Why are credit booms sometimes sweet and sometimes sour?

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Abstract

This paper investigates the commonalities and differences between benign credit booms and those that end up in banking crises by employing a Multinomial and a Sequential Logit model over a panel of industrial and developing countries. Some economic, political and institutional factors are found to play an important role in understanding the credit booms dynamics. In particular, this study shows that the quantity and price of credit, liquidity in the economy, economic growth, openness of the economy, government orientation, political stability and Central Bank independence are relevant to explain not only the occurrence of credit booms but also – and most importantly – whether they end up in a systemic banking crisis or not. While a better economic environment and Central Bank independence are essential for both industrial and developing countries to avoid credit booms from going badly, political factors seem to exert a stronger influence in developing countries.

Keywords: Credit booms; Multinomial Logit; Sequential Logit; Government Ideology; Central Bank Independence.

JEL classification: C25, D72, E32, E51.

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1. Introduction

Credit is beneficial to the economy as it helps to support investment and economic growth. But when credit grows too fast financing ends up being extended to riskier investment projects with lower net present value, frauds are more likely to occur and the overall quality of the projects that are backed up drops. This means that during credit crunches banks may become highly vulnerable, which can trigger systemic banking crises. According to our data, approximately 1 out of 4 credit booms end up this way. Hence, it is important to understand how to mitigate this trade-off between positive and negative aftermaths by distinguishing credit booms before they fully unfold.

This has been an important investigation topic in recent years. However, researchers have found it difficult to predict credit booms that end up in a systemic banking crisis ("bad" credit booms) and soft landings ("good" credit booms); they have also struggled to understand their fundamental differences. The literature has provided some mixed results and, in reality, the only identifiers that have been consistently associated with "bad" credit booms are larger magnitudes and longer durations (see Gourinchas et al. 2001; Barajas, et al. 2009; Arena et al. 2015; Dell'Ariccia et al., 2016). Most studies rely on binary choice probit/logit models where the dependent variable is typically a dummy that accounts for periods of abnormal credit growth that end up in a banking crisis. With such econometric approach, those studies have neglected the fact that we have indeed three outcomes in this dynamics: "good", "bad", and no credit boom. Hence, a Multinomial Logit would be a better fit to this particular analysis. Alternatively, these three events can be treated as a sequence of stages: in a first stage, we have the possibility of a credit boom occurring or not; in a second stage – if a credit boom occurs – it can be distinguished between “bad” or “good”. This means that a sequential logit model would be a more suitable econometric approach to explore this dynamics.

As a first contribution of this paper, we revisit the study of the drivers of “good” and “bad” credit booms by relying on these more adequate econometric techniques and on an extensive quarterly dataset for a panel of industrial and developing countries. Additionally, this paper provides some other significant contributions to the existing literature by going beyond the traditional economic framework and exploring the role of political aspects and of Central Bank Independence, factors that to date have not been accounted for yet.

Regarding the political determinants, there are reasons to assume that such environmental aspects can indeed affect credit booms dynamic since there is ample evidence suggesting that features like the electoral agenda, government ideology and political stability impact the overall macroeconomic performance – this linkage is developed further ahead in the text. As to the role that Central Banks can play in this process, we assume that since more independent Central Banks are less susceptible to political pressures based on popularity concerns, they are better equipped to intervene during credit expansions. This raises a particularly interesting question: Do more independent Central Banks actually affect the likelihood of a “bad” credit boom? Our results provide an affirmative answer by showing that “bad” credit booms are indeed less likely to occur under the watch of more independent Central Banks. A similar effect is found when right-wing parties are in office.

Finally, contrary to most studies, that tend to struggle in finding significant macroeconomic differences between innocuous and harmful credit expansions, our results reveal some important and robust dissimilarities between them and even between industrial and developing countries. The use of a richer dataset with quarterly data and suitable econometric techniques that do not disregard the periods of no credit booms are probably contributing decisively to this relevant outcome..

The rest of the paper is organized as follows. Section 2 reviews the existing literature on credit booms. Section 3 discusses the role of the political environment and of Central bank independence. Section 4 describes the data and methodology. The empirical analysis and the discussion of the results are presented in Section 5. Finally, Section 6 concludes.

2. Literature Review

The research on the causes of credit booms has mainly been developed from an empirical perspective and some key explanatory factors are emphasized by most of the studies in this field.[1] First, credit booms have been consistently linked to sharp increases in capital inflows, usually triggered by periods of disinflation or by low interest rates in developed economies, factors that consequently raise the supply of loanable funds (Gourinchas et al., 2001; Calderón and Kubota, 2012; Gourinchas and Obstfeld, 2012). Second, these surges are also associated with a higher ratio of private credit to bank deposits which are seen to lead to financial fragility (Borio and Disyatat 2011; Gourinchas and Obstfeld, 2012). In particular, rising inflows of foreign capital may lead to excessive monetary and credit expansions (Sidaoui et al., 2011), intensify the vulnerabilities associated with currency and maturity mismatches (Akyuz, 2009), and create distortions in asset prices (Agnello and Sousa, 2013; Agnello et al., 2012). Third, productivity shocks are also seen as a phenomenon that can pressure the capital stock to increase at a higher rate than GDP, thus strongly raising the credit-to-GDP ratio. Additionally, credit expansion is more likely to occur as

[1] See, for example, Mendoza and Terrones, 2008, 2012; Dell'Ariccia et al., 2016. For some recent theoretical papers on the subject, see Boissay et al. (2016) and Burnside et al. (2016).

the economic environment improves (Mendoza and Terrones, 2008, 2012; Meng and Gonzales, 2017). Finally, researchers point out that financial reforms associated with financial liberalization, the reduction in banks' reserve requirements and increases in the provision of financial services may also contribute to more liquidity and consequently to abnormal lending growth.[2]

To explain why some countries are more prone than others to credit expansions, researchers also point out to the relevance of some domestic differences. In particular, expansionary monetary and fiscal policies, less flexible exchange rate regimes and frailties in the supervision of the banking system are found to be related to the occurrence of credit booms (Elekdag and Wu 2013; Arena et al., 2015; Dell'Ariccia et al., 2016).

Banking crisis are often associated with excessive credit expansions. As such, credit plays, not just the traditional positive role of supporting investment and economic growth, but also - under certain circumstances – of harming the economy. What these circumstances are and what distinguishes "good" from "bad" episodes have been important topics of research in the literature that examines credit booms. Researchers tend to look at the aftermath of a credit expansion to reveal its nature, mainly by checking if it is followed or not by a banking crisis. Dell'Ariccia et al. (2016) point out that starting at a higher level of financial depth increases the probability of a boom ending badly. Arena et al. (2015) found that when credit booms ends in banking crisis, macroeconomic fluctuations seem to be larger and exhibit more sudden declines than in the soft landings. Meng and Gonzalez 2017 report that this is also the case when the size of the financial sector grows, especially above macroeconomic consistent levels. However, they do not find any association between "bad" booms and macroeconomic and financial policies – exception made to

[2] Mendoza and Terrones (2012) point that productivity surges, financial reforms, and massive capital inflow episodes appear before 20% to 50% of the peak of credit booms in industrial and emerging market economies.

the quality of regulations and supervision of the banking system. Gourinchas et al. (2001) do not find any relevant differences in key macroeconomic variables between “good” and “bad” booms. Overall, these and many other studies seem all to agree that credit booms gone badly are associated with larger magnitudes and longer durations. Nevertheless, none provides a statistical proof for these observations. One of the aims of this paper is to fill that gap in the literature by relying on adequate econometric techniques, especially in what concerns to their length and respective conditionings. Additionally, this paper also aims at extending this analysis by assessing the role of the political environment and Central Bank Independence in the dynamics of credit booms that leads to a soft landing or a banking crisis.

3. The role of the political environment and of Central Bank independence

In this paper, we explore the importance of the political environment and of Central Bank independence in explaining the likelihood of credit booms. Although unexplored from the econometric point of view, the relationship between politics and credit booms or financial crises has been debated in the related literature. For example, Calomiris and Haber (2014) analyse the political background of banking crises while McCarty et al. (2013) discuss how political and policy decisions in the US contributed to the housing and credit bubble that occurred in the first decade of this century; also Fernandez-Villaverde et al. (2013) examine the political dynamics of credit cycles in the Eurozone and its consequences.

