, can be used to calibrate the measures needed to reach a sound lending activity.

First, the distributions by banks and by vintages of the annual credit growth rates and of the new nonperforming ratios (Figure A3.1, Annex 3) indicate that only the second part of the rapid credit growth period is associated with a severe deterioration of the credit quality. More

[16]The regulation dummy is defined as taken the value of 1 for the quarters when macro-prudential measures (caps on DSTI and LTV) were in place and 0
otherwise. For more details on macro-prudential measures implemented by National Bank of Romania see Neagu et al. (2014).

specifically, the annual credit growth can be split in two distinct periods, before 2008/Q4 (with an average annual growth of around 50

credit growth (2007/Q1 2008/Q4), for a shorter period.[17] Therefore, we can infer that financial deepening might have played a role for the Romanian credit market, mainly during 2005/Q1 − 2006/Q4, as the significant credit growth rates recorded during this phase of the cycle did not materialize in an important deterioration in the quality of the banks′ credit portfolios (in line with Copaciu and Racaru (2006)).

A first conclusion that we can infer from this result is that the macro-prudential authorities should analyse the stories told by both excessive credit growth and unsustainable lending indicators when deciding on the measures that target risks stemming from lending activity.

Second, we compute concordance indicators (CI) at bank level between excessive credit growth and unsustainable lending indicators (Figure A3.2, Annex 3). The resulting picture is inconclusive, with individual banks CI values ranging from 0.4 to above 0.8 (total credit portfolios). From the macroprudential perspective, higher values of CI are desirable at both aggregate and bank level, because they indicate a high degree of synchronization between the two credit events (excessive credit growth and unsustainable lending). The macro-prudential measures should target the unsustainable lending. This result adds to the evidence that macro-prudential measures targeting only excessive credit growth might come with some unintended consequences for banks. This problem might be even more critical in the case of credit granted to non-financial companies, for which a higher heterogeneity is observed in terms of banks behaviour (6 banks out of 14 have a CI value below 0.6, while for 3 banks is above 0.9, Figure 3.2, Annex 3).

Third, we analyse the CI between individual banks′ cycles and the banking sector cycle. The results support the previous conclusion and validate the assumption that banks tend to synchronize their lending policies, especially in the case of household credit market (CI values are ranging between around 0.7 to 0.97, Table A3.1, Annex 3). These figures advocate the use of macro-prudential instruments (instead of micro-prudential measures), in order to cope with challenges from credit developments. Nevertheless, the authorities might unintentionally encourage this herding behaviour by imposing penalties on all banks (higher capital requirements).

3.2 Early warning indicators and thresholds signalling excessive credit growth and unsustainable lending

We use a multivariate panel *logit* model with the aim to: i) assess what indicators are better suited to monitor excessive credit growth and/or unsustainable lending and ii) identify suitable threshold values for debtor-based instruments (like *loan-to-value* or *debt-service-to-income*), for the purpose of calibrating such measures to prevent a credit event (ensure a sustainable lending activity). We control for macroeconomic and banking factors and for the macro-prudential measures (like caps on *debt-service-to-income* and on textitloan-to-value).We verify the results by looking at the structural changes over the credit cycle by running econometric analyses on both entire and pre-crisis periods[18]. The results are presented in Annex 4.

We also conduct robustness checks on other regulatory measures that targeted lending activity like prudential measures related to liquidity, provisions or monetary policy measures that were widely used by the National Bank of Romania. The results were inconclusive and are not

[17] We split the period of analysis into two periods, centred on the moment the financial crisis started in Romania (2008/Q4).

[18] We did not conduct a similar analysis for the post-crisis period due to short time series and high heterogeneity that make the econometric estimations less reliable.

presented in this paper. For monetary measures, we checked the effects stemming from one-side minimum required reserves (MRR) measures (strengthening) by creating a dummy variable with a value of 1 when the MRR rate is increased, and zero otherwise. The variable was introduced in all excessive lending regressions with various lags, but the results were not significant (the MRR rate did not contribute to the reduction of the probability of excessive credit growth)[19].

3.2.1 Indicators and thresholds signalling excessive credit growth

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We look at three types of explanatory variables[20]: (i) banks′ lending standards (LTV, DSTI[21], and LTI[22]), (ii) structural features of lending activity (share of new FX denominated loans in total loans[23]) and (iii) concentration and competition indicators.

The results[24] show that indicators of banks′ credit standards like LTV have relatively good signalling abilities for the excessive credit growth (Table A4.1 for total portfolio and Table A4.3 for household portfolio, Annex 4). Moreover, LTV has an important contribution to the probability of excessive credit growth, although its impact is of a lesser magnitude compared to other variables (like competition). An increase in the LTV level contributes to the probability of excessive credit growth in the case of the household portfolio by around 0.4 percentage points over the entire credit cycle period and between 0.8 to 1 percentage points during the expansion phase of the cycle.

After having examined the regressions results, we can take one step further and look at the thresholds values for these indicators. An LTV value over 75% for household lending corresponds to a probability of excessive credit growth ranging from 60% to 80% in the building-up phase of risks, significantly higher than the probability measured for LTV values lower than 75% (on average 35%, see Table A4.5, Annex 4).

By comparison, the DSTI indicator does not display a significant influence on excessive credit growth. If, instead, we test the interaction between DSTI and the regulation dummy, which reflects the restricted DSTI level, the term has a marginal contribution to the decrease of the probability of an excessive credit growth event (up to 0.6 percentage points during the pre-crisis period for the household portfolio).

The results should be interpreted with care considering at least the following two features. First, the impact of an increase in the LTV value on the excessive credit growth probability might be underestimated due to the assumptions used in constructing the LTV time series: (i) the collateral accepted on mortgage loans is homogeneous (it behaves similarly over time) - the same real estate index was employed to adjust the collateral values, (ii) the most recent information on collateral reflects the fair values and (iii) the majority of banks′ portfolio of household mortgage

[19]For more details on the impact of monetary policy measures on credit dynamics in the Romanian case see Neagu et al. (2014).

[20]Indicators on macroeconomic conditions and on banks′ financial stance generate the expected results and are not discussed here. The econometric estimations are presented in Annex 4.

