NIPE

Universidade do Minho

Documentos de Trabalho

Working Paper Series

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NIPE WP 15/ 2018

NÚCLEO DE INVESTIGAÇÃO EM POLÍTICAS ECONÓMICAS

UNIVERSIDADE DO MINHO

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URL:
http://www.nipe.eeg.uminho.pt/

«This work was carried out within the funding with COMPETE reference nº POCI-01-0145-FEDER-006683 (UID/ECO/03182/2013), with the FCT/MEC’s (Fundação para a Ciência e a Tecnologia, I.P.) financial support through national funding and by the ERDF through the Operational Programme on "Competitiveness and Internationalization – COMPETE 2020 under the PT2020 Partnership Agreement»

Economic and political drivers of the duration of credit booms*

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Abstract

This paper presents a new perspective on the study of credit booms by examining what determines their duration and by testing for relevant political features. The results from the estimation of a discrete-time duration model show that not only economic factors but also political dynamics play an important role in explaining the duration of credit booms. These are found to last longer when the economy is both growing faster and exhibits lower levels of liquidity in the banking system; but credit booms tend to be shorter when countries improve their current account position. Furthermore, their duration is affected by the electoral cycle as well as when centre parties are in office. Credit expansions that end in a banking crisis are also found to be statistically longer and their duration more sensitive to economic and political factors. Finally, we find strong evidence that Central Bank independence and the length of credit booms are inversely related.

Keywords: Credit Booms; Duration Analysis; Political Cycles; Ideology; Central Bank independence.

JEL classification: C41, D72, E32, E51.

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* We are thankful to Frederic Boissay, Alessandra Ferrari, Alistair Milne, Eric Pentecost, Ricardo Sousa, Justine Wood and the participants at the Economics Discipline Group Seminar, Loughborough University, for their very insightful comments and suggestions.

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1. Introduction

Credit plays an imperative role in supporting investment and economic growth. Nevertheless, recent history seems to be consistently telling us that lending is a game of balance: too little of it and economic activity may be strangled, jeopardizing future economic growth; too much of it can be equally harmful to growth since these so-called credit booms are followed, in some occasions, by moments of intense financial distress and banking crises.

The recent global financial crisis, triggered in part by a swift increase of mortgage loans in the United States, is one example of this outcome and has contributed to the belief that credit booms can be a recipe for disaster if they are left alone. The particularly nefarious and widespread aftermath of this crisis has fostered scholarly attention on the matter and reinforced the need for a better understanding of what drives credit surges, especially why some are benign while others create havoc (Reinhart and Rogoff, 2009; Boissay et al., 2016; Baron and Xiong, 2017). Most studies consistently associate credit booms gone badly with larger magnitudes and longer durations, and that this seems to be the only consensus found that actually helps us flag booms that might be malicious to the economy (Gourinchas et al., 2001; Barajas, et al., 2009; Arena et al., 2015; Dell'Ariccia et al., 2016; Meng and Gonzalez, 2017).

Therefore, for the overall understanding of the process – and also in terms of policy measures and implications – it is of crucial importance to understand what drives the duration of lending growth episodes, the mechanism behind their formation and the type of behaviour they exhibit over time. However, so far no such analysis has been developed; hence the present study intends to fill this gap in the literature. In doing so, we improve the existing research in a variety of ways. First, we implement for the first time a discrete-time duration model to the analysis of the duration of credit booms making use of an extensive quarterly dataset covering 67 countries from 1975q1 to 2016q4. This model has the important advantage of allowing for the inclusion of time-varying covariates and a duration dependence parameter. Second, we contribute to a better understanding of the aftermath of credit expansions by clarifying whether the drivers of the duration of credit booms that end up with or are followed by systemic banking crises are substantially different from other credit surges.

In addition to investigating whether the traditional economic variables used to explain the likelihood of credit booms contribute to explanation of their duration, this study draws attention to two new explanatory dimensions previously unexplored by the related literature, namely the political environment and Central Bank independence. As to the first, 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. There is also some debate found in the literature about this relationship. For example, McCarthy et al. (2013) discuss how political decisions and policy subtleties in the US contributed to the expansion of the housing and credit bubble that burst in 2007/08; Calomiris and Haber (2014) present historical evidence on the political origins of banking crises; and Fernandez-Villaverde et al. (2013) debate the political dynamics of credit cycles in the Eurozone and its consequences. Nevertheless, no formal econometric approach to this linkage has been explored. Regarding the role of Central Bank independence, we start by assuming that since more independent Central Banks are less susceptible to political pressures, they are better equipped to control the duration of credit expansions. This brings about a particularly interesting question: Do more independent central banks actually affect the duration of "bad" credit booms? Our results point in this direction and reveal that under the watch of more independent Central Banks "bad" booms are less likely to occur. This means that monetary, fiscal and political authorities play an important role in the timing, duration and consequences of these credit booms.

Additionally, we also present evidence that there are indeed some political characteristics that drive the duration of credit surges. In particular, their duration is disturbed in pre- and post-electoral periods and the presence of centre governments increases their longevity. Moreover, when we look at the aftermath of credit booms, we observe that "bad" credit booms are not only sensitive to the economic conditionings and to the political environment but also exhibit different drivers when compared to soft landings.

The rest of the paper is organized as follows. Section 2 reviews the existing literature on credit booms, and discusses the aspects related to the political dimension. Section 3 presents the econometric model. 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 literature that tries to understand the presence and dynamics of credit booms has mainly approached the subject from an empirical perspective and has consistently highlighted a few major explanatory factors (see, for instance, Mendoza and Terrones, 2008, 2012; Dell'Ariccia et al., 2016).[1] First, credit booms have been consistently associated with sharp increases in capital inflows that consequently raise the supply of loanable funds (Calderón and Kubota, 2012; Gourinchas and Obstfeld, 2012). These surges are usually associated with a rapid build-up of leverage or to a higher ratio of private credit to bank deposits (or lower liquidity) which, in turn, may 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), increase the vulnerabilities associated with currency and maturity mismatches (Akyuz, 2009), and create distortions in asset prices (Agnello and Sousa, 2013; Agnello et al., 2012). Additionally, productivity shocks can pressure the capital stock to increase at a higher rate than GDP, thus strongly raising the credit-to-GDP ratio. A better economic environment and over-optimism can also promote the build-up of a credit boom (Mendoza and Terrones, 2008, 2012; Baron and Xiong, 2017; Meng and Gonzales, 2017). Financial reforms associated with financial liberalization and increases in the provision of financial services may also contribute to abnormal lending growth.[2]

Besides these factors, researchers also point out to domestic differences that may account for the uneven incidence of booms across countries. Situations of expansionary

[1] For some recent theoretical papers on the subject see, for instance, Boissay et al. (2016) and Burnside et al. (2016).

[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.

monetary and fiscal policies, less flexible exchange rate regimes and weak supervision of the banking system are associated with the occurrence of credit booms (Elekdag and Wu 2013; Arena et al., 2015; Dell'Ariccia et al., 2016).

In this paper, we propose to add two previously unexplored dimensions that may play an important role in explaining the duration of credit booms: Central Bank independence (discussed and tested in section 5.3); and the political environment. 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 increase their chances of reelection (Nordhaus, 1975; Rogoff and Sibert, 1988; Rogoff, 1990). A different strand of literature, known as "partisan", argues that governments are not homogenous; instead, they exhibit different priorities when it comes to the economy. The most highlighted 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. As well, 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 (Hibbs, 1977; Alesina, 1987; Alesina and Sachs, 1988). 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 more frequent and larger booms of credit and the inverse should happen with left-wing governments. Nevertheless, higher degrees of government neutrality and also overall political stability like the presence of majority governments and reduced government turnover (ideological changes) are also expected to foster the length of credit booms.

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

As to the potential relationship between booms duration 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. Julio and Yook (2012), using a sample of 248 national elections from 48 countries for the period 1980-2005, report a 4.8% drop in investment in election years. They find that this decrease in investment is larger for closer elections and for firms in countries with fewer checks and balances on executive authorities, a more unstable government, and with more central government spending (see also, Jens, 2017; Canes-Wrone and Park, 2014). Thus, the disruption and uncertainty caused by elections might shrink the duration of credit booms. Instead, we could say that if opportunistic governments are successful boosting the economy prior to elections then these temporary positive shocks may fuel credit booms increasing their duration. Nevertheless, the required economic contraction that follows the election may mitigate or even cancel this effect.