There are arguments to reasonably assume that the length of credit booms might be influenced by the electoral agenda, political orientation, government support, and even political stability. Since the 1970s numerous papers have studied the connection between politics and the economy either by highlighting the relationship between economic performance and governments’ electoral success or by identifying politically driven policies affecting a significant number of macroeconomic variables.[3]

Of particular interest are the theories of "opportunistic" political business cycles suggesting that governments try to induce short-term economic expansions immediately before elections with the expectation that this may improve their chances of reelection (Nordhaus, 1975; Rogoff and Sibert, 1988; Rogoff, 1990). Conflicting with this idea we find the partisan" theory ((Hibbs, 1977; Alesina, 1987; Alesina and Sachs, 1988) which argues that governments are heterogeneous in the sense that they tend to exhibit different ideological preferences when it comes to the economy. The most emphasized difference is that left-wing governments pursue low unemployment at the cost of higher inflation, while right-wing governments prioritize low inflation at the expense of higher unemployment. Additionally, tendencies to increase taxation, to reinforce the state's intervention in the economy or to increase expenditures are considered traits more associated to left parties than with other parties.

When linking political ideology with credit expansions we believe that one of two opposing scenarios can occur. First, since right-wing governments are traditionally more prone to reduce state intervention, foster liberalization and to exert less control over the markets, one should expect them to contribute to an increase in the likelihood of a credit boom and the inverse should happen with left-wing governments. Broz (2010) shows that the expansion period of financial cycles is normally accompanied by the election of right-wing governments. Second, there are some traits generally associated with right-wing parties like a higher propensity for inflation control, smaller deficits and a lower inclination to implement income redistribution policies that may legitimize the opposite effect. The fact that the redistribution of income should be greater when left-wing governments are in power (see, for instance, Bradley et al. 2003; Iversen and Soskice, 2006) means that, under the left's rule, more people are expected to have access to credit or get involved in the

[3] For encompassing surveys, see Franzese (2002) and Paldam (2004).

financial markets.[4] This will contribute to an increase in the rate of credit expansion and the reverse should happen when right-wing parties are in office. It is important to note that those people accessing credit only because there are favourable income redistribution polices most likely are associated with a high risk of default or with lower quality of investment projects, thus potentially, increasing banks vulnerabilities. This means that right-wing governments may actually play a role in reducing the risk of bad credit booms.

Another environmental aspect to consider is that higher degrees of government neutrality and also overall political stability – like the presence of majority governments and reduced government turnover (ideological changes) – should produce a more stable economic environment, thus favoring credit growth and reducing the probability of bad credit booms occurring.

Regarding the linkage between lending growth and the electoral agenda, ample evidence is found relating policy uncertainty generated by elections and the delaying of investments, more so when the electoral race is tight (see, for example, Jens, 2017; and Canes-Wrone and Park, 2014). Thus, the disruption and uncertainty caused by elections might have a negative effect on credit expansion. As such elections may affect the likelihood of having credit booms or even their duration but there are no reasonable arguments to expect them to influence the outcome of a credit boom unless in the unlikely scenario of systematic elections in a short period of time.

From the theoretical perspective, monetary policy is also an important explanatory factor of credit booms as Central Banks are the main regulators of the quantity of money present in the system. During a credit expansion, Central Banks typically exhibit a loose monetary policy of low interest rates that makes it easier for economic agents to obtain credit which eventually leads to more and cheaper investments, thus helping credit to growth above normal levels or its fundamentals. They also play an important role in monitoring the financial system and in

[4] In fact, Popa (2013) shows that the size of the house price bubbles across countries is mainly related to the percentage of homeowners, with more homeowners linked to larger bubbles.

preventing markets – and the overall economy – from overheating. However, political pressures exerted by governments can constrain the work of Central Banks, reducing their desired independence via three main sources. First, the Central Bank board is typically selected by the parliament or by the government directly. Chappell et al. (1993) found that this appointment process is the primary channel through which political parties can influence Central Banks. Second, governments have the ability to send monetary policy signals to the Central Bank using, for instance, media appearances to convey their preferences for a looser or tighter monetary policy (Havrilesky, 1988, 1991). Third, governments can threaten Central Bank officials, their jobs or question the very existence of the institution (Lohmann, 1998). These and other aggressive strategies may be used by politicians to force the Central Bank's policy into a particular direction.

From the governments' perspective the policy of credit expansion is definitively a good thing. More investment and higher consumption makes people happier, and happier people tend to reward the incumbent electorally. Hence, it is reasonable to assume that governments are particularly fond of periods of abnormal credit expansion and they have no desire to deal with a credit crunch. They also know that monetary policy is an important tool to create, fuel or delay the crunch of a particular credit boom. As such, it is expected that less independent Central Banks may help to increase the frequency and intensity of credit booms; moreover, they are also expected to be less prone and free to intervene when the economy displays strong signs of overinvestment, excessive risk and/or overinflated market bubbles. This means that more central bank independence is expected to decrease the probability of a credit boom ending up in a banking crisis.

4. Data and methodology

To investigate credit booms quarterly data was collected for 67 countries (28 OECD or industrial economies and 39 developing or emerging market economies)[5] from 1975q1 to 2016q4. These countries were selected according to the availability of economic and political data and only include those countries or periods that exhibit regular/frequent and competitive elections.

The definition/identification of credit boom episodes is not an easy task. The literature offers some approaches but no clear consensus on the best methodology to identify them. There seems to be no right or wrong way to identify events of credit booms; each approach comes with its advantages and drawbacks (Gourinchas, et. al., 2001; Tornell and Westermann, 2002; Mendoza and Terrones, 2008, 2012; Barajas, et al., 2009; Calderón and Kubota, 2012; Dell'Ariccia et. al., 2016). To identify credit booms, we use the criteria developed by Gourinchas, et. al. (2001) – and later fine-tuned by Barajas et al. (2009) – with a threshold of 1.5.[6] Hence, a credit boom (*CreditBoom*) is defined as an episode where the deviation of the real bank credit to the private sector, as a percentage of real GDP, from a country-specific trend in country *i* at period *t* (with the trend being calculated up to that period *t*) exceeds a determined threshold.[7] In particular, a credit

[5] Argentina, Armenia, Australia, Austria, Belgium, Bolivia, Brazil, Bulgaria, Canada, Chile, Colombia, Costa Rica, Croatia, Cyprus, Czech Republic, Denmark, Dominican Republic, Ecuador, El Salvador, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Kenya, Korea Republic, Latvia, Lithuania, Luxembourg, Malaysia, Malta, Mexico, Morocco, Netherlands, New Zealand, Norway, Panama, Paraguay, Peru, Philippines, Poland, Portugal, Romania, Russia, Slovak Republic, Slovenia, South Africa, Spain, Sri Lanka, Sweden, Switzerland, Taiwan, Thailand, Turkey, Ukraine, United Kingdom, United States, Uruguay, Venezuela.

[6] In the Appendix we provide a detailed list of the episodes of credit booms identified by this procedure and general descriptive statistics for all variables used in this study.

[7] The advantage of the ratio of private credit-to-GDP is that it relates private credit to the size of the economy and corrects for the pro-cyclicality in bank lending. Moreover, using this criterion makes our analysis consistent, as then we split it by the kind of boom, where we also follow Barajas et al. (2009) in the distinction between "bad" and "good" credit booms. For other procedures see, for example, Mendoza and Terrones (2008, 2012) and Dell'Ariccia et al. (2016). While Dell'Ariccia et al. (2016) identify boom episodes by comparing the credit-to-GDP ratio in each year *t* and country *i* to a backward-looking, rolling, country-specific, cubic trend estimated over the period between years *t*-

boom takes place if the ratio of private credit to GDP meets the following condition: the deviation of this ratio from its estimated trend is greater than 1.5 times its standard deviation or the year-on-year growth rate of private credit to GDP exceeds 20 percent.[8] According to this definition, we identify 220 episodes of credit boom episodes. The distinction between credit booms that end up in a systemic banking crisis from those that land smoothly follows Barajas et al. (2009)[9]. Similarly to other studies our data suggests that "bad" credit booms last more on average (11 quarters) than those that end up in a soft landing (7 quarters).[10]

To account for the effect of the economic environment, we rely on a set of economic variables commonly found in the related literature: total gross capital inflows as percentage of GDP (*CapInflows*) as proxy for capital inflows; the ratio of private credit to bank deposits (*Credit/Deposits*) as a proxy for the liquidity in the banking system; interest rate spread (*IRspread*) to account for the relative price of credit (difference between the average lending rate and the deposit rate, in percentage); growth rate of real GDP (*RGDPgr*); inflation rate (*Inflation*); current account balance as percentage of GDP (*CurrAccount*); trade openness (*Openness*) measured by exports plus imports over GDP; overvaluation of the real effective exchange rate (*ApprecREER*) as a proxy for asset prices (increases in the REER index means a real appreciation); exchange rate

10 and *t*, Mendoza and Terrones (2008, 2012) use the deviation of the real credit per capita from its long-run trend to identify those booms.