[21]LTV and DSTI are calculated for household portfolio only due to data limitations and differences in credit characteristics for nonfinancial companies (for example, in the case of credit lines, an important form of credit for non-financial companies, the DSTI is not a proper indicator of the level of risk).

[22]LTI is calculated for non-financial companies only.

[23]The high share of FX lending is a vulnerability in many European countries. To manage such challenge for the financial stability, the European Systemic Risk Board issued a recommendation addressing this risk (Recommendation of the ESRB of 21 September 2011 on lending in foreign currencies).

[24]The definition of excessive credit growth indicators for both aggregate and household portfolios are presented in Annex 1. Considering the fact that the prudential measures targeted mainly the households portfolio, we focus on this sub-sector in this analysis.

loans remains on banks′ balance sheet (survival bias). Second, both LTV and DSTI indicators were subject to prudential regulation, limiting their quality as an early warning indicator.

Another indicator that we investigate is the share of new foreign denominated loans (FX share). This indicators has also a clear and statistically significant impact on excessive credit growth probability (up to 0.7−0.9 percentage points in the expansion phase of the cycle).

Market concentration (expressed as the Herfindahl−Hirschman Index) plays a significant role in influencing the probability of the excessive credit growth (the impact of one percentage point increase for the index results in 0.1 percentage point increase for both the total loan portfolio and the household portfolio). The effect is doubled in the pre-crisis period (2005/Q1−2008/Q4).

Competition indicators (*Competition_ca* and *Competion_pc*) are also important triggers for excessive credit growth probability. In the case of household lending, banks′ credit activity is much more influenced by other banks′ behaviour. They tend to lend more if they observe other banks engaging in aggressive tactics to earn market share, especially during the expansionary phase of the credit cycle. The impact of *Competition_ca* on the excessive credit growth probability varies between 2.1 and 2.2 percentage points for this portfolio, while on the total portfolio the impact is insignificant.

The second competition indicator (*Competion_pc*) also points out some interesting results. Banks tend to reduce their lending activity, if they detect that other banks are experiencing higher losses. For the aggregate portfolio, this indicator leads to an important reduction in excessive credit growth probability, with values between 1.1 and 1.6 percentage points, for the entire period analysed. Nevertheless, the indicator does not produce relevant results for the household portfolio, which might suggest that it impacts mainly the credit activity to non-financial companies.

3.2.2 Indicators and thresholds signalling unsustainable lending

In order to ensure a robust estimation for the model on unsustainable lending [25], we analyse the following two aspects. First, we evaluate whether the binary variable for unsustainable lending is showing a common pattern among banks. Second we check if the pre-crisis dataset contains sufficient observations of such credit event. We find that the unsustainable lending is a phenomenon characterizing mainly the period 2007/Q1−2009/Q2 (when the highest new non-performing loans ratios are displayed). Therefore, we extend the pre-crisis period used in the previous sub-section from 2005/Q1−2008/Q4 to 2005/Q1−2009/Q2, in order to get a more balanced interval of unsustainable lending.

We reach three main conclusions regarding the unsustainable lending (Tables A4.2 and A4.4, Annex 4). First, macro-prudential regulation proves to efficiently contribute to the reduction of the probability of unsustainable lending, especially in the pre-crisis period. Implementing macro-prudential measures like caps on LTV and DSTI contributed to the reduction of the probability of unsustainable lending by 18 percentage points.

Second, DSTI (for the household sector) and LTI (for the corporate sector) are important triggers for the probability of unsustainable lending. The highest impact stems from the LTI (a one percentage point increase in LTI brings more than 8 percentage points to the probability of unsustainable lending). Moreover, an LTI higher than 3 increases the probability of unsustainable

[25] The definition of unsustainable lending indicators for both aggregate and household portfolios are presented in Annex 1.

lending from 4 to 8.6 percentage points (Table A4.7, Annex 4). The DSTI indicator leads to 2 percentage points increase in the probability of unsustainable lending. We observe that a DSTI higher than 45% for the household financing corresponds to a probability of unsustainable lending higher than 32% over the cycle and of over 62% during the upward phase of the cycle (Table A4.6, Annex 4). This 45% DSTI threshold should be interpreted with some care, as the indicator was influenced by prudential regulation throughout the credit cycle, therefore its early warning signal quality is affected by the policy actions.

The share of FX loans also influences the probability of unsustainable lending. The increase in the variable by one percentage point brings an additional 0.2 percentage points to the above mentioned probability (and 0.5 to 0.6 percentage points in the upswing phase of the cycle).

Third, similarly to what we observe for excessive credit growth in the case of household lending, banks tend to behave more aggressively (to increase their risk tolerance) if they notice other banks engaging in this type of behaviour. One percentage point increase in the $Competition\_ca$ leads to an increase of the probability of unsustainable lending of 0.9 percentage points (over the entire period analysed).

4 Conclusions

We embark on the task to identify the adequate measures that the macro-prudential authority could apply in order to mitigate and prevent a credit event (excessive credit growth/unsustainable lending). In this respect, we use micro and macro data for the Romanian banking sector in a multivariate panel *logit* model with fixed effects, focusing on several categories of explanatory variables: banks′ lending standards (debt-service-to-income, loan-to-value, loan-to-income, and the share of new FX lending), competition and concentration indicators, prudential regulation, banks′ financial conditions (profitability, solvency and leverage, loan-to-deposit ratio and credit quality), and macroeconomic environment and monetary policy stance. We use the Romanian banking sector as a case study for two reasons: micro data availability and long (almost ten years) experience of this country with macro-prudential instruments like DSTI and LTV. We follow a three step approach and reach four main conclusions.

First, we find that excessive credit growth does not always tell the proper story about the unsoundness of the lending developments. Therefore, it is useful to complement the indicator for excessive credit growth with an indicator about unsustainable lending. Working with both concepts allows capturing the financial deepening process that might be roofed within a rapid lending activity. This issue is important especially for the emerging countries. For example, we find that financial deepening might have been a characteristic in the Romanian credit market, mainly during 2005/Q1-2006/Q4 and contributed to excessive credit growth.