Although lending booms are often related to financial crises (see, for instance, Reinhart and Rogoff, 2009; Boissay et al., 2016) not all credit booms end in turmoil nor are they a necessary condition for the advent of a banking crisis. On the one hand, since credit booms essentially boost investment some may actually be a good thing as they fuel economic growth and when they end the economy can exhibit fundamental improvements. On the other hand, uncontrolled credit growth might also lead to a rapid build-up of leverage, riskier loans, and asset prices bubbles generating unhealthy economic conditions. Researchers tend to look at the aftermath of a credit boom to reveal its benign or malignant nature, mainly by checking if it is followed or not by a banking crisis. However, they have struggled to predict "bad" and "good" credit booms and to understand their fundamental differences. Dell'Ariccia et al. (2016) point out that starting at a higher level of financial depth increases the probability of a boom ending badly. In the same direction, Meng and Gonzalez (2017) highlight that when the size of the financial sector grows the risk of a boom becoming "unhealthy" increases. They do not find any association between "bad booms" and macroeconomic and financial policies – exception made to the quality of regulations and supervision of the banking system. Most studies consistently associate credit booms gone badly with larger magnitudes and longer durations (see Gourinchas et al., 2001; Barajas et al., 2009; Arena et al., 2015; Castro and Kubota, 2013; Dell'Ariccia et al., 2016; Meng and Gonzalez, 2017) but none examines what determines their length. We also use this duration model to assess whether the argument that "bad" credit booms are longer is statistically valid or not.

3. Econometric model

For the duration analysis provided in this study, we start by assuming that the duration variable (*T*) is defined as the number of periods (quarters) a credit boom lasts. Its probability distribution will be given by the cumulative distribution function *F(t)=Pr(T<t)*, from which the survivor function, *S(t)=Pr(T≥t)=1-F(t)*, can be obtained. This is an important function in duration analysis as it measures the probability of an event survive for *t* or more periods. Another useful function is the hazard function, *h(t)=f(t)/S(t)*, where *f(t)* represents the density function. The hazard function measures the rate at which credit boom spells end at time *t*, given that they lasted until that moment. In other words, it measures the probability of exiting from a boom state in moment *t* conditional on the length of time in that state. This function helps to characterise the path of duration dependence.

Although the time spell of a credit boom is a continuous-time process, the available data are discrete (quarters).[4] At the same time, the potential conditioning factors of the duration of credit booms vary over time. For these reasons, discrete-time duration methods are more appropriate for this study than continuous-time methods.[5]

Prentice and Gloeckler (1978) develop a discrete-time version of the proportional hazards duration model, with the respective discrete-time hazard function given by:

$$P_{it} = \Pr\left[T_i = t \mid T_i \geq t, \mathbf{x}_{it}\right] = 1 - e^{-h_t e^{\boldsymbol{\beta}'\mathbf{x}_{it}}} = 1 - e^{-e^{\lambda_t + \boldsymbol{\beta}'\mathbf{x}_{it}}}, \quad \Leftrightarrow \ln\left[-\ln(1-P_{it})\right] = \lambda_t + \boldsymbol{\beta}'\mathbf{x}_{it} \qquad \textbf{(1)}$$

[4] Allison (1982, p.70) states that when those *"… discrete units are very small […] it is usually acceptable to ignore the discreteness and treat time as if it was measured continuously. [However,] when the time units are very large - months, quarters, years, or decades - this treatment becomes problematic."*

[5] For examples of empirical applications of these models in Economics, see Sichel (1991), Zuehlke (2003), Castro (2010), Agnello et al. (2013), Castro and Martins (2013) and Agnello et al. (2015, 2018).

where t denotes the moment in time when the value of each independent variable is observed. Given that time is discrete, t corresponds to the amount of time (measured in quarters) during which the event has been "running" or has been "active", i.e. the amount of time since the beginning of the event or the time span.[6] This model is equivalent to the complementary log-log (or cloglog) function, where $\lambda_t \ (= \ln h_t)$ represents the logarithm of an unspecified (baseline hazard) function of time; $\mathbf{x}_{it}$ is a vector of time-varying regressors.

One suitable and quite popular specification for λ_t is the discrete-time analogue to the continuous-time Weibull model, which yields:

$$\lambda_t = \ln h_t = \alpha + (p-1)\ln t, \qquad \textbf{(2)}$$

where t denotes the moment in time that the value of each independent variable is observed and measures the duration of the event until that time; p parameterizes the duration dependence parameter.[7] If p>1, the conditional probability of a turning point occurring increases as the phase gets older, i.e. there is positive duration dependence; if p<1 there is negative duration dependence; finally, there is no duration dependence if p=1. Therefore, by estimating p, we can test for duration dependence in credit boom phases.

Prentice and Gloeckler (1978) and Allison (1982) show that the discrete-time log-likelihood function for a sample of $i = 1,\ldots,n$ spells/booms can be written as follows:

$$\ln L = \sum_{i=1}^{n}\sum_{j=1}^{t_i} y_{it} \ln\left(\frac{P_{ij}}{1-P_{ij}}\right) + \sum_{i=1}^{n}\sum_{j=1}^{t_i} \ln\left(1-P_{ij}\right), \qquad \textbf{(3)}$$

where the dummy variable y_{it} is equal to 1 if credit boom i in a given country ends at time t, and 0 otherwise. We estimate this model by Maximum Likelihood, substituting P_{ij} by **(1)** and λ_t by **(2)**. This implies that the discrete-time log-likelihood function will be conditional on both time and the conditions observed for the different control variables at time t.

[6] Countries do not experience a credit boom at the same time: sometimes, there is partial overlapping; other times, no overlapping occurs. Hence, we have different starting points for the events/spans across countries.

[7] In the continuous-time Weibull duration model the baseline hazard is $h_t = \gamma p t^{p-1}$, where p>0, γ>0 and γ is a constant (for details see Castro, 2010). Hence, $\lambda_t = \ln h_t = \ln(\gamma p t^{p-1}) = \alpha + (p-1)\ln t$, with $\alpha = \ln(\gamma p)$ and $t = DurCreditBoom$.

4. Data and methodology

To proceed with the duration analysis, we collected quarterly data for 67 countries (28 industrial countries and 39 developing or emerging market economies) from 1975q1 to 2016q4 on real credit. We use quarterly information on credit because it is more appropriate to assess cyclical movements and volatility associated with crisis episodes. The measure of credit considered is the deposit money bank claims on the private sector taken from the line 22d of the IMF's International Financial Statistics (*IFS*). The amount of credit is expressed in real terms by dividing the nominal credit by the CPI index (at the end of the quarter).

The next step is to identify credit booms to compute the respective duration. Defining a credit boom is not an easy task because there is no consensus in the literature on the best methodology to identify them. What is an *abnormal* deviation in credit growth and also what is *normal* growth are both questions open to debate. There seems to be no right or wrong way to identify credit boom episodes, as such the literature presents different approaches, each one 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). Most procedures compare a country's real credit per capita or the credit-to-GDP ratio to their non-linear trend. However, they diverge in some features, mainly: (i) the filtering of credit and GDP series independently or directly as a ratio; (ii) and whether the trend, the thresholds or both are specific to each country.

In this study, we employ the criteria developed by Gourinchas, et. al. (2001) – and later updated by Barajas et al. (2009) – to identify credit booms.[8] This method identifies a credit boom by looking at the growth of credit in the economy, proxied by the bank credit to the private sector as a percentage of GDP, *L/y*. Thus, Gourinchas et al. (2001) define a credit boom as an episode where the deviation of the ratio *L/y* from a country-specific trend in country *i* at period *t* (with the trend being calculated up to that period *t*) exceeds a

[8] 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. Using this criterion makes our analysis consistent. Following Barajas et al. (2009) we also distinguish between "bad" and "good" credit booms. For other procedures see, for example, Mendoza and Terrones (2008, 2012) and Dell'Ariccia et. al. (2016).

determined threshold. In particular, we define that a credit boom takes place if the ratio of private credit to GDP meets the following condition: the deviation of *L/y* from its estimated trend is greater than 1.5 times its standard deviation or the year-on-year growth rate of *L/y* exceeds 20 percent. 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 considered other more restrictive thresholds: 1.75 and 2.0.