[8] The HP-filter is used to compute the trend, where the value of Lagrange Multiplier employed in the maximization problem is λ=1600 (for quarterly data). For robustness, we also consider later other more restrictive thresholds (1.75 and 2.0).

[9] The episodes of systemic banking crises are obtained from Laeven and Valencia (2008, 2010, 2012) and updated for the more recent years following their procedure.

[10] Tables A1-A4 in the Appendix provide list of countries used in the estimations, credit booms date and respective duration, definition of all variables, descriptive statistics for the episodes and duration of credit booms and summary statistics for all variables used in this study.

flexibility, proxied by the coarse classification of the exchange rate regime developed by Reinhart and Rogoff (2004), and updated by Ilzetzky, et. al. (2009) and similar sources mentioned in that paper for more recent years (*ExchRateFlex*).[11]

To account for the yet unexplored influence of the political factors, we employ a set of variables borrowed from the political business cycles and partisan literature. Some try to capture different dimensions of political instability that may affect how credit booms play out: *YrBefElection* and *MajorityGov*, dummy variables that take the value of 1 in the 4 quarters before the election, and when we are in presence of majority governments; and *NGovChanges* that records the number of government changes (due to elections or not) over the previous five years. Since parties from different political quadrants may have different policy agendas they wish to implement when in office, we use a government ideology dummy (*Right*) equal to 1 for right-wing governments (0, otherwise) to account for the impact of political ideology.

Our baseline specification also accounts for the role of following institutional factors: Central Bank independence measured by the Cukierman-Webb-Neyapti weighted index and updated by Garriga (2016). As previously discussed more independent Central banks are expected to be more efficient in preventing "bad" booms; and Monetary Union (*MU*), a dummy variable that takes the value of 1 when the country's monetary policy is in the hands of a regional monetary union.

Instead of relying on a binary distinction between periods of credit booms (1) and no credit booms (0) as other studies do, we allow for the presence of three outcomes in this dynamics: no credit boom (0); "good" credit boom (1); and "bad" credit boom. Hence, a Multinomial Logit model, as an extension of the logistic models, is the required procedure to be used in this case.

[11] In Table A.2 of the appendix we provide detailed information on all variables used and their respective sources.

Given that now there are three categories, we set "no credit boom" as the base-category. As such, this requires the calculation of two equations, one for each category relative to the base in order to describe the relationship between the likelihood of a "good" or "bad" credit boom and the set of economic, political and institutional variables:

$$ln\frac{P(Y_{it}=m)}{P(Y_{it}=0)} = \boldsymbol{Econ}'_{it}\boldsymbol{\alpha}_m + \boldsymbol{Pol}'_{it}\boldsymbol{\beta}_m + \boldsymbol{Inst}'_{it}\boldsymbol{\gamma}_m\ , \quad m = 1, 2 \tag{1}$$

Hence, for each case, there will be two predicted log odds. Computing the probabilities is a little more complicated than in the standard logistic regression. We now have,

$$P(Y_{it} = m) = \frac{\exp(\boldsymbol{Econ}'_{it}\boldsymbol{\alpha}_m + \boldsymbol{Pol}'_{it}\boldsymbol{\beta}_m + \boldsymbol{Inst}'_{it}\boldsymbol{\gamma}_m)}{1+\sum_{m=1}^{2}\exp(\boldsymbol{Econ}'_{it}\boldsymbol{\alpha}_m + \boldsymbol{Pol}'_{it}\boldsymbol{\beta}_m + \boldsymbol{Inst}'_{it}\boldsymbol{\gamma}_m)}\ , \quad m = 0, 1, 2 \tag{2}$$

The respective log-likelihood function for *n* individuals is the generalisation of that for the binomial logit or probit model:

$$lnL = \sum_{i=1}^{n}\sum_{t=1}^{T}\sum_{m=0}^{2} d_{itm} lnP(Y_{it} = m)\ , \quad m = 0, 1, 2 \tag{3}$$

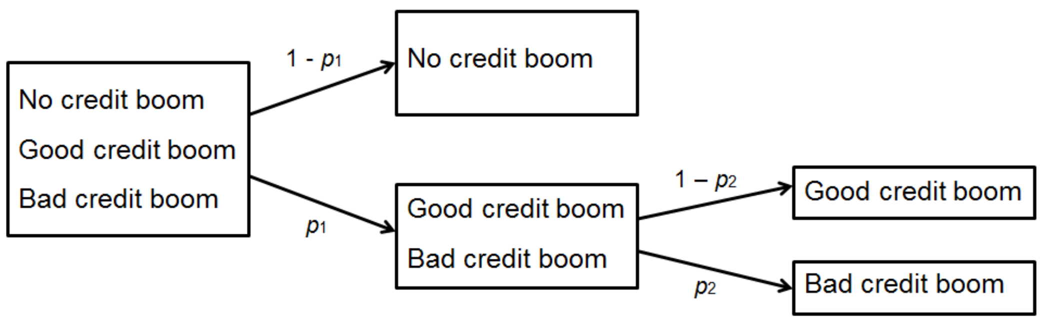
where d_{im}=1 if outcome *m* is observed in country *i* at quarter *t* and 0 otherwise.

A note on the interpretation of the parameters is now in order as, like in the standard logistic regression, the marginal effects are not the estimated coefficients. The estimated coefficient for a certain variable, x_k, correspond to the derivate of the respective log odds ratio. For example, for $\frac{P(Y_{it}=2)}{P(Y_{it}=0)}$, it will be $\partial ln\frac{P(Y_{it}=2)}{P(Y_{it}=0)} / \partial x_k = \beta_{2k}$. The marginal effect of variable x_k on the probability of a "bad" credit boom is then given by $\frac{\partial P(Y_{it}=2)}{\partial x_k} = P_k(\beta_{2k} - \sum_{m=1}^{2} P_m\beta_{mk})$, which is not necessarily of the same sign as the parameter involved. For the purpose of this study, we are interested in estimating both the marginal effects for each outcome and the odds ratios for the contrast between "bad" and "good" credit booms, i.e. $\partial ln\frac{P(Y_{it}=2)}{P(Y_{it}=1)} / \partial x_k = \beta_{2/1,k}$.[12]

[12] For details on this model see Greene (2012, pp. 763-766).

Alternatively, these three events can be treated simultaneously as a sequence of stages: in a first stage, we have the possibility of a credit boom occurring or not; in a second stage – if a credit boom occurs – it can be distinguished between "bad" or "good". This means that a Sequential Logit model would be a more suitable econometric approach to explore this dynamics. Figure 1 describes the sequential process.