Second, we discover that banks tend to lend more if they observe other banks engaging in more aggressive tactics to earn market share, building up the path for excessive credit growth. An increase with one percentage point of the indicator signalling this type of competition raises the probability of the excessive credit growth between 1.0 and 2.2 percentage points. Loan-to-value (LTV), loan-to-income (LTI), debt-service-to-income (DSTI) and the share of FX lending prove also to influence to a large extent this probability. As regards the probability of unsustainable lending, DSTI (for the household sector) and LTI (for the corporate sector) are important triggers, as well. The highest impact comes from LTI (a one percentage point increase in this indicator brings more than 8 percentage points to the probability of unsustainable lending). The share of FX loans also influences the probability of unsustainable lending. The increase of this share by one percentage point brings an additional 0.2 percentage points to the above mentioned probability (and 0.5 to 0.6 percentage points during the upswing phase of the cycle).

Third, we identify some thresholds for LTV, DSTI and LTI that significantly decrease the probability of excessive credit growth or unsustainable lending. An LTI value higher than 3 enhances the probability of unsustainable lending between 4.5 to 8.6 percentage points, more than double the average marginal effects of lower LTI values. We observe that a DSTI value higher than 45% corresponds to a probability of unsustainable lending higher than 32% over the entire period (and over 62% during the upswing phase of the credit cycle). A value of LTV over 75% corresponds to a probability of excessive credit growth ranging from 60% to 80% in the building-up phase of risks, significantly higher than the probability measured for LTV values lower than 75%. These thresholds might be operationalized into macro-prudential instruments, as caps on DSTI, LTI and LTV.

Forth, banks usually exhibit a high degree of herding behaviour when unsound lending manifests, supporting the use of macro-prudential instruments instead of micro-prudential measures. We reach this conclusion by building up concordance indicators between individual banks′ credit cycle and the overall credit cycle. This approach also allows grasping some flavour about the unintended consequences for banks, when macro-prudential instruments are implemented. The more-prudent banks would bear the same regulatory cost as the less-prudent banks. As such, the authorities might unintentionally encourage herding behaviour, because of penalties imposed on all banks through macro-prudential instruments. An alleviation of the micro-prudential burden applicable to the more-prudent banks might be a good counterbalance solution.

The discussion on the soundness of lending activity should be further extended, for the purposes of the macro-prudential policy, from the *lenders view* to the *debtors view*. In the first approach (*lenders view*), a higher rate of credit growth is usually associated with low information producing intensity regarding borrowers′ worthiness, and possible overestimation by banks of their ability to deal with future risks stemming from new credit exposures. In the second approach (*debtors view*), the vulnerabilities in the system are born due to the rapid increase in the level of borrowers ′ indebtedness. Both views are important for the financial stability objective, and each of the vulnerability might be targeted with macro-prudential instruments tailored mainly for debtors (like DSTI or LTV caps) or lenders (like provisions, risk weights, capital buffers, etc.).

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A Annex 1 - The definition of the dependent variables

Table A1.1: The definition of the dependent variables (the binary variables for the two credit events studied - excessive credit growth and unsustainable lending)

Portfolio	Credit event	Dependent variables	Calculation methodology	Threshold
Total portfolio	Excessive credit growth	Excess	Annual growth rate of loans to households and firms over RON 20,000 (adjusted for inflation and exchange rate effects).	Calculated at the system level for the period 2004/Q4-2013/Q2: average value plus one standard deviation*.
	Unsustainable lending	Unsustainable	NPL ratio for new loans granted to households and firms. The newly granted loans are considered as non-performing if they record 90+ days past due payments at some point over the entire period analyzed (2004/Q4 -2013/Q2). Data is available only for loans over RON 20,000.	Calculated at the system level for the period 2004/Q4-2012/Q4: average value plus one standard deviation*.
Household portfolio	Excessive credit growth	Excess	Annual growth rate of loans to households over RON 20,000 (adjusted for inflation and exchange rate effects).	Calculated at the system level for the period 2004/Q4-2013/Q2: average value plus two** standard deviations*.
	Unsustainable lending	Unsustainable	NPL ratio for new loans granted to households. The newly granted loans are considered as non-performing if they record 90+ days past due payments at some point over the entire period analyzed (2004/Q4 - 2013/Q2). Data is available only for loans over RON 20,000.	Calculated at the system level for the period 2004/Q4-2012/Q4: average value plus one standard deviation*.

Note:

* The standard deviation is calculated over the entire period included in the analysis.
** We apply a multiplying parameter of two to reduce the noise in the dependent variable.

A Annex 2 - Data coverage and summary statistics

Table A2.1: Bank specific financial indicators – summary statistics (2005/Q1-2012/Q4)

Variable	No. obs.	Explanation	Mean	Median	Std. Dev.	Min	Max	Expected sign
Profitability								
ROE	448	Profit to capital	1.53	4.52	21.36	-209.61	42.03	positive
ROA	448	Profit to total assets	0.31	0.44	1.74	-9.81	4.44	positive
Solvency and leverage								
Solvency Ratio*	448	Own funds to risk weigthed assets	16.30	14.26	6.38	8.31	49.25	positive/ negative
Leverage (Tier 1 ratio)**	448	Tier 1 capital to total assets	8.33	8.08	3.04	3.02	24.33	positive
Loans/Deposits ***	448	Loans to households and non-financial companies divided by deposits	142.95	112.47	99.86	15.24	592.14	positive/ negative
Credit quality								
New nonperforming loans ratio (New NPL ratio)	448	NPL ratio for new loans granted to households and firms	10.79	6.79	10.61	0.04	57.95	negative
Loan Loss Provisions Ratio	448	Loan loss provisions to credit	7.06	4.17	7.21	0.08	30.56	negative
Credit activity								
Credit/Assets	448	The share of credit in total assets	61.96	63.82	10.51	13.06	80.43	positive
Share of new FX household loans (FX Lending)	447	The share of FX loans in total new loans	66.06	73.2	27.23	0	100	positive
Share of loans granted to real estate and construction sectors	448	The share of new loans granted to real estate and construction sectors in total loans granted to firms	21.85	16.04	17.9	0.43	93.33	positive

Note:
* The sign of solvency ratio on the probability of a credit event can be mixed, as higher values of the solvency ratio can lead to an excessive increase in lending, but not necessarily to an
unsustainable lending.
** Leverage ratio defined as the share of total own funds to total assets was also tested and it did not exhibit a different behaviour.
*** The expected sign is mixed: i) it might be positive, as it was observed before the crisis (most of banks received resources from their parent banks) or ii) negative, if the bank considers it has

reached a limit in terms of funding risks, or the market is less willing to finance the parent bank, which in turn reduces the support for its subsidiaries.