Table 1 presents some descriptive statistics for the number of episodes identified with this method (Obs.), their mean duration (Mean), standard deviation (S.D.), minimum (Min.) and maximum (Max.), accounting for different thresholds: 1.5, 1.75 and 2.0. OECD and Non-OECD countries and different periods of time are also considered in this analysis. Simultaneously, we distinguish between credit booms that end up in a systemic banking crisis from those that benefit from a soft landing. Like Barajas et al. (2009), we define the first episodes as "*bad credit booms*" and the others as *"good credit booms"*. Later, in the empirical analysis, we will also assess what factors matter the most for their duration.

Based on the identification strategy of Barajas et al. (2009), we consider "bad" booms as credit booms that are followed by a systemic banking crisis either immediately or within eight quarters of their final period. Episodes of systemic banking crises are obtained from Laeven and Valencia (2008, 2010, 2012) and updated for the more recent years following their procedure. These authors consider that a country experiences a systemic banking crisis if its banking system faces significant signs of financial stress (indicated by significant bank runs, losses, and bank liquidations) and moreover, if we observe significant policy interventions in response to the losses in the banking system.

[Insert Table 1 around here]

Depending on how restrictive the threshold is, we are able to identify between 176 and 220 credit boom episodes over our entire sample period. Around two-thirds of the episodes took place in developing or emerging economies and, over time, most of the episodes of lending booms occur in the 1990s. On average, credit booms last around 8 quarters but they are longer in the 1990s and 2000s (around 9 quarters). However, their mean duration is very similar when we compare the OECD with the Non-OECD countries.

From Table 1 we can also conclude that not all lending booms end up in a crisis. In fact, only approximately 1 out of every 4 credit booms coincides or is followed by systemic banking crises. Another interesting feature is that, on average, those booms last more (11 quarters) than those that end up in a soft landing (around 7 quarters). Barajas et al. (2009), Dell'Ariccia et al. (2016) and Meng and Gonzalez (2017) notice that "bad" credit booms are larger and usually last longer than "good" credit booms. Nevertheless, is that difference statistically significant? This is an issue that we are going to explore deeply in the next section using, for the first time in this kind of analysis, a duration model. In particular, we will test whether there is a significant difference in the average duration of "bad" and "good" credit booms, as well as in their duration dependence parameter (p). At the same time, we will also assess which factors play a major role in the length of both kinds of booms.

The list of countries used in this study is shown at the bottom of Table 1. Those were selected according with the availability of economic and political data. This means that we consider only those countries for which: (i) there is reasonable data on deposit money bank claims on the private sector; (ii) and there are regular and competitive elections and changes in the political orientation of the government over the time period considered in this study.

By organizing the data into spells of credit we can compute their duration, i.e. the number of quarters in which a country is experiencing a credit boom (*DurCreditBoom*). To explain the duration we resort to some economic variables considered relevant by the literature that studies the likelihood of having credit booms. These variables are:[9]

- Ratio of private credit to bank deposits (*Credit/Dep*). This is a proxy for liquidity in the banking system, where deposits are measured as the sum of demand and time deposits. We anticipate that credit booms become longer with lower liquidity, i.e. credit booms will build up with credit growing faster than deposits.

[9] Data sources: IMF's IFS for *Credit/Deposits, IRspread, Inflation*, *Openness* and *ApprecREER*; IMF's Balance of Payments Statistics (BOP) for *CapInflows*; Datastream and national sources for real GDP (local currency); and World Bank's World Development Indicators (WDI) for *CurrAccount*.

- Foreign direct investment (FDI) as percentage of GDP as the main proxy for capital inflows (*CapInflows*). In line with the literature, we conjecture that capital inflows are positively related to the duration of credit booms.
- Growth rate of real GDP (*RGDPgr*) is the proxy for the economic performance. According to the literature a better economic environment favours credit booms, consequently, we expect that it may also make them last longer.
- Inflation rate (*Inflation*) is used as a proxy for monetary stability. It is not easy to conjecture a sign for its impact: on one hand, price instability may bring a boom to an end faster; on the other hand, it may promote a longer boom if the monetary policy is loose.
- Current account balance as percentage of GDP (*CurrAccount*). Meng and Gonzales (2017) show that an improved current account balance favours the occurrence of credit booms. However, this does not mean that they will be longer, as a positive stance may mean more cash or deposits available and less need for further credit. So, credit booms might be shorter when the current account balance improves.
- Overvaluation of the real effective exchange rate (*ApprecREER*) as a proxy for asset prices. An increase in the REER means a real appreciation; Overvaluation is measured as the deviation of the REER index from its HP-filtered trend. As an increase in this variable translates into a rise in asset prices, this might lead to an augment in credit to keep up with that rise. Whether booms are longer or shorter is open to the empirical analysis.
- Exchange rate flexibility (*ExchRateFlex*) is proxied by the coarse classification of the exchange rate regime developed by Reinhart and Rogoff (2004), and updated by Ilzetzky, Reinhart and Rogoff (2009) and similar sources mentioned in that paper for more recent years. The index varies between 1 and 6; higher values indicate a more flexible exchange rate arrangement. According to Dell'Ariccia et al. (2016, p.16): "In economies with fixed exchange rate regimes, monetary policy is directed towards maintaining a fixed exchange rate and is, therefore, unable to respond effectively to the build-up of a credit boom." So, we expect that more flexible exchange rate arrangements promote shorter booms.

To account for the yet unexplored influence of political features on the duration of credit booms, we employ the following variables borrowed from the political business cycles and partisan literature:[10]

- Before elections dummy (*BefElect#*). This variable takes the value of 1 for a given number of quarters (#) before the election quarter and 0 otherwise. In the baseline model we consider 2 quarters before the election quarter.[11] The uncertainty in the months leading to the elections might shrink the duration of credit booms but, at the same time, if opportunistic governments are successful in giving a significant boost to the economy prior to elections then these temporary positive shocks can eventually fuel credit booms increasing their duration. Nevertheless, the required economic contraction that follows the election may mitigate or even cancel the pre-electoral effect.
- Political orientation dummies: *Right*, *Left*, *Centre*. These dummies take the value of 1 when the government if formed by a right-wing, left-wing or centre party, respectively, and 0 otherwise.[12] Since right-wing governments are traditionally more prone to reduce state intervention, foster liberalization and to exert less control over the markets, we expect them to contribute to more frequent and larger booms of credit and the inverse should happen with left-wing governments.
- Majority government dummy (*MajGov*), which takes the value of 1 when the government formed by a governing party that has an absolute majority of seats in the parliament.

[10] The data for political variables were collected from the Database of Political Institutions 2015. This is an annual base, but as we have information on the date of all elections, we use that information to change the annual nature of the data for all political variables to quarterly data at election points. For those changes not accounted by elections we left them annually-based. Hence, our quarterly variables (except the election dummies) are only partially quarterly variables, but they are clearly more accurate than their annual counterparts.

[11] Later, in the sensitivity analysis, we use different number of quarters, election quarter dummy (*ElectQ*), election year dummy (*ElectYr*) and dummies for quarters after the election (*AftElect#*).

[12] The DPI divides parties into three groups based on an evaluation of a party's orientation with respect to economic policy. The right-wing parties includes conservative, Christian democratic, and other right-wing parties; the left-wing parties includes communist, socialist, social democratic, and other left-wing parties; and the Centre includes parties defined as centrists or which party position can best be described as centrist.

- Party tenure (*PartyTenure*), which records the number of quarters that the government party has been in power. Overall, the political stability provided by the presence of majority governments and reduced government turnover (i.e. ideological changes) are expected to foster the length of credit booms.
- Finally, we also control for the impact of the political system (Presidential, semi-Presidential or Parliamentary). We use the dummy *ParlSys*, which takes the value of 1 for parliamentary systems and 0, otherwise.

Other economic and political variables are also considered in the sensitivity analysis and robustness checks reported in Annex.

5. Empirical results

This section reports the main results from the estimation of the discrete-time duration model employed in this study. The main findings are emphasized first, then some sensitivity analyses and robustness checks are provided and the last sub-section addresses the role of the Central Bank independence on the duration of credit booms.

5.1 Main findings

The empirical evidence that arises from the estimation of the basic Weibull model specification is summarised in Table 2. This table is divided into three blocks, one for each threshold – 1.5, 1.75 and 2.0 – used in the definition of the credit booms according to Gourinchas et al. (2001). The estimate of *p* measures the magnitude of the duration dependence and a one-sided test is used to detect the presence of positive duration dependence, i.e. whether $p>1$ or not; the sign '+' indicates significance at a 5% level.