Figure 1. The sequential transition process



The first transition consists of a dynamics between no credit boom, on the one hand, and "good" or "bad" credit boom, on the other. The second transition consists of a dynamics between "good" and "bad" credit booms, as this path was followed in first transition. The sequential logit models the probabilities of passing these transitions. This is done by estimating a logistic regression for each transition:

$$P(Y_{it} \in \{good, bad\}) = \Lambda(\boldsymbol{Econ}'_{it}\boldsymbol{\alpha}_1 + \boldsymbol{Pol}'_{it}\boldsymbol{\beta}_1 + \boldsymbol{Inst}'_{it}\boldsymbol{\gamma}_1) \quad (4)$$

$$P(Y_{it} \in \{bad\}|Y_{it} \in \{good, bad\}) = \Lambda(\boldsymbol{Econ}'_{it}\boldsymbol{\alpha}_2 + \boldsymbol{Pol}'_{it}\boldsymbol{\beta}_2 + \boldsymbol{Inst}'_{it}\boldsymbol{\gamma}_2) \quad (5)$$

Equation (4) shows that the probability labelled p_1 in Figure 1 is related to the explanatory variables through the logistic function $\Lambda(.)$, while equation (5) shows the same for the probability labelled as p_2. The logistic distribution function $\Lambda(.)$ is, as usual, given by $\Lambda(.) = \frac{\exp(.)}{1+\exp(.)}$. The coefficients on the regressors can be interpreted as changes in the log odds ratios, while the respective constants represent the baseline log odds of passing the first and second transitions. To interpret the results we rely on the respective odds ratios.[13] This also makes them comparable with odds ratios estimated with the multinomial logit.

5. Empirical results

Table 1 presents the results of the Multinomial and Sequential Logit estimations. The marginal effects are reported first for the probability of each event (*NoCB*, *GoodCB* or *BadCB*) and then the odds-ratios for the contrast *Bad* versus *Good* credit booms.[14] As the probability of no credit boom is equal to one minus the sum of the probabilities of the other two, we will focus our analysis on the results provided in columns 2 and 3; at the same time they will be compared with the respective odds-ratios estimates (column 4). The odds ratios for this contrast are also estimated employing a simple Logit model, where only events of booms are considered (column 5). The last two columns report the results (odds ratios) from the estimation of the Sequential Logit model. All economic variables are lagged one period to avoid simultaneity problems and to account for the usual delays in the reporting of economic data.

[Insert Table 1 around here]

[13] For details on this model see Buis (2008, 2013). The *seqlogit* package developed by Buis (2013) for Stata is implemented to estimate this model. An important advantage of this estimator is that it makes it easier to test hypotheses across transitions since the entire model is estimated simultaneously and, at the same time, to compute the marginal effects for the explanatory variables on the outcome of the process for each of the sequential contrasts. This is a generalization of the multinomial logit in a ranking of multiple separate and sequential choices.

[14] The factor change in the odds, usually called odds-ratio, represents generically the expected change in the odds of outcome j versus outcome l for a unit change in the variable x_k, and is equal to $\exp(\beta_{j|l,k})$.

Our findings reveal important differences between both types of booms but they also identify some commonalities. On one hand, the likelihood of "bad" credit booms is fuelled by capital inflows, higher credit-to-deposits ratio and lower interest rate spread. On the other hand, a decrease in the inflows of capital and a higher relative price of credit drive "good" credit booms, leading to soft landings. The contrast between *Bad* and *Good* (column 4) corroborates this trend, in the sense that the probability of a "bad" credit boom increases (decreases), relatively to "good" ones, when capital inflows and the credit-to-deposits ratio (interest rate spread) increase. In terms of odds-ratios, we observe that a percentage-point increase in *TotCapInflows*, *Credit/Deposits* and *IRspread* lead to a change of the odds by a factor of, respectively, 1.7366, 1.0598 and 0.9764, *ceteris paribus*.[15] In contrast, a higher economic growth and trade openness increase both probabilities equally, hence no significant difference is found in the estimated odds for the contrast *Bad/Good* associated with those variables. Moreover, a better current account stance contributes to decrease both probabilities (and to increase the probability of no boom), but in this case the higher liquidity it generates favours the occurrence of a soft landing. An overvaluation of the REER favours the build-up of a bad boom, while a more flexible exchange rate regime seems to drive credit booms to a soft landing.

Regarding the political conditionings, no clear evidence of an electoral cycle was found, but it becomes clear that right-wing governments are prone to avoid credit booms, especially those that are expected to end up in a banking crisis (relatively to good ones). These governments are known to have a higher propensity for inflation control, smaller deficits and a lower inclination to implement income redistribution policies, hence these policy preferences may contribute to reduce

[15] For example, for the case of the interest rate spread this means that when it increases one percentage point a bad credit boom becomes less likely than a good, as the odds-ratio is significantly lower than one. In the other two cases we have the expected opposite effect.

the probability of credit booms evolving under the right's rule. Simultaneously, right-wing governments are also found to be less willing to implement redistribution policies that generally lead to the entrance into the credit market of people or projects that exhibit higher risk of default, thus reducing the danger of bad credit booms.

Regarding the number of government changes we get a surprising result. Even though political instability (i.e. more government changes) does not affect the appearance of credit booms, if they develop under such instability, there is a greater chance of them ending badly (see the respective marginal effect in column 3 and odds-ratio higher than one in column 4).

Our findings also show that "bad" credit booms are less likely to occur (relatively to "good" ones) under the watch of more independent Central Banks.[16] As these institutions generally play an important role in monitoring the financial system and in preventing markets – and the overall economy – from overheating, they are at the centre of most discussions about how to prevent financial and banking crisis. Our results show that Central Banks can have an active role in controlling "bad" credit surges when they are allowed to establish the monetary policy independently from political pressures and electoral or ideological conveniences. Bad credit booms also seem to be (marginally) more likely when the country's monetary policy is in the hands of a regional monetary union. This might be related to contagion effects and a lower national control over the monetary policy.

[16] Results proved to be robust to different measures of Central Bank independence, namely to the use of the unweighted Central Bank independence index computed by Garriga (2016) *and* when resorting to the weighted and unweighted indices developed by Hicks and Bodea (see http://www.princeton.edu/~rhicks/data.html). These results are available upon request.

The odds-ratios effects obtained with the multinomial logit are confirmed by a simple logit[17] (column 5) where only events of booms are considered, which means that we are contrasting the probability of “bad” against “good” credit booms.

The results from the estimation of the Sequential Logit are presented in columns 6 and 7. The simultaneous estimation of the two stages identified in the credit booms process not only confirms all previous results for the contrast between “bad” and “good” booms but also shows interesting findings for the contrast between credit booms and no credit booms. More specifically, credit booms (in general) are more likely with higher levels capital inflows, credit-to-deposits ratio, economic growth, trade openness, overvaluation of REER, political stability and under monetary unions. But they are less likely with a higher interest rate spread, better current account stance, right-wing governments, and with a higher degree of Central Bank independence.

From this sequential estimation, we can also emphasise that “bad” credit booms (in particular) are more likely, relatively to “good” credit booms, when capital inflows and credit-to-deposits increase, REER is overvalued, and when there is political instability. This last result is even more striking when compared with the one we get in the first stage: while political instability prevents the occurrence of credit booms, when they happen they are more likely to end badly as consequence of that instability. However, “bad” (“good”) credit booms have proven to be less (more) likely when the interest rate spread increases, the current account balance improves, with a more flexible exchange rate regime, with right-wing governments and with more independent Central Banks.

[17] In this case the dependent dummy variable takes the value of 1 when a “bad” credit boom is identified, and 0 for “good” ones.

In sum, the results suggest that the quantity and price of credit, liquidity in the economy, economic growth, openness of the economy, political orientation and stability and an independent Central Bank are important factors to explain not only the occurrence of credit booms but also – and most importantly – whether they end up in a systemic banking crisis or not.[18]

As an additional exercise, we split our sample in two groups: industrial countries (essentially OECD countries) and the others (essentially developing countries). The idea is to check whether or not these heterogeneous groups are differently affected by the economic, political and institutional determinants. The respective results are presented in Table 2. In general, the results from the Multinomial Logit are corroborated by the Sequential Logit.

[Insert Table 2 around here]

One important finding from this disaggregated analysis is that political instability (i.e. more government changes) favour the build-up of bad credit booms in developing countries. In this group, "bad" credit booms – and credit booms, in general (see column 9) are also less likely when right-wing parties are in office. More specifically, the odds-ratio coefficient is significantly lower than one in the contrast *Bad/Good* in both multinomial and sequential logit estimations. The political effects seem to be less relevant in the case of industrial countries, when we contrast "bad" with "good" booms.