Table A2.1: Bank specific financial indicators – summary statistics (2005/Q1-2012/Q4) - cont.

Variable	No. obs.	Explanation	Mean	Median	Std. Dev.	Min	Max	Expected sign
Market power								
Size	448	Logarithm of total assets	9.98	10.05	0.46	8.68	10.87	positive
Herfindahl–Hirschman Index (HHI)	448	The sum of squared share of the sample banks multiply by 10000 (calculated based on total credit portfolio granted to households and non-financial companies)	834	762	173	624	1115	positive
Competition indicators								
Competition_ca	448	Credit as percentage of total assets relative to the system (see equation 7 from Data and Methodology)	-0.16	-1.75	10.13	-23.02	41.47	positive
Competition_pc	448	Loan loss provisions as percentage of credit portfolio relative to the system (see equation 8 from Data and Methodology)	0	0.5	4.33	- 16.41	9.72	negative
Credit standards								
Loan-to-value (LTV|HH)	430	Loan to collateral value calculated for new mortgage loans (for household loans (HH) only, without loans under "Prima Casa" program, rescheduled or refinanced loans, see equation 4 from Data and Methodology)	65.20	65.17	22.44	16.3	230.66	positive
Debt-service-to-income (DSTI|HH)	436	Monthly payments calculated from constant annuities/ Monthly net income (for household loans (HH) only, see equation 5 from Data and Methodology)	32.70	30.19	14.23	0.23	149.83	positive
Loan-to-income (LTI|NFC)	448	Loans to operational income, calculated for new loans (for non-financial companies loans (NFC) only, without rescheduled loans, see equation 6 from Data and Methodology)	6.19	5.52	3.17	0.46	24.88	positive

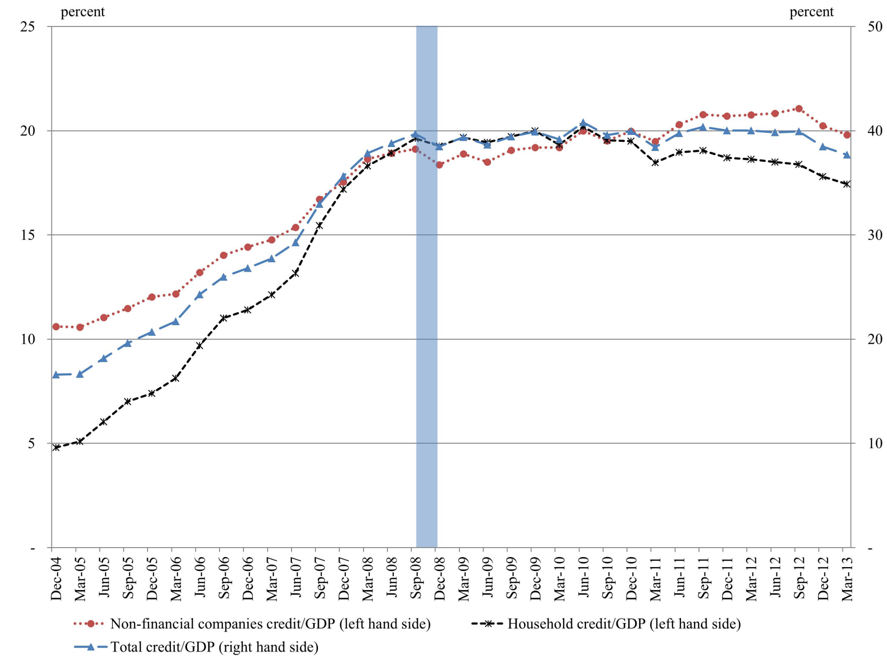
Source: Central Credit Register, Ministry of Public Finance, National Bank of Romania, own calculations.

Table A2.3: Macroeconomic indicators - summary statistics (2005/Q1-2012/Q4)

Variable	Obs.	Mean	Median	Std. Dev.	Min	Max
GDP growth rate	448	2.76	2.74	2.17	-1.55	6.53
Unemployment	448	5.47	5.20	1.19	3.71	8.36
Disposable Income (%GDP)	448	28.61	28.63	1.07	26.87	31.11
Disposable Income (%YoY)	448	2.74	2.94	2.62	-1.82	6.89

Source: National Bank of Romania.