The results reported in Table 2 provide strong evidence of positive duration dependence for credit booms, independently on how restrictive the threshold criterion is. This indicates that the likelihood of a credit boom's termination increases as time goes by, confirming the results of Castro and Kubota (2013). Moreover, *p* has proven to be statistically lower than 2 in most estimations. This means that the second-order derivative's statistical analysis of the baseline hazard function indicates the presence of decreasing (or constant) positive duration dependence. Putting it differently, the probability of a credit boom ending at time *t*, given that it lasted until that period, increases over time, but at a decreasing rate.[13]

[Insert Table 2 around here]

In this preliminary analysis, we start by estimating a very basic specification without accounting for any regressors, fixed or time effects (column 1). Then we test for the presence of random (column 2) and country-specific effects (column 3). The LR test shows that none of these effects are statistically significant. In fact, Claessens et al. (2011, p.17) note that with a limited number of observations/spells per country, fixed effects may have to be ruled out. Hence, to simplify the analysis we account for the eventual heterogeneity between industrial and developing or emerging countries, more specifically, OECD and Non-OECD countries. This procedure (partially) solves the problem and allows us to test for differences in the mean duration of credit booms between those two groups of countries. Hence, in column 5, we add the dummy variable *OECD* to the model (it takes the value 1 for OECD countries; 0 otherwise). We observe that the coefficient associated with this variable is never significant, which means that the mean duration of credit booms in those two groups of countries might be similar. This result is in line with what we have observed in Table 1.

To control for time-effects – given the nature of the data (spells) – we rely on decade-dummies, one for each decade (*Dec70*, *Dec80*, *Dec90*, *Dec00*, *Dec10*; *Dec70* is the base-category). These have proven to be globally significant, indicating that credit booms were, on average, significantly longer in the 1990s and 2000s but shorter in more recent years.

Next, we use this basic specification to test whether "bad" credit booms are statistically longer than soft landings or not. To do so, we add to the model a dummy *BadCB*, which is equal to one for "bad" credit booms, i.e. those that end up or were followed by a systemic banking crisis (0, otherwise). Clearly, "bad" credit booms present a lower likelihood of ending, i.e. they are, on average, significantly longer than booms that end in a soft landing. Allowing

[13] For details on the second-order derivative, see Castro (2010).

for a change in the duration dependence parameter (Δp) between "good" (p) and "bad" credit boom episodes (p+Δp) we observe a significant difference in the duration dependence parameter between them (see column 7): p is statistically lower for credit booms that are followed by a banking crisis, so the likelihood of they end over time increases at a lower rate than "good" credit booms. This finding confirms that "bad" credit booms have a higher propensity to last longer than "good" credit booms. Separate regressions for those different episodes confirm this trend (see columns 8 and 9). This finding is in line with what we observe see Table 1 and provides a statistical proof for what is argued in the literature.[14]

The next phase of this analysis is the inclusion of economic and political conditionings in the model, estimate their impact on the duration of credit booms and assess whether the results presented so far remain valid. Table 3 reports those results for the three thresholds and, for now, without distinguishing between "bad" and "good" credit booms. The first variables to be considered are the economic (all lagged one period to avoid simultaneity problems; see columns 1, 4 and 7); then the political variables are added (see columns 2, 5 and 8). Columns 3, 6 and 9 report the results from instrumental variables estimations where *Cred/Dep*, *CapInflows*, *RGDPgr* and *PartyTenure* are assumed to be endogenous to account for any likely endogeneity issues. In general, the results are robust across the three definitions (1.5, 1.75 and 2.0) and the findings obtained so far remain valid.

[Insert Table 3 around here]

Regarding the economic variables, the estimates confirm most of our expectations. First, a higher credit-to-deposits ratio (*Credit/Dep*), i.e. lower level of liquidity in the banking system, leads to longer credit booms. Credit growing faster than deposits paves the way for booms. Hence, the higher the credit to deposits ratio, the longer the boom in credit will last. Unsurprisingly, credit booms also last longer when the economy is growing faster: an increase in the GDP growth rate (*RGDPgr*) has a significant negative impact on the likelihood of a credit

[14] See Gourinchas et al. (2001), Barajas, et. al. (2009), Arena et. al. (2015), Dell'Ariccia et al., (2016) and Meng and Gonzalez, (2017).

boom ending over time.[15] On the contrary, a better current account position (*CurrAccount*) is associated with shorter credit booms. In fact, an improvement in the current account balance means more cash/liquidity available and less need for further credit, hence, implying shorter credit booms. These are the most robust findings for the economic determinants.

Capital inflows (*CapInflows*) are positively associated with the likelihood of a credit boom ending over time, i.e. to shorter credit booms (although this effect is not always significant; it becomes significant when political variables are added and for 1.75 and 2.0 thresholds). This may contradict our initial expectation based on the findings from the literature on the determinants of credit booms. However, this is not a strange result because even in that literature we find that FDI inflows can be negatively associated with the likelihood of credit booms (see, for example, Calderon and Kubota, 2012). Hence, these capital inflows may indeed contribute to shorter booms, in part, because these flows might be partially supported, at an initial stage, by foreign credit, increasing the country's liquidity (deposits) before translating into new credits and, in another part, due to the instability and uncertainty they can generate (Calderón and Kubota, 2012). Hence, according to our findings, the positive effect on the duration of credit booms is largely and mainly explained by a boost in the ratio *Credit/Dep*, while FDI inflows might be mitigating its impact.

Inflation affects positively the length of credit booms, but this result is not robust to some changes in the covariates, e.g. the effect disappears when political variables are included. On the contrary, with political variables, it is possible to unveil the positive effect that an overvaluation of the real effective exchange rate (*ApprecREER*) has on the length of credit booms. An increase here translates into a rise in asset prices, which ends up leading to a surge in credit, therefore, contributing for longer booms. Nevertheless, a more flexible exchange rate regime (*ExchRateFlex*) has not proven to have a significant impact on the duration of credit booms.

[15] Computing the derivative of the hazard function P_{it} – see equation (1) above – in order to *RGDPgr* (at the the means of the other regressors), we get an approximate meaningful estimate for the magnitude of the effect over the hazard rate. In this case, we estimate that when the real GDP growth rate increases by one percentage point the hazard of a credit boom ending decreases by about 1.2 percentage points.

The inclusion of political variables does not seem to affect the impact of the main economic variables. This might be an indication that the correlation between the economic and political dynamics is not high. More importantly, controlling for the political environment helps to deep our understanding about the behaviour of credit booms and its duration.

The electoral period seems to be important for the length of credit booms. In the period of six months before the elections (*BefElect2*) the likelihood of a credit boom ending (given that it has lasted until that moment) increases, which means that it is quite possible that the political uncertainty in the months leading to the elections induces economic agents to postpone important investments, thus, cooling down those booms' dynamics. Following up on this argument, one should also expect a strong boost in investment after the elections, when the political uncertainty dissipates. Consequently, that would increase the duration of credit booms. Additional results reported in the Annex (see column 5 in Table A.1) indeed corroborate this idea by showing that, after elections, booms have a higher propensity to increase their length. Overall, the pre- and post-electoral effects can be attributed to shifts in uncertainty around election times that modify investment behaviour making the duration of credit booms lower before elections and higher after. However, when we control for the two effects in the same regression the pre-electoral effect disappears (see column 6 in Table A.1), shading some doubts on the existence of a full political cycle. The prevailing post-electoral effect may also have its roots in the well documented "honeymoon effect" that describes the frequent increase in popularity (and in confidence) exhibited by recently elected governments (see, for instance, Veiga and Veiga 2004). This electoral dynamics is an interesting result that unveils a political cycle found to be hidden inside the process of credit duration.

Regarding partisan effects, neither left- nor right-wing governments seem to influence the duration of credit booms but, surprisingly, booms have proven to be longer under centre governments and tend to be shorter with majority governments. We believe that both results are signalling that credit booms like a stable economic environment and minimal intervention to flourish and last longer. Centre governments are known to have weaker ideological agendas. Hence, the policies that they implement tend to be less intrusive and more neutral than those arising from the other political quadrants. As such, periods when they are in office tend to generate less uncertainty among economic agents and foster economic predictability. Additionally, Alesina et. al. (1997) show that partisan cycles are harder to recognize in systems with coalition governments arguing that these are more prone to moderation in policy-making, therefore reducing the magnitude of partisan cycles. Furthermore, coalition governments are known to be related with higher spending than majoritarian ones (Persson et al., 2007), a behaviour that is beneficial to the duration and expansion of credit episodes. Regarding the other political variables, no significant effects were found.