A higher level of Central Bank independence reduces the likelihood of having a credit boom in industrial countries, in particular. However, all countries seem to benefit from a more independent monetary authority during the build-up phase since it helps to reduce the probability of a systemic banking crisis in the bust phase. On the contrary, credit booms have proven to be

[18] All the results reported in Table 1 are robust to other alternative and more restrictive thresholds (1.75 and 2.0) for the identification of credit booms (see Tables A.5 and A.6 in the Appendix).

more likely in monetary unions, with a higher propensity to end badly especially in the group of industrial countries.

Regarding the economic variables, while “bad” credit booms seem to be mitigated by exchange rate flexibility, they tend to evolve over time with higher credit-to-deposits ratio, lower interest rate spread worse current account position, trade openness and exchange rate appreciation in both groups of countries. However, capital inflows and economic growth matter more for the build-up of “bad” booms in industrial countries than in developing ones. Additionally, the results from the Sequential Logit also show that: (i) economic growth, current account position and trade openness are important drivers of credit booms in both groups of countries; (ii) capital inflows matter more in the industrial countries; (iii) credit to deposits ratio and the interest rate spread play a major role in the credit boom dynamics in the group of developing countries.

In sum, while a better economic environment and Central Bank independence are essential for both groups of countries to avoid credit booms from ending up in systemic banking crises, the political factors seem to exert a stronger influence in developing countries.

6. Conclusions

This work extends the existing literature on credit booms by using a wider variety of econometric methodologies and by studying the particular impact of political factors and of Central Bank independence. The empirical analysis suggests the existence of a significant number of relevant economic differences between “good” and “bad” credit booms, contrary to previous empirical studies that have struggled to find ample evidence of economic differences between them. On the one hand, credit booms that are driven by high levels of capital inflows and/or by increases in the ratio of credit to deposits and those that are generally supported by lower interest rates tend to have an increased likelihood of ending up in a full blown banking crisis. On the other hand, a decrease in the inflows of capital and a higher relative price of credit seems to drive "healthier" credit booms leading to soft landings. In contrast, higher economic growth and trade openness appear to increase both probabilities equally.

The proposed existence of alternative, non-economic explanations for the behaviour of credit expansions proved to be true. We found strong statistical evidence that "bad" credit booms tend to be less frequent when right wing parties are in office, albeit the probability of having a credit boom is found to be lower during these periods. Also, credit booms developing under politically unstable environments seem to have a greater chance of ending badly. In contrast, this tendency for disaster decreases under the watch of more independent Central Banks. It seems that Central Banks can have an active role in controlling potentially "bad" credit surges provided they are allowed to establish the monetary policy independently from political pressures.

A further analysis of the results for the sub-samples of industrial and developing countries revealed that political factors are detrimental to explain the dynamics of credit booms towards a systemic banking crisis in developing countries, while a better economic environment and Central Bank independence are essential for both groups of countries to avoid that outcome. This further reinforces the idea that monetary authorities and the political environment play an important role in the unfolding of credit booms into a sweet or a sour ending.

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Table 1. Determinants of "good" and "bad" credit booms

	Multinomial Logit				Logit	Sequential Logit	
	Pr(*NoCB*) (mg.eff.)	Pr(*GoodCB*) (mg.eff.)	Pr(*BadCB*) (mg.eff.)	Bad/Good (odds-ratio)	Bad/Good (odds-ratio)	CB*vs*NoCB (odds-ratio)	Bad*vs*Good (odds-ratio)
MgEffects	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
TotCapInflows	0.0100	-0.0314**	0.0214***	1.7366***	2.3421***	1.1752**	2.4037***
	(0.0113)	(0.0123)	(0.0038)	(0.2185)	(0.7456)	(0.0911)	(0.7921)
Credit/Deposits	-0.0015	-0.0017	0.0032***	1.0598***	1.0602***	1.1082***	1.0629***
	(0.0012)	(0.0012)	(0.0005)	(0.0137)	(0.0149)	(0.0187)	(0.0148)
IRspread	-0.0004	0.0015**	-0.0011*	0.9764**	0.9460***	0.9696**	0.9446***
	(0.0008)	(0.0006)	(0.0006)	(0.0106)	(0.0140)	(0.0143)	(0.0139)
RealGDPgr	-0.0132***	0.0096***	0.0036*	0.9832	1.0204	1.1193***	1.0509
	(0.0028)	(0.0025)	(0.0019)	(0.0336)	(0.0422)	(0.0290)	(0.0421)
Inflation	-0.0010	0.0008	0.0001	0.9965	0.9821	1.0030	0.9820
	(0.0010)	(0.0008)	(0.0008)	(0.0132)	(0.0200)	(0.0114)	(0.0200)
CurrAccount	0.0198***	-0.0060***	-0.0138***	0.8629***	0.8628***	0.7820***	0.8696***
	(0.0015)	(0.0013)	(0.0011)	(0.0170)	(0.0189)	(0.0160)	(0.0186)
Openness	-0.0847***	0.0576***	0.0271**	0.9245	0.8831	11.3252***	0.8867
	(0.0191)	(0.0160)	(0.0128)	(0.2083)	(0.2440)	(4.9180)	(0.2477)
ApprecREER	-0.2686**	0.0358	0.2328**	19.6854*	11.0649**	9.6946**	15.0363**
	(0.1315)	(0.1122)	(0.0907)	(32.6911)	(21.9646)	(10.0959)	(30.1049)
ExchRateFlex	-0.0116	0.0155**	-0.0040	0.8381*	0.7471**	0.9374	0.7575**
	(0.0081)	(0.0069)	(0.0056)	(0.0861)	(0.0902)	(0.0984)	(0.0916)
YrBefElection	0.0044	-0.0056	0.0012	1.0632	1.1273	0.8896	1.1575
	(0.0158)	(0.0135)	(0.0106)	(0.2051)	(0.2363)	(0.1097)	(0.2421)
RightGov	0.0639***	-0.0065	-0.0574***	0.4757***	0.3956***	0.6296***	0.4097***
	(0.0143)	(0.0120)	(0.0103)	(0.0865)	(0.0829)	(0.0815)	(0.0852)
MajorityGov	0.0454***	-0.0407***	-0.0047	1.2905	1.5989**	1.1086	1.4631*
	(0.0154)	(0.0129)	(0.0106)	(0.2448)	(0.3535)	(0.1566)	(0.3172)
NGovChanges	-0.0058	-0.0118	0.0176***	1.4182***	1.4755***	0.8170**	1.4312***
	(0.0102)	(0.0088)	(0.0067)	(0.1756)	(0.1907)	(0.0749)	(0.1846)
CBI	0.0163	0.0191	-0.0354**	0.5292*	0.3640**	0.2515**	0.3340**
	(0.0391)	(0.0335)	(0.0166)	(0.2558)	(0.1849)	(0.1359)	(0.1697)
MU	-0.0546**	0.0227	0.0318*	1.2673	1.1656	4.1056***	1.0728
	(0.0247)	(0.0210)	(0.0165)	(0.3824)	(0.3983)	(1.3779)	(0.3666)
#Observations		3157			678	3157	
#Countries		47			47	47	
#Episodes		*64*	*24*		*24/64*	*88*	*24/64*
LogL		-1812.9			-360.3	-1610.4	
SBIC		3948.0			844.4	3905.7	
McFadden-R^2		0.144			0.211	0.240	

Notes: Estimations considering the Gourinchas et al. (2001) criteria with standard deviation threshold equal to 1.5. The number of credit boom episodes, by kind, is reported at the bottom of the table. The multinomial logit is estimated for 3 outcomes: no credit boom (*NoCB*); "good" credit boom (*GoodCB*); and "bad" credit boom (*BadCB*). The marginal effects for the respective probabilities are reported in columns 1-3. Column 4 presents the multinomial logit odds-ratio estimates for the contrast between "bad" and "good" credit booms. The odds ratios from the estimation of a simple logit model restricted to the subsample of credit booms to assess only the contrast between "bad" and "good" credit booms are reported in columns 5 and 6. Columns 7 and 8, present the estimated odds rations for the sequential logit model, where the first branch represents the contrast between credit booms and no credit booms and the second branch (or twig) is restricted to booms episodes to assess the effects for the contrast between "bad" and "good" credit booms. Decade dummies are used in all estimations to account for time effects. Fixed effects are accounted for only for the contrast between credit booms and no credit booms; they have to be excluded in the contrast between "bad" and "good" credit booms. In fact, Claessens et al. (2011, p.17) note that with a limited number of observations, spells or episodes per country, fixed effects may have to be ruled out. The Schwartz Bayesian Information Criterion, SBIC=-2LogL+kLog(N), where k is the number of regressors and N is the number of observations. The McFadden-R^2=1-LogL/LogL_0, where LogL_0 is the log-likelihood of the model with only a constant term.