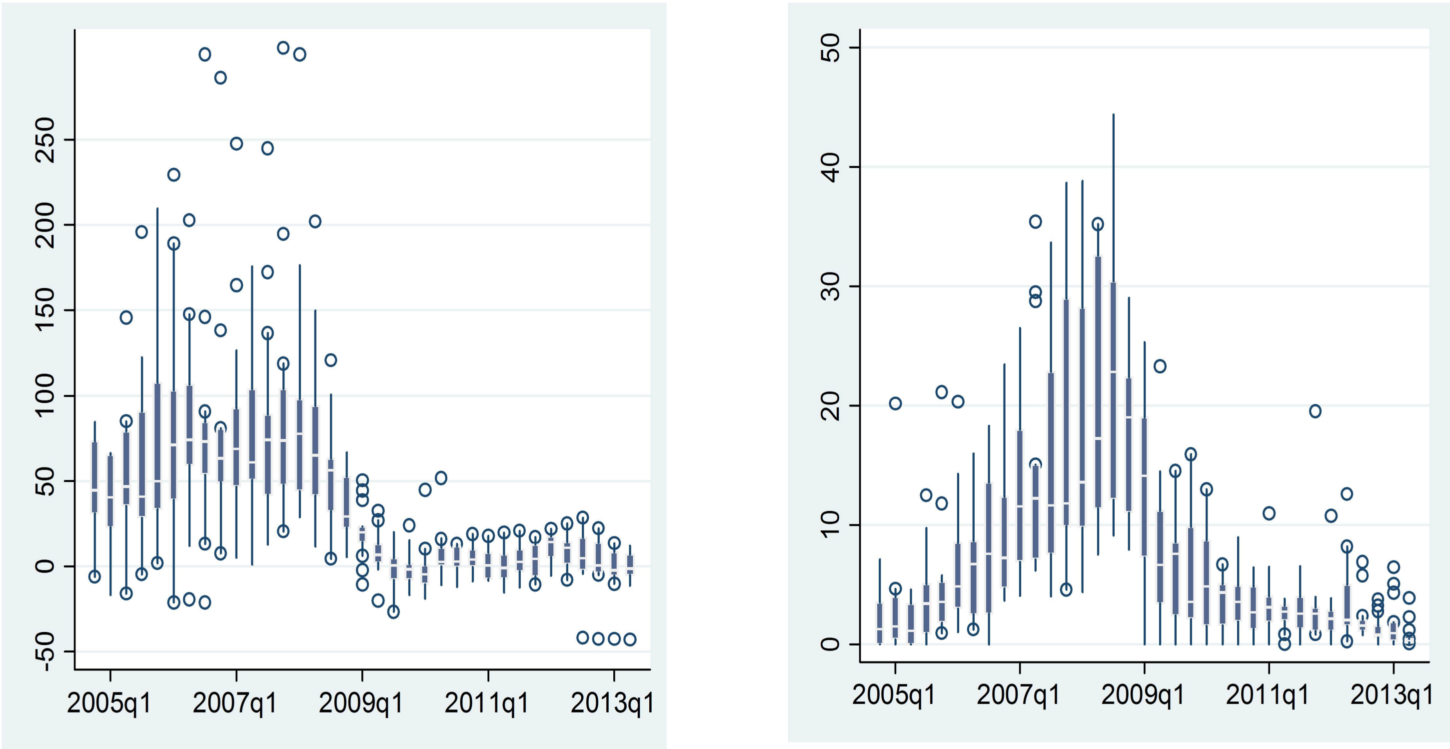
Figure A2.1: The level of financial intermediation (credit-to-GDP)



Source: National Bank of Romania.

A Annex 3 - Synchronization of the credit cycles

Figure A3.1: The distributions by banks and by vintages of the annual credit growth rates* (left panel) and of the new nonperforming loan ratios** (right panel) for 2005/Q1 - 2013/Q2



Note:
* Annual growth rate of loans to households over RON 20,000 (adjusted for inflation and exchange rate effects).
** NPL ratio for new loans granted to households. The newly granted loans are considered as non-performing if they record 90+ days past due payments at some point over the entire period analyzed

(2004/Q4 -2013/Q2). Data is available only for loans over RON 20,000.

Figure A.3.2: Concordance indicator between the excessive credit growth and the unsustainable lending by banks and by portfolios

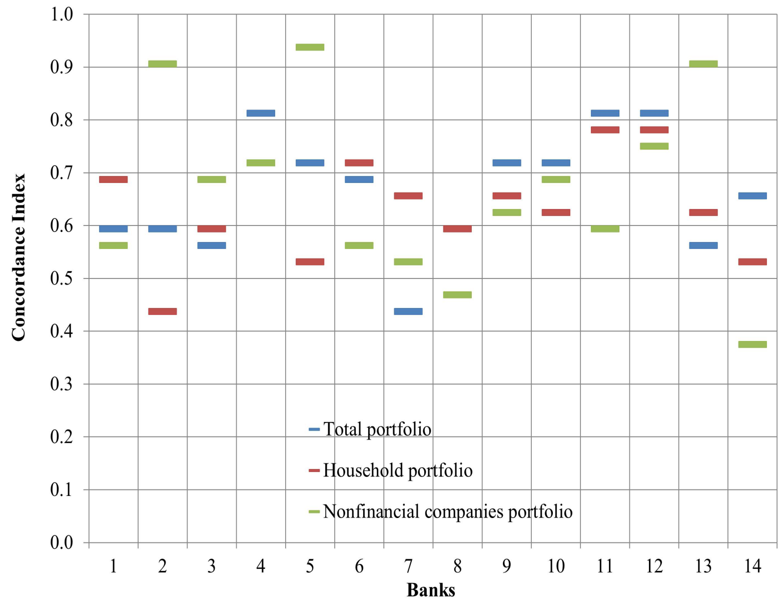


Table A.3.1: Concordance indicator between the individual banks′ credit cycles and the banking sector credit cycle for the total portfolio (households and firms) and for the household portfolio

	Total portfolio		Household portfolio	
	Excessive credit	Unsustainable credit	Excessive credit	Unsustainable credit
Mean	0.82	0.79	0.85	0.84
Median	0.81	0.80	0.88	0.84
Min	0.69	0.50	0.72	0.69
Max	0.97	0.91	0.97	0.97
Std. Dev.	0.09	0.11	0.08	0.08

A Annex 4 - Results

Table A4.1: Margin effects on the probability of excessive credit growth - total portfolio (households and firms)