Even though we use lags of the economic variables to account for simultaneity problems, the endogeneity issue is also addressed by implementing an instrumental variables approach. In the first-step potential endogenous economic variables (*Cred/Dep*, *CapInflows* and *RGDPgr*) are instrumented with their four lags and a dummy that takes the value of one when a country is hit by a banking crisis. It is expected that such crises may affect the credit-to-deposits ratio, the inflows of capital and growth. Those crises may also influence the length of time a party is in office. For example, most EU political tenure ended with the recent crisis. Hence, we also assume *PartyTenure* to be endogeneous. All instruments have proven not to be weak in the first-step OLS estimations. In the second-step the fitted values for those four potentially endogenous regressors are used in the estimation of the duration model. The results of this study remain unchanged and we also conclude that endogeneity is not an issue in our analysis as the Durbin-Wu-Hausman test does not reject the exogeneity hypothesis.[16]

Overall, we conclude that not only the economic but also the political environment matters for the understanding of the duration of credit booms.[17] At this stage, two additional

[16] We also considered other variables as potentially endogenous and other instruments but the conclusions were similar. For example, we assumed that the timing of elections might be driven by banking crises, but this instrument has proven to be weak and the endogeneity hypothesis was rejected.

[17] Some results of some sensitivity analyses and robustness checks are reported in the Annex. Despite all those experiments with alternative economic and political proxies and additional variables (for which available data are more limited), the main results and conclusions of this study remain qualitatively and quantitatively

and important questions arise: (i) Is their impact similar in industrial and developing countries? (ii) Are they equally important to explain the length of "bad" and "good" credit booms? These are two issues that we explore in more detail in the next sub-section.

5.2 Industrial versus Developing countries and "bad" versus "good" credit booms

Even though the mean duration of credit booms has not proven to be significantly different between OECD and Non-OECD countries (except when economic variables are included – see Table 3), this does not mean that the pattern of duration dependence must be the same. Hence, we start by testing whether it is statistically different between both groups of countries. Columns 1, 4 and 7 in Table 4 report those results for each of the thresholds considered. In this case, Δp represents the estimated difference in the duration dependence parameter between OECD (industrial) and Non-OECD (developing and emerging) countries, whilst $(p+\Delta p)_{\text{OECD}}$ is the value of the duration dependence parameter for OECD countries. Results are clear in showing a significant difference in the duration dependence parameter, indicating that the likelihood of credit booms ending over time is higher in the group of Non-OECD countries. This conclusion is corroborated by separate estimations for both groups of countries (see columns 2 and 3, 5 and 6, 8 and 9, for each threshold respectively). Hence, we can conclude that credit booms in developing countries have a higher propensity to end (quicker) over time than in industrial countries, despite the lack of significant and consistent differences found in their mean durations (see Table 1).

[Insert Table 4 around here]

In separate estimations for these two groups we observe that capital inflows, GDP growth, appreciation of the REER and majority governments play a significant role in industrial countries, whilst credit booms in developing countries are mainly driven by the ratio of credit to deposits, current account balance, electoral cycle, and political orientation.

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unchanged. Moreover, with the additional controllers we also find that trade openness and financial risk play a relevant role in the duration of credit booms.

A similar approach is followed to check whether the difference in the duration dependence parameter between "bad" and "good" credit booms remains after controlling for economic and political factors and to find out which are the most relevant conditionings in each case. Regressions 1, 4 and 7 in Table 5 confirm the significant difference in the duration dependence parameter pointed out in Table 2. Moreover, the remaining separate regressions for each threshold corroborate this finding. Thus, our results are aligned with the rest of the literature that identifies "bad" credit booms has having a higher propensity to last longer than "good" ones using alternative methodological approaches.

[Insert Table 5 around here]

Regarding the controllers, we find some significant differences that are worth emphasizing. First, a higher ratio of credit to deposits, smaller capital inflows, higher GDP growth, and the presence of centre governments are the main determinants of longer "bad" credit booms. Second, these booms have also proven to be longer in parliamentary regimes and when a party remains in office for extended periods of time, reinforcing the idea that political stability fosters the duration of lending episodes. Third, "good" credit booms have a lower propensity to end when GDP is growing faster, inflation increases, the current account balance deteriorates, the exchange rate appreciates above its trend and in the presence of coalition governments. Finally, "good" booms appear to be longer in OECD countries.

In more generic economic terms, the duration of "bad" credit booms seems to be influenced by the supply of credit and liquidity (*Credit/Dep* and *CapInflows*). In particular, a rise in the supply of credit will increase output and decrease the price of credit (the interest rate), prolonging the boom over a longer period of time. Instead, "good" booms can be seen as supported by demand-driven factors as they are mainly affected by inflation, exchange rate and the stance of current accounts. This may mean that policymakers must avoid measures that fuel the supply of credit, like lower taxes, more permissive regulation or very low interest rates, and that can put the economy in an unsustainable credit path.

5.3 The duration of Credit Booms and Central Bank independence

Central Banks embarking in a loose monetary policy of low interest rates make it easier for economic agents to obtain credit. Individuals can then invest more and at cheaper conditions, contributing to the expansion of credit and to the perpetuation of its growth. Here, we test whether Central Bank independence can explain the duration of credit booms.

Political pressures can affect and impair the role that Central Banks play in the in the credit booms dynamics. It is expected that more independent Central Banks are more prone and free to intervene when the economy displays strong signs of overinvestment, excessive risk and/or inflated market bubbles. For governments the policy of credit expansion is actually 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 no government wants to have a credit crunch on his watch, so the rational course of action is to find ways to prolong the boom. One way of doing so is through monetary policy. Governments do not exert direct control over it, but indirectly they can influence Central Banks via three sources. First, the board of the Central Bank is typically selected by 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 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, an aggressive posture may be used to force the Central Bank to follow a determined policy. Threatening its officials or questioning the existence of the institution are examples of possible governmental strategies to pressure Central Banks (Lohmann, 1998).

To analyse this issue we add to our specification an index that measures the degree of Central Bank independence (*CBIndep*). This is the Cukierman-Webb-Neyapti weighted Central Bank Independence (CBI) index constructed by Garriga (2016). This index varies between 0 and 1 and the closer it is from 1, the more independent the Central Bank is. The results are presented in Table 6 for the entire sample, for OECD and Non-OECD subsamples and for separate regressions with “bad” credit booms and soft landings.

[Insert Table 6 around here]

Considering the entire sample first (columns 1 and 2), we observe that the CBI index is a relevant predictor and presents the expected sign. More specifically, higher degrees of independence increase the likelihood of a credit boom ending. This means that more independent Central Banks react more quickly to the build-up of credit in the economy by adjusting the interest rate accordingly. This reaction prevents credit booms from perpetuating in time. One reason for this faster reaction might be the fact that more independent Central Banks are less susceptible to political pressures based on popularity concerns.

Belke and Potrafke (2012) show that monetary policy has been influenced by government ideology in OECD countries with left-wing governments exhibiting lower (higher) short-term nominal interest rates than right-wing governments when Central Bank independence is low (high). Lead by their result, we test for likely ideological influences on the conduct of monetary policy by interacting *CBIndep* with *Left* and *Centre*. The respective results, reported in column 2, show that the impact of *CBIndep* on the length of credit booms remains highly significant but it is counteracted when centre governments are in office (even though the coefficient on the interaction is only marginally significant).

To assess the role of CBI in industrial and developing countries, two additional estimations are reported in columns 3 and 4. One noteworthy result is that CBI is more relevant for the length of credit expansions in industrial countries. In fact, their likelihood of ending increases significantly over time the more independent a Central Bank is. Hence, promoting even more Central bank independence in industrial countries can be one way to control for the longevity of credit expansions and also influence their ultimate outcome, since the literature systematically associates longer booms with banking crisis. Separate analysis for bad and good credit booms reinforces this idea by showing that a higher degree of Central Bank independence helps to reduce the length of those booms that end in crises. Cutting short these booms may help to attenuate the nefarious effects of the banking distress that follows.[18]

6. Conclusions

This paper provides significant new insights on the dynamics of lending surges. Relying on a completely new approach relative to what has been done so far in the related literature, we test for the presence of duration dependence in episodes of credit booms and, for the first time, examine the role of economic and political variables on the duration of credit expansions. We also assess the relevance of Central Bank independence in this dynamic and analyse the economic and political drivers of those credit booms that end up or are followed by systemic banking crises as well as whether they are more likely to last longer or not.