Table 2. Industrial versus developing countries

	Multinomial Logit						Sequential Logit			
	Industrial			Developing			Industrial		Developing	
	Pr(*GoodCB*) (mg.eff.)	Pr(*BadCB*) (mg.eff.)	Bad/Good (odds-ratio)	Pr(*GoodCB*) (mg.eff.)	Pr(*BadCB*) (mg.eff.)	Bad/Good (odds-ratio)	CB*vs*NoCB (odds-ratio)	Bad*vs*Good (odds-ratio)	CB*vs*NoCB (odds-ratio)	Bad*vs*Good (odds-ratio)
MgEffects	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
TotCapInflows	-0.0214**	0.0090***	1.4749***	-0.0481	-0.0408	0.7696	1.2436**	1.3017***	0.9408	1.3373
	(0.0106)	(0.0031)	(0.1994)	(0.0431)	(0.0405)	(0.4623)	(0.1108)	(0.1236)	(0.3613)	(0.8241)
Credit/Deposits	-0.0068**	0.0088***	1.2698***	-0.0015	0.0035***	1.0518***	1.0359	1.2693***	1.1262***	1.0609***
	(0.0031)	(0.0017)	(0.0610)	(0.0016)	(0.0007)	(0.0150)	(0.0447)	(0.0847)	(0.0233)	(0.0153)
IRspread	0.0123***	-0.0015	0.8557**	0.0018**	-0.0033***	0.9503***	0.9987	0.8006***	0.9650**	0.8771***
	(0.0040)	(0.0031)	(0.0649)	(0.0009)	(0.0009)	(0.0132)	(0.0513)	(0.0684)	(0.0157)	(0.0200)
RealGDPgr	0.0110***	-0.0052**	0.8338***	0.0140***	0.0044	0.9787	1.0846**	0.7513***	1.1644***	1.0367
	(0.0036)	(0.0024)	(0.0499)	(0.0044)	(0.0033)	(0.0484)	(0.0432)	(0.0545)	(0.0460)	(0.0800)
Inflation	-0.0010	-0.0005	1.0054	0.0008	-0.0007	0.9883	1.0215	0.8898	1.0031	0.8851***
	(0.0025)	(0.0019)	(0.0476)	(0.0013)	(0.0013)	(0.0187)	(0.0325)	(0.0804)	(0.0134)	(0.0309)
CurrAccount	-0.0074***	-0.0128***	0.8369***	-0.0049*	-0.0188***	0.8175***	0.7490***	0.8727***	0.8171***	0.8137***
	(0.0016)	(0.0014)	(0.0279)	(0.0027)	(0.0022)	(0.0286)	(0.0233)	(0.0315)	(0.0269)	(0.0364)
Openness	0.0439**	0.0991***	4.2414***	0.0765**	-0.0390	0.3833***	9.0025***	6.3747**	7.2940***	0.3012**
	(0.0224)	(0.0158)	(1.6634)	(0.0321)	(0.0243)	(0.1412)	(7.4941)	(5.2269)	(4.7991)	(0.1637)
ApprecREER	-0.1530	0.5967***	5.0649***	0.2576	-0.2454*	0.0101**	4.2622***	5.4691***	2.3482	4.7954**
	(0.1722)	(0.1231)	(1.6013)	(0.1717)	(0.1358)	(0.0214)	(2.2593)	(1.7142)	(3.1044)	(1.6941)
ExchRateFlex	0.0040	0.0168**	1.2762	0.0473***	-0.0364***	0.4906***	0.9996	2.0358***	0.8201	0.3347***
	(0.0094)	(0.0078)	(0.2436)	(0.0123)	(0.0098)	(0.0754)	(0.1639)	(0.5496)	(0.1205)	(0.0701)
YrBefElection	-0.0035	-0.0075	0.9035	-0.0066	-0.0056	0.9764	0.8830	1.4074	0.8729	0.6355
	(0.0157)	(0.0115)	(0.2583)	(0.0247)	(0.0185)	(0.2795)	(0.1485)	(0.5003)	(0.1712)	(0.2308)
RightGov	-0.0092	-0.0024	1.0827	0.0306	-0.1665***	0.1135***	0.8814	1.6913	0.3332***	0.0428***
	(0.0145)	(0.0112)	(0.2983)	(0.0230)	(0.0211)	(0.0379)	(0.1460)	(0.5775)	(0.0836)	(0.0200)
MajorityGov	-0.0521***	-0.0335***	0.9138	-0.0027	0.0172	1.2546	0.5303***	0.9109	2.1745***	0.6416
	(0.0152)	(0.0120)	(0.2646)	(0.0238)	(0.0188)	(0.3578)	(0.1104)	(0.3731)	(0.4606)	(0.2438)
NGovChanges	-0.0088	0.0023	1.1784	-0.0209	0.0273**	1.5527**	0.8402	1.0332	0.7717	1.9938***
	(0.0106)	(0.0080)	(0.2349)	(0.0157)	(0.0113)	(0.2777)	(0.0991)	(0.2282)	(0.1227)	(0.4577)
CBI	-0.0453	-0.2035***	0.0275***	0.1325**	0.0158	0.5609*	0.0649***	0.0120***	0.4397	0.1784*
	(0.0428)	(0.0357)	(0.0235)	(0.0610)	(0.0457)	(0.2932)	(0.0600)	(0.0122)	(0.3420)	(0.1604)
MU	0.0373	0.1146***	6.1643***	0.0470	0.1616***	6.1845**	4.2062***	6.4319***	15.8519***	2.7966
	(0.0263)	(0.0247)	(3.5728)	(0.0793)	(0.0445)	(4.5470)	(2.3169)	(3.6692)	(11.9713)	(2.3357)
#Observations		1926			1206		1926		1206	
#Countries		22			25		22		25	
#Episodes	32	17		26	13		59	32/17	39	26/13
LogL		-915.2			-779.9		-823.5		-649.1	
SBIC		2133.4			1843.6		2124.3		1738.0	
McFadden-R^2		0.185			0.192		0.267		0.327	

Notes: See Table 1.