	Eq.1	Eq.2	Eq.3	Eq.4	Eq.5	Eq.6	Eq.7	Eq.8	Eq.9	Eq.10	Eq.11	Eq.12
	2005/Q1 - 2012/Q4						2005/Q1 - 2008/Q4					
Disposable Income/GDP_{t-4}	1.5 (0.41)	0.6 (0.70)	2.0 (0.17)	1.1 (0.48)	0.2 (0.89)	2.1 (0.13)	31.7*** (0.00)	26.8*** (0.01)	15.5*** (0.00)	28.1*** (0.00)	24.4*** (0.01)	15.1*** (0.00)
HHI_{t-4}	0.1*** (0.00)	0.1*** (0.00)	0.1*** (0.00)	0.1*** (0.00)	0.1*** (0.00)	0.1*** (0.00)	0.2*** (0.00)	0.2*** (0.00)	0.2*** (0.00)	0.2*** (0.00)	0.2*** (0.00)	0.2*** (0.00)
$Competition\_ca_{t-4}$	0.3 (0.56)	0.3 (0.15)	0.2 (0.40)				0.5 (0.54)	1.1** (0.03)	0.3 (0.51)			
$Competition\_pc_{t-4}$				-1.5*** (0.00)	-1.1** (0.02)	-1.6** (0.02)				-18.9*** (0.00)	-19.5*** (0.00)	-4.5 (0.23)
$LTV(HH)_{t-4}$	0.1 (0.15)	0.1** (0.03)		0.1 (0.22)	0.1* (0.07)		0.5*** (0.00)	0.6*** (0.00)		0.5*** (0.00)	0.6*** (0.00)	
$DSTI_{t-1}$* $Regulation_{t-1}$	0.0 (0.83)	-0.0 (0.90)	-0.2* (0.07)	0.0 (0.71)	0.0 (0.90)	-0.2* (0.08)	0.4 (0.12)	-0.06** (0.02)	-0.4** (0.04)	0.2 (0.13)	0.2 (0.24)	-0.3** (0.05)
$FXLending_{t-1}$		0.3*** (0.00)			0.3*** (0.00)			0.9*** (0.00)			0.7*** (0.00)	
$LTI(NFC)_{t-1}$			1.3*** (0.00)			1.5*** (0.00)			1.4 (0.42)			2.0 (0.24)
Observations	298	298	339	298	298	339	112	112	148	112	112	148
Log Likelihood	-46.64	-42.04	-63.34	-45.74	-42.29	-62.31	-36.18	-30.98	-52.88	-30.87	-27.28	-52.09
R2	0.751	0.776	0.711	0.756	0.774	0.716	0.435	0.516	0.424	0.518	0.574	0.432
ROC	0.983	0.987	0.977	0.984	0.987	0.977	0.926	0.938	0.905	0.941	0.949	0.906

Note: The table presents the comprehensive results of the logit panel model with fixed effects for banks, using quarterly data, estimated for two periods: (i) 2005/Q1-2012/Q4 - the first six columns, and (ii) 2005/Q1-2008/Q4 the last six columns. The dependent variable is the binary variable for the excessive credit growth (Excess, see Annex 1 for more details). The values represent the average marginal effects on the probability of excessive credit growth and the p-values in parentheses, where * p<0.10, ** p<0.05, *** p<0.01. The specification of the second equation is presented below:

$$Eq.2 : ln\frac{P(Excess=1)}{1-P(Excess=1)} = -46.7^{***} + 0.15 * DisposableIncome/GDP_{t-4} + 0.03^{***} * HHI_{t-4} + 0.08 * Competition\_ca_{t-4} + 0.03^{*} * LTV(HH)_{t-4} - 0.003 * (DSTI_{t-1} * Regulation_{t-1}) + 0.07^{***} FXLending_{t-1}$$

Table A4.2: Margin effects on the probability of unsustainable credit growth - total portfolio (households and firms)

	Eq.1	Eq.2	Eq.3	Eq.4	Eq.5	Eq.6	Eq.7	Eq.8
	2005/Q1 - 2012/Q4				2005/Q1 - 2009/Q2			
$LossLoans/Loans_{t-4}$	-2.7***	-2.7***	-2.8***	-2.9***	-2.2*	-2.1**	-2.3*	-2.1**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.09)	(0.05)	(0.07)	(0.01)
$Competition\_ca_{t-4}$	-0.1	-0.1			0.4	0.4		
	(0.73)	(0.83)			(0.56)	(0.57)		
$Competition\_pc_{t-4}$			-2.6*	-2.4*			0.9	2.0
			(0.07)	(0.08)			(0.84)	(0.59)
$DSTI(HH)_t$	0.7***	0.7***	0.7***	0.7***	2.0***	2.0***	2.0***	2.0***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$Regulation_t$		-12.7**		-12.3**		-17.5**		-18.0**
		(0.03)		(0.05)		(0.01)		(0.01)
$LTI(NFC)_t$	4.1***	4.2***	4.3***	4.4***	7.7***	8.2***	7.6***	8.3***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$FXLending_t$	0.2*	0.2**	0.2*	0.2**	0.5***	0.5***	0.5***	0.6***
	(0.07)	(0.04)	(0.05)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	286	286	286	286	160	160	160	160
Log Likelihood	-106.80	-104.50	-105.12	-102.95	-51.62	-48.04	-52.01	-48.29
R2	0.389	0.402	0.399	0.411	0.527	0.560	0.523	0.557
ROC	0.891	0.892	0.896	0.897	0.941	0.947	0.938	0.946

Note: The table presents the comprehensive results of the logit panel model with fixed effects for banks, using quarterly data, estimated for two periods: (i) 2005/Q1-2012/Q4 - the first four columns, and (ii) 2005/Q1-2008/Q4 the last four columns. The dependent variable is the binary variable for the unsustainable credit growth (Unsustainable, see Annex 1 for more details). The values represent the average marginal effects on the probability of unsustainable credit growth and the p-values in parentheses, where * p < 0.10, ** p < 0.05, *** p < 0.01. The first two regression equations are presented below:

$Eq.1 : ln\frac{P(Unsustainable=1)}{1-P(Unsustainable=1)} = -5.7^{***} - 0.22^{***} * LossLoans/Loans_{t-4} - 0.01 * Competition\_ca_{t-4} + 0.006^{**} * DSTI + 0.34^{***} * LTI(NFC)_t + 0.02^{*} * FXLending_t$

$Eq.2 : ln\frac{P(Unsustainable=1)}{1-P(Unsustainable=1)} = -6^{***} - 0.23^{***} * LossLoans/Loans_{t-4} - 0.01 * Competition\_ca_{t-4} + 0.006^{**} * DSTI - 1.08^{**} * Regulation_t + 0.36^{***} * LTI(NFC)_t + 0.02^{**} * FXLending_t$

Table A4.3: The marginal effects on the probability of excessive credit growth - household portfolio