Using discrete-time duration model and an extensive quarterly dataset, we obtain robust evidence of positive duration dependence in the episodes of credit booms and provide strong statistical support to the idea that "bad" credit booms have a higher propensity to last longer than others. This reinforces the notion found in the literature that the prime suspect for bad booms is duration, meaning that, like in so many other things in life, moderation in the length of lending surges seems to be pivotal to a benign aftermath. This study also shows that some economic dynamics are key to explaining the duration of lending episodes. These are found to last longer when the economy is growing faster and when there is a shortage of liquidity in the banking system/economy.

In addition to the economy, this study also presents explanations for the duration of credit booms that arise from the political environment. Centre governments and coalitions are found to positively affect the duration of credit surges. Evidence of a political cycle is also detected as the duration of credit booms was found to be lower (higher) before (after) elections. This is a pattern that can be related to shifts in uncertainty affecting economic

[18] Additional experiments with the unweighted CBI index developed by Garriga (2016), the CBI data of Hicks and Bodea (available at http://www.princeton.edu/~rhicks/data.html) and different thresholds (1.75 and 2.0) were also performed but the main conclusions remain unchanged. Those results are available upon request.

agents' investment behaviour around election times. This specific explanatory channel seems to reflect the idea that less government intervention, less political, and, to some extent, less policy uncertainty increases the duration of credit booms.

Regarding the type of credit boom, some interesting conclusions were reached: the length of "bad" credit booms is specially influenced by growth, the supply of credit and liquidity; while "good" booms, are mainly supported by demand-driven factors like inflation, exchange rate, the stance of current accounts and growth. Since this paper strongly reinforces the idea found in the literature that differences in duration are the best sign to predict what comes after, decreasing their length will reduce the likelihood of them ending badly. As such, one way for policy decision-makers to play an important role here is through an efficient management of their duration. They should pay close attention to credit booms when they last more than a reasonable period of time, being our best estimate of a "reasonable" period around 2 years (our sample average). For this task the independence of the Central Bank has proven to be an important factor as the more independent they are, the shorter the booms of credit will be, thus reducing the probability of them ending in a systemic banking crisis. Moreover, higher levels of CBI are found to cut short those booms that end in banking crisis, which probably prevents banks from becoming even more vulnerable.

Our findings also suggest that any kind of policy intervention aimed at controlling their length should be preferentially directed towards the supply of credit and liquidity. More specifically, policies that help to lower the ratio of credit-to-deposits to a level consistent with the potential of the economy and/or to increase liquidity in the banking system – for example, attracting foreign direct investment – would be preferable. Alternatively, slowing down economic growth also seems to work, although affecting both "good" and "bad" booms. Nevertheless, implementing measures intended to reduce the supply of credit or remove pressure from unsustainable economic growth is never an easy task since they are very hard to justify, unpopular and apparently counterintuitive.

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List of Tables

Table 1: Descriptive statistics for the episodes and duration of credit booms

	#Spells	Mean	St.Dev.	Min.	Max.
***Threshold:* 1.5**					
All countries	220	8.04	5.82	1	32
OECD countries	76	8.28	5.31	1	27
Non-OECD countries	144	7.91	6.08	1	32
Decades:					
1975-1979	8	4.63	2.20	2	9
1980-1989	30	6.17	3.27	2	16
1990-1999	59	9.18	5.64	2	27
2000-2009	48	9.33	6.46	2	32
2010-2016	28	3.25	1.96	1	9
"Bad" credit booms	55	10.62	6.74	2	32
"Good" credit booms	165	7.18	5.22	1	32
***Threshold:* 1.75**					
All countries	199	8.26	6.00	1	32
OECD countries	64	8.73	5.60	1	27
Non-OECD countries	135	8.04	6.19	1	32
Decades:					
1975-1979	7	5.00	2.08	3	9
1980-1989	27	6.30	3.39	2	16
1990-1999	54	9.35	5.78	2	27
2000-2009	43	9.70	6.74	2	32
2010-2016	25	3.04	2.07	1	9
"Bad" credit booms	50	11.08	6.91	2	32
"Good" credit booms	149	7.32	5.36	1	31
***Threshold:* 2.0**					
All countries	176	8.66	6.19	1	32
OECD countries	59	8.76	5.78	2	27
Non-OECD countries	117	8.61	6.41	1	32
Decades:					
1975-1979	7	5.00	2.08	3	9
1980-1989	24	6.42	3.54	2	16
1990-1999	49	9.80	5.85	2	27
2000-2009	41	9.56	6.95	2	32
2010-2016	16	2.50	1.46	1	5
"Bad" credit booms	49	11.20	6.93	2	32
"Good" credit booms	127	7.68	5.60	1	31

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). According to their criteria, we consider that 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. For robustness, we also allow for two more restrictive thresholds: 1.75 and 2.0.

List of Countries: 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.

Table 2: Duration dependence in credit booms

Ts: 1.5	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
p	1.455+,d	1.455+,d	1.957+,c	1.455+,d	1.712+,d	1.788+,d	1.844+,d	1.714+,d	1.983+,c
	(0.070)	(0.081)	(0.115)	(0.071)	(0.079)	(0.085)	(0.091)	(0.162)	(0.103)
Δp							-0.242***		
							(0.077)		
p+Δp							1.603+,d		
							(0.094)		
BadCB						-0.574***			
						(0.168)			
OECD				-0.016	-0.126	-0.100	-0.091	-0.183	-0.089
				(0.143)	(0.148)	(0.149)	(0.149)	(0.292)	(0.174)
Dec80					-0.302	-0.181	-0.189	-0.892*	0.036
					(0.228)	(0.233)	(0.234)	(0.466)	(0.264)
Dec90					-0.695***	-0.547***	-0.556***	-1.032***	-0.397*
					(0.188)	(0.195)	(0.196)	(0.349)	(0.226)
Dec00					-1.338***	-1.328***	-1.347***	-1.732***	-1.234***
					(0.207)	(0.210)	(0.210)	(0.440)	(0.240)
Dec10					0.897***	0.922***	0.941***	0.616	1.012***
					(0.240)	(0.243)	(0.244)	(0.658)	(0.266)
Const	-2.792***	-2.793***	-3.553***	-2.786***	-2.629***	-2.668***	-2.785***	-2.865***	-2.775***
	(0.145)	(0.164)	(0.610)	(0.160)	(0.198)	(0.205)	(0.213)	(0.438)	(0.248)
#Obs.	1781	1781	1781	1781	1781	1781	1781	584	1197
#Spells	220	220	220	220	220	220	220	55	165
LogL	-649.4	-649.4	-608.8	-649.4	-608.1	-601.7	-602.7	-163.2	-436.7
SBIC	1313.7	1321.2	1726.6	1321.2	1268.6	1263.2	1265.3	371.0	922.9
LR test		0.499	0.198		0.000				
Ts: 1.75	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
p	1.429+,d	1.429+,d	1.926+,c	1.429+,d	1.715+,d	1.807+,d	1.868+,c	1.697+,d	1.988+,c
	(0.077)	(0.085)	(0.121)	(0.077)	(0.087)	(0.095)	(0.101)	(0.187)	(0.115)
Δp							-0.262***		
							(0.080)		
p+Δp							1.606+,d		
							(0.103)		
BadCB						-0.639***			
						(0.175)			
OECD				-0.069	-0.214	-0.185	-0.177	-0.367	-0.134
				(0.152)	(0.160)	(0.161)	(0.161)	(0.320)	(0.187)
Dec80					-0.315	-0.188	-0.198	-0.834*	-0.006
					(0.238)	(0.242)	(0.243)	(0.502)	(0.272)
Dec90					-0.692***	-0.518***	-0.538***	-0.890**	-0.420*
					(0.196)	(0.202)	(0.204)	(0.366)	(0.237)
Dec00					-1.384***	-1.391***	-1.413***	-1.802***	-1.292***
					(0.222)	(0.225)	(0.225)	(0.492)	(0.255)
Dec10					0.987***	1.029***	1.040***	0.838	1.076***
					(0.251)	(0.255)	(0.255)	(0.675)	(0.278)
Const	-2.786***	-2.787***	-3.501***	-2.763***	-2.642***	-2.695***	-2.821***	-3.127***	-2.752***
	(0.160)	(0.174)	(0.820)	(0.172)	(0.208)	(0.217)	(0.224)	(0.491)	(0.259)
#Obs.	1656	1656	1656	1656	1656	1656	1656	554	1102
#Spells	199	199	199	199	199	199	199	50	149
LogL	-594.9	-594..9	-557.4	-594.8	-555.2	-548.0	-549.4	-149.6	-397.0
SBIC	1204.7	1212.1	1618.8	1211.8	1162.2	1155.3	1158.1	343.4	842.9
LR test		0.497	0.208		0.000				
Ts: 2.0	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
p	1.455+,d	1.455+,d	2.029+,c	1.455+,d	1.724+,d	1.817+,d	1.880+,d	1.735+,d	1.992+,c
	(0.083)	(0.092)	(0.135)	(0.083)	(0.093)	(0.102)	(0.109)	(0.182)	(0.128)
Δp							-0.249***		
							(0.083)		
p+Δp							1.631+,d		
							(0.109)		
BadCB						-0.614***			
						(0.181)			
OECD				0.013	-0.086	-0.035	-0.030	-0.376	0.081
				(0.160)	(0.167)	(0.169)	(0.169)	(0.323)	(0.196)
Dec80					-0.385	-0.264	-0.274	-0.826*	-0.102
					(0.252)	(0.256)	(0.257)	(0.502)	(0.294)
Dec90					-0.744***	-0.576***	-0.593***	-0.934**	-0.469*
					(0.205)	(0.212)	(0.213)	(0.370)	(0.2526)
Dec00					-1.366***	-1.374***	-1.396***	-1.809***	-1.261***
					(0.229)	(0.232)	(0.232)	(0.494)	(0.266)
Dec10					1.246***	1.344***	1.349***	1.259*	1.379***
					(0.304)	(0.311)	(0.310)	(0.675)	(0.351)
Const	-2.900***	-2.900***	-3.673***	-2.905***	-2.724***	-2.782***	-2.917***	-3.213***	-2.852
	(0.175)	(0.190)	(0.621)	(0.189)	(0.224)	(0.235)	(0.244)	(0.484)	(0.291)
#Obs.	1535	1535	1535	1535	1535	1535	1535	549	986
#Spells	176	176	176	176	176	176	176	49	127
LogL	-533.6	-533.6	-494.8	-533.6	-499.1	-492.9	-494.37	-145.8	-345.3
SBIC	1081.9	1089.3	1488.4	1089.3	1049.6	1044.6	1047.2	335.8	738.8
LR test		0.496	0.153		0.000				