Appendix

Table A1. Credit booms dates and respective duration

Country	Begin	End	Duration	Country	Begin	End	Duration
Argentina	1997q1	1999q1	9	Japan	1998q2	2001q3	14
Australia	1989q1	1991q2	10	Korea Republic	2002q2	2004q1	9
Australia	2007q4	2009q2	7	Korea Republic	2008q1	2009q2	6
Austria	2005q2	2006q3	6	Latvia	1997q2	1999q1	8
Bolivia	1990q2	1995q1	20	Latvia	2000q3	2008q2	32
Bolivia	1996q4	1998q4	9	Latvia	2009q3	2010q3	5
Brazil	2006q3	2008q4	10	Luxembourg	2005q2	2006q4	7
Bulgaria	2001q4	2009q3	32	Luxembourg	2007q4	2008q4	5
Canada	1981q2	1982q3	6	Malta	2000q2	2002q1	8
Canada	2001q4	2003q2	7	Malta	2008q2	2009q2	5
Canada	2006q3	2006q4	2	Mexico	1989q1	1995q3	27
Chile	2007q3	2009q1	7	Netherlands	1996q1	1998q1	9
Colombia	1997q3	1999q2	8	Norway	1984q4	1991q2	27
Colombia	2006q3	2009q1	11	Norway	1997q3	1998q4	6
Costa Rica	1998q1	2001q1	13	Norway	2006q2	2006q4	3
Costa Rica	2007q1	2009q3	8	Paraguay	2001q2	2003q1	8
Croatia	1997q4	1998q4	5	Paraguay	2007q3	2009q2	8
Croatia	2001q1	2003q3	11	Paraguay	2010q2	2010q4	3
Cyprus	2000q1	2001q4	8	Peru	1995q3	1999q1	15
Cyprus	2007q1	2008q2	6	Philippines	1983q2	1984q3	6
Czech Republic	1996q2	1998q3	10	Philippines	1993q2	1998q3	22
Czech Republic	2005q2	2008q3	14	Poland	2006q3	2009q2	12
Denmark	1986q3	1986q4	2	Portugal	1997q1	2003q1	25
Denmark	1987q4	1990q4	13	Portugal	2007q4	2009q1	6
Denmark	2000q3	2000q4	2	Romania	1998q3	1999q1	3
Ecuador	1993q3	1995q4	10	Romania	2001q4	2009q2	31
Ecuador	1997q3	1998q4	6	Russian Federation	1998q3	2002q2	16
Ecuador	2001q1	2002q2	6	Russian Federation	2006q1	2009q2	14
Estonia	1996q2	1998q2	9	Slovak Republic	1996q2	1998q2	9
Estonia	2005q3	2009q1	15	Slovenia	2004q1	2009q2	22
Finland	1989q1	1993q1	17	South Africa	2001q2	2002q1	4
Finland	2007q4	2008q4	5	South Africa	2006q1	2009q1	13
France	1978q1	1979q4	8	Spain	2006q4	2009q2	11
France	2007q3	2008q4	6	Sweden	2001q1	2003q3	11
Germany	2000q1	2001q4	8	Thailand	1995q4	1999q2	15
Germany	2008q4	2009q3	4	Thailand	2010q2	2010q3	2
Greece	2007q3	2008q4	7	Ukraine	1999q3	2004q3	20
Greece	2010q2	2011q1	4	Ukraine	2005q3	2009q3	17
Hungary	2000q1	2001q1	5	United Kingdom	2007q4	2009q1	6
Hungary	2003q2	2004q3	6	United States	1978q3	1980q1	7
Hungary	2007q4	2009q1	6	United States	1988q4	1990q4	9
Iceland	1997q4	2001q2	15	United States	2007q2	2009q1	8
Iceland	2004q1	2008q3	19				
Italy	1991q4	1993q4	9				
Italy	1999q1	2001q4	12				
Italy	2010q2	2011q1	4	***Average duration***			***10.4***

Notes: This list only reports those countries and events of credit booms that are used in the estimations Credit booms identified using Gourinchas et al. (2001) and Barajas et al. (2009) criterion.

Table A2. Description of variables and respective sources

Variable	**Description**	**Source**
CreditBoom	Defined as an episode where the deviation of the real bank credit to the private sector, as a percentage of real GDP, from a country-specific trend in country *i* at period *t* (with the trend being calculated up to that period *t*) exceeds a determined threshold. A credit boom takes place if the ratio of private credit to GDP meets the following condition: the deviation of this ratio from its estimated trend is greater than 1.5 times its standard deviation or the year-on-year growth rate of private credit to GDP exceeds 20 percent.	Own calculations.
TotCapInflows	Total gross capital inflows as percentage of GDP (*CapInflows*). Includes information from three main components: foreign direct investment, portfolio investment and other investment liability inflows.	IMF's Balance of Payments Statistics (BOP). GDP: World Development Indicators (WDI).
Credit/Deposits	Ratio of private credit to bank deposits (*Credit/Deposits*). Deposits are measured as the sum of demand and time deposits.	IMF-International Financial Statistics (IFS), lines 24 and 25.
IRspread	Difference between the average lending rate and the deposit rate, in percentage.	IMF – IFS
RealGDPgr	year-over-year GDP growth rate.	Datastream and national sources
Inflation	year-over-year percentage change of the consumer price index (CPI)	IMF – IFS
CurrAccount	Current account balance as percentage of GDP.	WDI
Openness	exports plus imports over GDP.	IMF - IFS
ApprecREER	Overvaluation of the real effective exchange rate. An overvaluation is measured as the deviation of the REER index from its HP-filtered trend	IMF - IFS
ExchRateFlex	Exchange rate flexibility. Set by the coarse classification of the exchange rate regime. The coarse index varies between 1 and 6: higher values indicate a more flexible exchange rate arrangement.	Reinhart and Rogoff (2004), and Ilzetzky, Reinhart and Rogoff (2009).
*YrBefElection**	Dummy equal to 1 in the 4 quarters before the election.	Database of Political Institutions 2015 (DPI).
*RightGov**	Dummy equal to 1 for right-wing governments.	DPI
*MajorityGov**	Dummy equal to 1 in presence of majority governments.	DPI
NGovChanges	Number of government changes (due to elections or not) over the previous five years.	DPI
CBI	Cukierman-Webb-Neyapti index.	Garriga (2016)
MU	Dummy equal to 1 when the country's monetary policy is in the hands of a regional monetary union.	National sources.

* The DPI is in an annual database, so we constructed a quarterly version of the data. Since we had quarterly information on the date of all elections, we used this information to change the annual nature of the data for the variables to quarterly data at election points. For those changes found in the annual data that were not accounted by elections we opted by leaving them annually-based.

Table A3: Descriptive statistics for the episodes and duration of credit booms

	#Spells	Mean	St.Dev.	Min.	Max.
All countries (67)	220	8.04	5.82	1	32
OECD countries (28)	76	8.28	5.31	1	27
Non-OECD countries (39)	144	7.91	6.08	1	32
"Bad" credit booms	55	10.62	6.74	2	32
"Good" credit booms	165	7.18	5.22	1	32

Notes: This table reports the number of episodes/spells (#Spells), the mean duration (Mean), the standard deviation (St.Dev.), the minimum (Min.) and the maximum (Max.) duration for credit booms. The data are quarterly and comprises 67 countries over the period 1975q1-2016q4. Credit booms are identified using the works of Gourinchas et al. (2001) and Barajas et al. (2009). A credit boom takes place when the deviation of the ratio of credit to GDP from its trend exceeds 1.5 times of its standard deviation or the (year-on-year) growth in the credit-GDP ratio exceeds 20 percent.

Table A4. Descriptive statistics for the variables

Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
CreditBoom	3935	0.24	0.43	0	1
TotCapInflows	3883	0.19	1.05	-7.96	19.22
Credit/Deposits	3935	5.96	7.47	0.28	105.88
Irspread	3933	6.27	8.12	-17.12	121.00
RealGDPgr	3934	3.13	3.20	-14.81	14.04
Inflation	3935	5.90	7.43	-3.82	101.55
CurrAccount	3935	-1.26	5.31	-25.55	17.47
Openness	3935	0.73	0.41	0.16	3.58
ApprecREER	3888	0.00	0.06	-0.65	0.41
ExchRateFlex	3935	2.36	1.13	1	6
ElectionQtr	3935	0.07	0.25	0	1
RightGov	3237	0.45	0.50	0	1
CentreGov	3237	0.12	0.33	0	1
LeftGov	3237	0.42	0.49	0	1
MajorityGov	3760	0.69	0.46	0	1
NGovChanges	3863	1.51	0.77	0	5
CBI	3932	0.59	0.24	0.13	0.90
MU	3935	0.13	0.34	0	1
BankCrisis	3934	0.05	0.21	0	1

Notes: This table reports the number of observations for each variable, their mean (Mean), standard deviation (Std.Dev.), minimum (Min.) and maximum (Max.) for the maximum number of countries that could be used in the estimations (47 countries) over the period 1975q1-2016q4.