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	2005/Q1 - 2012/Q4					2005/Q1 - 2008/Q4				
$Leverage\_ratio_{t-4}$	2.2***	2.3***	2.3***	2.1***	2.4***	5.1***	5.6***	5.3***	4.9***	5.7***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HHI_{t-4}	0.0***	0.0**	0.0(0.70)	0.0***	0.0	0.1***	0.1**	0.0	0.1***	0.0
	(0.00)	(0.01)		(0.00)	(0.66)	(0.00)	(0.01)	(0.73)	(0.00)	(0.68)
$Real\_estate\_indt-4$	3.6***	3.0***	3.5***	3.3***	3.4***	8.3***	7.2***	8.0***	7.8***	8.2***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$Competition\_ca_{t-4}$	0.8***	0.9***	1.1***	0.8***	1.1***	2.0***	2.1***	2.5***	2.0***	2.7***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
$Regulation_{t-1}$	-0.1				1.6	-0.3				3.7
	(0.97)				(0.63)	(0.97)				(0.65)
$LTV(HH)_{t-4}$		-0.1			-0.0		-0.4			-0.1
		(0.25)			(0.73)		(0.25)			(0.73)
$DSTI_{t-1}$			-0.7***		-0.7**			-1.7***		-1.7**
			(0.00)		(0.02)			(0.00)		(0.02)
$DSTI_{t-1}$*				-0.1					-0.1	
$Regulation_{t-1}$				(0.47)					(0.47)	
Observations	364	356	364	364	356	156	148	156	156	148
Log Likelihood	-47.22	-45.67	-44.19	-46.99	-43.58	-47.22	-45.67	-44.17	-46.98	-43.57
R2	0.76	0.76	0.78	0.77	0.77	0.55	0.55	0.58	0.55	0.57
ROC	0.98	0.98	0.98	0.98	0.98	0.940	0.94	0.94	0.93	0.94

Note: The table presents the comprehensive results of the logit panel model with fixed effects for banks, using quarterly data, estimated for the following two periods: (i) 2005/Q1-2012/Q4 - the first five columns, and (ii) 2005/Q1-2008/Q4 the last five columns. The dependent variable is the binary variable of the excessive credit growth (Excess, see Annex 1 for more details). The values represent the average marginal effects on the probability of excessive credit growth and the p-values in parentheses, where * p < 0.10, ** p < 0.05, *** p <0.01. We present below the specifications for Eq. 5 and Eq. 10.

$$Eq.5 : ln\frac{P(Excess=1)}{1-P(Excess=1)} = -7.9 + 0.62^{***} * LeverageRatio_{t-4} + 0.002 * HHI_{t-4} + 0.89^{***} * Lnpret_{t-4} + 0.29^{***} * Competition\_ca_{t-4} + 0.41 * Regulation_{t-1} - 0.01 * LTV(HH)_{t-4} - 0.18^{**} * DSTI_{t-1}$$

$$Eq.10 : ln\frac{P(Excess=1)}{1-P(Excess=1)} = -7.6 + 0.62^{***} * LeverageRatio_{t-4} + 0.002 * HHI_{t-4} + 0.88^{***} * Lnpret_{t-4} + 0.29^{***} * Competition\_ca_{t-4} + 0.39 * Regulation_{t-1} - 0.01 * LTV(HH)_{t-4} - 0.18^{**} * DSTI_{t-1}$$

Table A4.4: The marginal effects on the probability of unsustainable credit growth - household portfolio with contemporaneous lending standards

	Eq.1	Eq.2	Eq.3	Eq.4	Eq.5	Eq.6	Eq.7	Eq.8	Eq.9	Eq.10	Eq.11	Eq.12
			2005/Q1 - 2012/Q4						2005/Q1 - 2009/Q2			
$Competition\_ca_{t-4}$	0.9***	1.0***	1.0***	0.9***	1.0***	1.0***	1.5*	1.5*	1.8***	1.3***	1.3*	1.3*
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.08)	(0.06)	(0.00)	(0.00)	(0.06)	(0.05)
$Solvency\_ratio_{t-4}$	-0.7*	-0.7*	-1.1***	-0.9***	-0.7**	-0.7*	-2.1***	-2.1***	-2.7***	-2.1***	-1.9***	-2.0***
	(0.06)	(0.06)	(0.00)	(0.01)	(0.05)	(0.05)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
$LossLoans/Loans_{t-4}$	-4.2***	-4.2***	-3.8***	-3.5***	-3.9***	-4.0***	-0.5	-0.3	-1.8*	0.7	0.5	0.5
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.47)	(0.62)	(0.06)	(0.29)	(0.53)	(0.48)
$DSTI(HH)_t$	1.4***	1.4***			1.2***	1.2***	3.5***	3.3***			2.8***	2.8***
	(0.00)	(0.00)			(0.00)	(0.00)	(0.00)	(0.00)			(0.00)	(0.00)
$Regulation_t$		-4.9	-6.8			-4.2		-13.3**	-17.0**			-11.2*
		(0.18)	(0.20)			(0.28)		(0.02)	(0.04)			(0.08)
LTV_t				0.5***	0.2	0.2				1.4***	0.6**	0.6**
				(0.00)	(0.24)	(0.32)				(0.00)	(0.01)	(0.03)
Observations	287	287	288	278	278	278	143	143	144	136	136	136
Log Likelihood	-84.17	-83.05	-102.12	-92.39	-81.86	-81.09	-49.07	-47.37	-75.23	-55.87	-44.87	-43.79
R2	0.43	0.44	0.31	0.36	0.44	0.44	0.49	0.50	0.22	0.39	0.51	0.52
ROC	0.91	0.91	0.86	0.89	0.91	0.91	0.92	0.93	0.80	0.90	0.94	0.94

Note: The table presents the comprehensive results of the logit panel model with fixed effects for banks, using quarterly data, estimated for the following two periods: (i) 2005/Q1-2012/Q4 - the first six columns, and (ii) 2005/Q1-2009/Q2 the last six columns. The dependent variable is the binary variable for the unsustainable credit growth (Unsustainable, see Annex 1 for more details). The values represent the average marginal effects on the probability of unsustainable credit growth and the p-values in parentheses, where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. We present below the specifications for Eq. 6 and Eq. 12.