Notes: Estimations for the duration of credit booms considering Gourinchas et al. (2001) and Barajas et al. (2009) criteria with thresholds equal to 1.5, 1.75 and 2.0, respectively. Robust standard errors are reported in parentheses; ***, **, * - statistically significant at 1%, 5% and 10% level, respectively; + indicates that *p* is significantly higher than one using a one-sided test with a 5% significance level; *d*, *c*, and *i* indicate decreasing, constant or increasing positive duration dependence, respectively; *Δp* is the estimated difference in the duration dependence parameter between "bad" and "good" credit booms; *p+Δp* is the value of the duration dependence parameter for credit booms that ended in a banking crisis (hard landing or "bad" credit booms). The Schwartz Bayesian Information Criterion (SBIC) is computed as follows: *SBIC=-2LogL+kLogN*, where *k* is the number of regressors and *N* is the number of observations (spells). The *LR test* reports the p-value of the test for random effects (column 2), fixed/country effects (column3), and decade-dummies effects (column 5). Columns 8 and 9 present separate regression results for hard ("bad") and soft ("good") landing credit booms, respectively.

Table 3: Duration credit booms: economic and political determinants

	Threshold: 1.5			Threshold: 1.75			Threshold: 2.0		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
p	1.866[+,c]	2.122[+,c]	2.104[+,c]	1.894[+,c]	2.109[+,c]	2.077[+,c]	1.863[+,c]	2.048[+,c]	2.020[+,c]
	(0.102)	(0.164)	(0.162)	(0.112)	(0.180)	(0.177)	(0.116)	(0.186)	(0.183)
Credit/Dep	-0.017***	-0.032***	-0.042***	-0.018***	-0.033***	-0.042***	-0.018***	-0.033***	-0.042***
	(0.007)	(0.010)	(0.012)	(0.007)	(0.010)	(0.012)	(0.007)	(0.010)	(0.012)
CapInflows	0.004	0.005*	0.011**	0.035*	0.059***	0.034*	0.034*	0.057***	0.030
	(0.003)	(0.003)	(0.005)	(0.020)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
RGDPgr	-0.140***	-0.126***	-0.139***	-0.128***	-0.120***	-0.132***	-0.131***	-0.115***	-0.125***
	(0.024)	(0.041)	(0.039)	(0.025)	(0.043)	(0.041)	(0.027)	(0.044)	(0.041)
Inflation	-0.004**	-0.004	-0.006**	-0.004**	-0.004	-0.006**	-0.004**	-0.004	-0.006**
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
CurrAccount	0.033**	0.079***	0.139***	0.040**	0.080***	0.134***	0.038**	0.082***	0.140***
	(0.017)	(0.025)	(0.050)	(0.017)	(0.025)	(0.047)	(0.018)	(0.025)	(0.044)
ApprecREER	-0.466	-2.026*	-0.340	-0.376	-1.868*	-0.122	-0.550	-1.859*	-0.134
	(0.674)	(1.131)	(1.826)	(0.672)	(1.113)	(1.781)	(0.688)	(1.107)	(1.721)
ExchRateFlex	0.090	-0.070	-0.150	0.136	0.001	-0.099	0.132	-0.015	-0.117
	(0.078)	(0.109)	(0.132)	(0.084)	(0.117)	(0.146)	(0.088)	(0.121)	(0.145)
BefElect2		0.394*	0.948**		0.381*	0.951*		0.253	0.881*
		(0.228)	(0.487)		(0.221)	(0.494)		(0.282)	(0.492)
Left		0.088	0.298		0.091	-0.315		0.095	-0.346
		(0.220)	(0.356)		(0.234)	(0.364)		(0.243)	(0.364)
Centre		-1.041***	-1.031***		-1.187***	-1.298***		-1.229***	-1.329
		(0.337)	(0.346)		(0.373)	(0.365)		(0.392)	(0.319)
MajGov		0.681***	1.219**		0.629**	1.195**		0.639**	1.163***
		(0.255)	(0.490)		(0.267)	(0.488)		(0.283)	(0.446)
PartyTenure		-0.003	-0.047		-0.003	-0.046		-0.003	-0.046
		(0.002)	(0.033)		(0.003)	(0.031)		(0.003)	(0.027)
ParlSys		-0.395	-0.229		-0.486*	-0.293*		-0.447	-0.383
		(0.279)	(0.217)		(0.290)	(0.154)		(0.308)	(0.293)
OECD	-0.365*	-0.385	-0.919	-0.443*	-0.492	-0.867	-0.370*	-0.469	-1.066
	(0.219)	(0.269)	(0.965)	(0.231)	(0.298)	(0.969)	(0.210)	(0.315)	(0.967)
Dec80	-0.075	0.072	0.237	-0.013	0.168	0.345	-0.053	0.052	0.116
	(0.268)	(0.353)	(0.379)	(0.287)	(0.367)	(0.400)	(0.306)	(0.408)	(0.427)
Dec90	-0.750***	-0.794***	-0.456**	-0.731***	-0.680**	-0.494**	-0.714***	-0.775***	-0.580*
	(0.217)	(0.268)	(0.229)	(0.226)	(0.283)	(0.247)	(0.239)	(0.291)	(0.306)
Dec00	-1.054***	-0.934***	-0.810***	-1.212***	-1.022***	-0.988**	-1.141***	-1.082***	-0.707*
	(0.229)	(0.269)	(0.279)	(0.262)	(0.297)	(0.447)	(0.272)	(0.304)	(0.362)
Dec10	0.301	0.368	0.452	0.520	0.703	0.691	0.869	1.144	1.382*
	(0.650)	(0.863)	(0.838)	(0.651)	(0.855)	(0.838)	(0.675)	(0.841)	(0.832)
Const	-2.404***	-2.432***	-1.118	-2.677***	-2.663***	-1.287	-2.667***	-2.471***	-0.863
	(0.350)	(0.563)	(1.106)	(0.383)	(0.608)	(1.102)	(0.402)	(0.626)	(1.137)
#Obs.	1456	983	983	1364	915	915	1291	861	861
#Spells	165	112	112	150	102	102	140	96	96
LogL	-445.3	-291.8	-288.3	-408.6	-267.0	-264.0	-384.5	-252.2	-248.9
SBIC	992.6	721.4	714.4	918.3	670.4	664.2	869.3	639.6	632.9
Endog.Test			1.65			1.81			2.29
			{0.801}			{0.771}			{0.682}