Table A5. Robustness checks with threshold equal to 1.75

	Multinomial Logit				Logit	Sequential Logit	
	Pr(*NoCB*) (mg.eff.)	**Pr(*GoodCB*)** (mg.eff.)	**Pr(*BadCB*)** (mg.eff.)	**Bad/Good** (odds-ratio)	**Bad/Good** (odds-ratio)	**CB*vs*NoCB** (odds-ratio)	**Bad*vs*Good** (odds-ratio)
MgEffects	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
TotCapInflows	0.0070	-0.0315**	0.0245***	1.9292***	3.0164***	1.1509*	3.1612***
	(0.0130)	(0.0141)	(0.0039)	(0.2996)	(1.2712)	(0.0852)	(1.3617)
Credit/Deposits	-0.0013	-0.0018	0.0031***	1.0644***	1.0767***	1.1036***	1.0780***
	(0.0012)	(0.0012)	(0.0005)	(0.0145)	(0.0184)	(0.0188)	(0.0178)
IRspread	-0.0009	0.0016***	-0.0007	0.9758**	0.9319***	0.9776	0.9310***
	(0.0007)	(0.0006)	(0.0006)	(0.0107)	(0.0149)	(0.0143)	(0.0147)
RealGDPgr	-0.0146***	0.0094***	0.0052***	1.0042	1.0531	1.1324***	1.0878*
	(0.0027)	(0.0024)	(0.0018)	(0.0360)	(0.0488)	(0.0302)	(0.0487)
Inflation	-0.0007	0.0006	0.0001	0.9978	1.0011	0.9988	1.0001
	(0.0010)	(0.0008)	(0.0007)	(0.0140)	(0.0195)	(0.0117)	(0.0197)
CurrAccount	0.0192***	-0.0062***	-0.0130***	0.8617***	0.8509***	0.7858***	0.8588***
	(0.0015)	(0.0012)	(0.0011)	(0.0182)	(0.0213)	(0.0165)	(0.0210)
Openness	-0.0377*	0.0206	0.0171	1.0818	0.9285	3.1526**	0.9114
	(0.0195)	(0.0166)	(0.0128)	(0.2742)	(0.3068)	(1.5408)	(0.3018)
ApprecREER	-0.1513	-0.0094	0.1607*	12.2596	9.3434**	3.0914	10.9581**
	(0.1268)	(0.1068)	(0.0860)	(21.1079)	(11.1677)	(3.2674)	(10.9296)
ExchRateFlex	-0.0025	0.0084	-0.0059	0.8470	0.7218**	0.8718	0.7317**
	(0.0079)	(0.0068)	(0.0054)	(0.0915)	(0.0924)	(0.0939)	(0.0938)
YrBefElection	-0.0041	-0.0001	0.0042	1.0679	1.0452	0.9810	1.0716
	(0.0153)	(0.0129)	(0.0102)	(0.2163)	(0.2382)	(0.1239)	(0.2441)
RightGov	0.0666***	-0.0071	-0.0595***	0.4293***	0.2547***	0.5432***	0.2692***
	(0.0140)	(0.0116)	(0.0101)	(0.0834)	(0.0633)	(0.0733)	(0.0661)
MajorityGov	0.0402***	-0.0301**	-0.0101	1.1135	1.8022**	1.0655	1.6039*
	(0.0148)	(0.0124)	(0.0100)	(0.2193)	(0.4556)	(0.1541)	(0.3952)
NGovChanges	-0.0084	-0.0148*	0.0232***	1.6405***	1.7499***	0.8925	1.7008***
	(0.0100)	(0.0087)	(0.0063)	(0.2123)	(0.2488)	(0.0835)	(0.2412)
CBI	0.0486	0.0011	-0.0497**	0.4581	0.3831*	0.1713***	0.3378**
	(0.0376)	(0.0318)	(0.0252)	(0.2293)	(0.2093)	(0.0944)	(0.1845)
MU	-0.0079	0.0002	0.0077	1.0838	0.8052	2.6150***	0.7318
	(0.0246)	(0.0205)	(0.0170)	(0.3621)	(0.3093)	(0.8958)	(0.2815)
#Observations		3157			620	3157	
#Countries		45			45	45	
#Episodes		*55*	*19*		*19/55*	*74*	*19/55*
LogL		-1697.5			-308.0	-1492.5	
SBIC		3717.3			738.2	3670.0	
McFadden-R^2		0.153			0.264	0.255	

Notes: See Table 1. Estimations considering the Gourinchas et al. (2001) criteria with standard deviation threshold equal to 1.75.

Table A6. Robustness checks with threshold equal to 2.0

	Multinomial Logit				Logit	Sequential Logit	
	Pr(*NoCB*) (mg.eff.)	Pr(*GoodCB*) (mg.eff.)	Pr(*BadCB*) (mg.eff.)	Bad/Good (odds-ratio)	Bad/Good (odds-ratio)	CB*vs*NoCB (odds-ratio)	Bad*vs*Good (odds-ratio)
MgEffects	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
TotCapInflows	0.0059	-0.0301**	0.0242***	1.9417***	3.1983***	1.1520*	3.3343***
	(0.0119)	(0.0129)	(0.0039)	(0.2988)	(1.3828)	(0.0863)	(1.4676)
Credit/Deposits	-0.0018*	-0.0012	0.0031***	1.0596***	1.0737***	1.1098***	1.0743***
	(0.0011)	(0.0010)	(0.0005)	(0.0139)	(0.0177)	(0.0195)	(0.0172)
IRspread	-0.0010	0.0017***	-0.0007	0.9739**	0.9292***	0.9777	0.9282***
	(0.0007)	(0.0005)	(0.0006)	(0.0107)	(0.0149)	(0.0145)	(0.0147)
RealGDPgr	-0.0136***	0.0083***	0.0053***	1.0079	1.0602	1.1149***	1.0934**
	(0.0027)	(0.0023)	(0.0018)	(0.0367)	(0.0488)	(0.0305)	(0.0487)
Inflation	-0.0007	0.0006	0.0001	0.9964	1.0004	0.9925	1.0000
	(0.0010)	(0.0008)	(0.0007)	(0.0142)	(0.0191)	(0.0121)	(0.0192)
CurrAccount	0.0192***	-0.0062***	-0.0130***	0.8665***	0.8620***	0.7717***	0.8709***
	(0.0015)	(0.0012)	(0.0011)	(0.0186)	(0.0218)	(0.0169)	(0.0215)
Openness	-0.0591***	0.0412***	0.0179	0.8959	0.7464	4.5896***	0.7298
	(0.0188)	(0.0155)	(0.0128)	(0.2261)	(0.2543)	(2.3351)	(0.2487)
ApprecREER	-0.1708	0.0091	0.1618*	10.6100	8.1338**	4.4246	9.7218**
	(0.1235)	(0.1024)	(0.0861)	(18.4897)	(6.7731)	(4.7688)	(9.0406)
ExchRateFlex	-0.0004	0.0062	-0.0058	0.8628	0.7505**	0.9347	0.7617**
	(0.0077)	(0.0065)	(0.0054)	(0.0942)	(0.0982)	(0.1039)	(0.0997)
YrBefElection	-0.0009	-0.0033	0.0042	1.0986	1.0776	0.9836	1.1054
	(0.0149)	(0.0125)	(0.0102)	(0.2259)	(0.2503)	(0.1287)	(0.2561)
RightGov	0.0713***	-0.0119	-0.0595***	0.4530***	0.2598***	0.4694***	0.2823***
	(0.0138)	(0.0112)	(0.0101)	(0.0892)	(0.0653)	(0.0667)	(0.0701)
MajorityGov	0.0227	-0.0128	-0.0099	0.9742	1.6708**	1.3991**	1.5086
	(0.0146)	(0.0121)	(0.0100)	(0.1959)	(0.4285)	(0.2128)	(0.3779)
NGovChanges	-0.0058	-0.0176**	0.0234***	1.7030***	1.7678***	0.8907	1.7171***
	(0.0098)	(0.0085)	(0.0063)	(0.2256)	(0.2546)	(0.0857)	(0.2460)
CBI	0.0630*	-0.0133	-0.0497**	0.5274	0.4904	0.0820***	0.4385
	(0.0364)	(0.0302)	(0.0252)	(0.2661)	(0.2695)	(0.0478)	(0.2408)
MU	0.0273	-0.0345*	0.0072	1.4808	0.8642	2.1827**	0.8019
	(0.0246)	(0.0206)	(0.0170)	(0.5110)	(0.3391)	(0.7842)	(0.3156)
#Observations		3157			596	3157	
#Countries		45			45	45	
#Episodes		*50*	*19*		*19/50*	*69*	*19/50*
LogL		-1630.8			-300.6	-1416.4	
SBIC		3583.8			722.5	3517.7	
McFadden-R^2		0.163			0.259	0.273	

Notes: See Table 1. Estimations considering the Gourinchas et al. (2001) criteria with standard deviation threshold equal to 2.0.

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