$Eq.6 : ln\frac{P(Unsustainable=1)}{1-P(Unsustainable=1)} = -1.65 + 0.103^{***} * Competition\_ca_{t-4} - 0.08^{**} * Solvency\_ratio_{t-4} - 0.429^{***} * LossLoans/Loans_{t-4} + 0.119^{***} * DSTI_t - 2.333^{*} * Regulation_t + 0.052 * DSTI * Regulation + 0.017 * LTV_t$

$Eq.12 : ln\frac{P(Unsustainable=1)}{1-P(Unsustainable=1)} = -6.03 + 0.13^{***} * Competition\_ca_{t-4} - 0.19^{**} * Solvency\_ratio_{t-4} + 0.05^{***} * LossLoans/Loans_{t-4} + 0.26^{**} * DSTI_t - 1.255 * Regulation_t + 0.01 * DSTI * Regulation + 0.05^{*} * LTV_t$

Table A4.5: The marginal effects on the probability of unsutainable credit growth for households' portfolio with lagged lending standards

	Eq.1	Eq.2	Eq.3	Eq.4	Eq.5	Eq.6	Eq.7	Eq.8	Eq.9	Eq.10	Eq.11	Eq.12
	2005/Q1 - 2012/Q4						2005/Q1 - 2009/Q2					
$Competition\_ca_{t-4}$	1.1***	1.1***	1.0***	0.9**	0.9**	1.0***	1.7**	1.8***	1.9***	1.2**	1.1**	1.3**
	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.00)	(0.04)	(0.04)	(0.04)
$Solvency\_ratio_{t-4}$	-0.3	-0.4	-1.2***	-0.000	-0.000	-0.1	-1.1*	-1.3**	-2.9***	-0.5	-0.4	-0.6
	(0.48)	(0.29)	(0.00)	(0.90)	(0.95)	(0.72)	(0.07)	(0.03)	(0.00)	(0.34)	(0.46)	(0.22)
$LossLoans/Loans_{t-4}$	-4.1***	-4.1***	-3.9***	-3.5***	-3.6***	-3.5***	-2.3	-2.2	-2.4**	1.7	1.4	1.6
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.44)	(0.49)	(0.03)	(0.42)	(0.54)	(0.51)
$DSTI(HH)_{t-4}$	0.8***	0.7**			0.000	0.000	2.3***	1.9***			0.4	0.3
	(0.01)	(0.01)			(0.88)	(0.92)	(0.00)	(0.00)			(0.46)	(0.60)
$Regulation_{t-4}$		-13.7***	-12.4**			-11.3**		-20.6*	-22.3**			-12.4
		(0.00)	(0.03)			(0.02)		(0.06)	(0.02)			(0.17)
LTV_{t-4}				0.6***	0.6***	0.5***				1.6***	1.5***	1.5***
				(0.00)	(0.00)	(0.00)				(0.00)	(0.00)	(0.00)
Observations	259	259	288	251	251	251	118	118	144	110	110	110
Log Likelihood	-88.35	-83.80	-100.36	-79.97	-79.96	-76.10	-56.21	-54.19	-74.47	-42.51	-42.23	-40.92
R2	0.37	0.40	0.32	0.42	0.42	0.45	0.31	0.33	0.23	0.44	0.44	0.46
ROC	0.89	0.90	0.87	0.90	0.90	0.92	0.85	0.85	0.80	0.90	0.90	0.90

Note: The table presents the comprehensive results of the logit panel model with fixed effects for banks, using quarterly data, estimated for the following two periods: (i) 2005/Q1-2012/Q4 - the first six columns, and (ii) 2005/Q1-2009/Q2 the last six columns. The dependent variable is the binary variable for the unsustainable credit growth (Unsustainable, see Annex 1 for more details). The values represent the average marginal effects on the probability of unsustainable credit growth and the p-values in parentheses, where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. We present below the specifications for Eq. 6 and Eq. 12.

$Eq.6: ln\frac{P(Unsustainable=1)}{1-P(Unsustainable=1)} = -2.19 + 0.11^{**} * Competition\_ca_{t-4} - 0.01 * Solvency\_ratio_{t-4} - 0.36^{***} * LossLoans/Loans_{t-4} + 0.02 * DSTI_{t-4} + 2.22 * Regulation_{t-4} - 0.11 * DSTI * Regulation + 0.05 * LTV_{t-4}$

$Eq.12: ln\frac{P(Unsustainable=1)}{1-P(Unsustainable=1)} = -5.48 + 0.11^{**} * Competition\_ca_{t-4} - 0.05 * Solvency\_ratio_{t-4} + 0.13 * LossLoans/Loans_{t-4} + 0.02 * DSTI_{t-4} - 1.69 * Regulation_{t} + 0.02 * DSTI * Regulation + 0.12^{***} * LTV_{t-4}$

Table A4.6: The average value of the probability of excessive credit growth for different LTV values

	Total portfolio (Eq.2, Eq.8 - Table A4.1)		Household portfolio (Eq.2, Eq.4 - Table A4.3)	
	2005/Q1-2012/Q4	2005/Q1-2008/Q4	2005/Q1-2012/Q4	2005/Q1-2008/Q4
40%	28.3*** (0.00)	55.6*** (0.00)	14.0*** (0.00)	34.5*** (0.00)
75%	33.0*** (0.00)	74.3*** (0.00)	25.3*** (0.00)	60.6*** (0.00)
100%	36.5*** (0.00)	84.9*** (0.00)	36.3*** (0.00)	79.8*** (0.00)
Observations	298	112	354	148

Table A4.7: The average value of the probability of unsustainable lending for different DSTI values

	Total portfolio (Eq.2, Eq.6 - Table A4.2)		Household portfolio (Eq.6, Eq.12 - Table A4.4)	
	2005/Q1-2012/Q4	2005/Q1-2009/Q2	2005/Q1-2012/Q4	2005/Q1-2009/Q2
20%	20.5***	18.3***	8.3***	11.3**
	(0.00)	(0.00)	(0.00)	(0.00)
45%	38.4***	68.8***	32.1***	69.3***
	(0.00)	(0.00)	(0.00)	(0.00)
75%	61.1***	94.4***	57.8***	98.6***
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	286	160	286	136

Table A4.8: The average marginal effects of LTI on the unsustainable lending probability - total portfolio (Unsustainable, Eq. 2 and Eq. 6 - Table A4.2)

	LTI > 3	LTI ≤ 3	LTI > 3	LTI ≤ 3
	2005/Q1 - 2012/Q4		2005/Q1 - 2009/Q2	
LTI(NFC)	4.5***	2.1***	8.6***	3.9***
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	42	134	16	16