Notes: See Table 2. Estimations for the duration of credit booms considering Gourinchas et al. (2001) and Barajas et al. (2009) criteria with thresholds equal to 1.5, 1.75 and 2.0, respectively. Robust standard errors are reported in parentheses; ***, **, * - statistically significant at 1%, 5% and 10% level, respectively; + indicates that *p* is significantly higher than one using a one-sided test with a 5% significance level; *d*, *c*, and *i* indicate decreasing, constant or increasing positive duration dependence, respectively. All economic variables are lagged one period to avoid simultaneity problems. In columns 3, 6 and 9 are reported the results from instrumental variables estimations where *Cred/Dep*, *CapInflows*, *RGDPgr* are instrumented with their respective 4 lags and a dummy for periods of banking crises, while *PartyTenure* is instrumented with the banking crisis dummy. The results from the Durbin-Wu-Hausman endogeneity test are reported at the bottom of the table (respective *p*-value in curly-brackets).

Table 4: Duration of credit booms: industrial versus developing countries

	Threshold: 1.5			Threshold: 1.75			Threshold: 2.0		
	All	**OECD**	**Non-OECD**	**All**	**OECD**	**Non-OECD**	**All**	**OECD**	**Non-OECD**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
p	$2.225^{+,c}$	$2.051^{+,c}$	$2.408^{+,c}$	$2.214^{+,c}$	$2.026^{+,c}$	$2.371^{+,c}$	$2.153^{+,c}$	$2.047^{+,c}$	$2.364^{+,c}$
	(0.165)	(0.281)	(0.256)	(0.182)	(0.358)	(0.268)	(0.189)	(0.409)	(0.275)
Δp	-0.224**			-0.257**			-0.261**		
	(0.112)			(0.125)			(0.124)		
$(p+\Delta p)_{OECD}$	$2.000^{+,c}$			$1.957^{+,c}$			$1.892^{+,c}$		
	(0.187)			(0.205)			(0.211)		
Credit/Dep	-0.034***	-0.056	-0.033**	-0.034***	-0.068	-0.040***	-0.034***	-0.066	-0.042***
	(0.010)	(0.058)	(0.014)	(0.010)	(0.062)	(0.015)	(0.010)	(0.068)	(0.015)
CapInflows	0.005*	0.030*	0.005	0.060***	0.039	0.125*	0.058***	0.024	0.126*
	(0.003)	(0.018)	(0.005)	(0.019)	(0.037)	(0.066)	(0.019)	(0.037)	(0.065)
RGDPgr	-0.132***	-0.178**	-0.116*	-0.125***	-0.181*	-0.121*	-0.120***	-0.118	-0.129*
	(0.042)	(0.077)	(0.071)	(0.045)	(0.098)	(0.072)	(0.045)	(0.096)	(0.073)
Inflation	-0.004	0.011	-0.004	-0.004	0.016	-0.004	-0.004	0.018	-0.004
	(0.003)	(0.015)	(0.004)	(0.003)	(0.016)	(0.004)	(0.003)	(0.017)	(0.004)
CurrAccount	0.078***	0.073**	0.084**	0.079***	0.071	0.112***	0.082***	0.077*	0.122***
	(0.025)	(0.036)	(0.040)	(0.025)	(0.044)	(0.041)	(0.025)	(0.045)	(0.042)
ApprecREER	-2.041*	-6.558**	-1.412	-1.859*	-6.700**	-1.341	-1.878	-7.778**	-1.269
	(1.131)	(2.700)	(1.378)	(1.113)	(3.040)	(1.298)	(1.157)	(3.354)	(1.315)
ExchRateFlex	-0.066	-0.154	-0.041	0.007	-0.111	0.012	-0.006	-0.119	-0.035
	(0.109)	(0.160)	(0.174)	(0.118)	(0.178)	(0.174)	(0.121)	(0.184)	(0.182)
BefElect2	0.381*	-0.184	0.738**	0.364	-0.379	0.737**	0.235	-0.258	0.574*
	(0.217)	(0.452)	(0.309)	(0.260)	(0.532)	(0.322)	(0.280)	(0.538)	(0.345)
Left	0.107	-0.020	0.166	0.112	-0.071	0.254	0.121	-0.069	0.308
	(0.222)	(0.348)	(0.335)	(0.237)	(0.401)	(0.336)	(0.246)	(0.492)	(0.342)
Centre	-1.059***	-1.079	-1.424***	-1.204***	-1.210	-1.378***	-1.242***	-0.599	-1.567***
	(0.339)	(0.684)	(0.502)	(0.374)	(0.974)	(0.518)	(0.393)	(1.022)	(0.542)
MajGov	0.648**	1.067**	0.260	0.587**	1.054*	0.198	0.591**	1.054	0.243
	(0.254)	(0.541)	(0.321)	(0.267)	(0.610)	(0.333)	(0.281)	(0.728)	(0.350)
PartyTenure	-0.002	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.005	-0.004
	(0.002)	(0.004)	(0.004)	(0.003)	(0.005)	(0.004)	(0.003)	(0.006)	(0.004)
ParlSys	-0.369	-0.494	-0.506	-0.481*	-0.653	-0.558	-0.429	-0.404	-0.530
	(0.263)	(0.708)	(0.371)	(0.279)	(0.731)	(0.365)	(0.286)	(0.847)	(0.360)
Dec80	0.090	-0.263	0.225	0.189	-0.375	0.464	0.063	-0.943	0.621
	(0.355)	(0.705)	(0.506)	(0.370)	(0.836)	(0.533)	(0.410)	(0.881)	(0.558)
Dec90	-0.776***	-0.315	-0.949***	-0.656**	-0.164	-0.678	-0.754**	-0.519	-0.638
	(0.270)	(0.475)	(0.367)	(0.284)	(0.553)	(0.415)	(0.294)	(0.563)	(0.435)
Dec00	-0.942***	-0.406	-1.390***	-1.024***	-0.188	-1.435***	-1.095***	-0.320	-1.359***
	(0.268)	(0.455)	(0.371)	(0.295)	(0.516)	(0.379)	(0.305)	(0.561)	(0.386)
Dec10	0.265	-0.478	1.379	0.588	-0.240	1.363	1.059	0.912	1.338
	(0.889)	(1.118)	(1.099)	(0.885)	(1.220)	(1.108)	(0.872)	(1.557)	(1.135)
Const	-2.594***	-2.835**	-2.625***	-2.838***	-2.905*	-2.952***	-2.644***	-3.132*	-2.808***
	(0.553)	(1.402)	(0.872)	(0.603)	(1.661)	(0.946)	(0.622)	(1.901)	(0.978)
#Obs.	983	420	563	915	372	543	861	340	521
#Spells	112	46	66	102	38	64	96	35	61
LogL	-291.2	-119.4	-158.9	-266.6	-100.9	-154.2	-251.6	-93.00	-147.9
SBIC	720.2	353.6	438.2	669.6	314.3	428.2	638.4	296.7	414.6

Notes: See Tables 2 and 3. Δp is the estimated difference in the duration dependence parameter between industrial (OECD) and developing (Non-OECD) countries; $(p+\Delta p)_{OECD}$ is the value of the duration dependence parameter for industrial countries. For each threshold are reported the results for the estimations with "All", "OECD" and "Non-OECD" countries, respectively. All economic variables are lagged one period to avoid simultaneity problems.

Table 5: Duration of "bad" and "good" credit booms

	Threshold: 1.5			Threshold: 1.75			Threshold: 2.0		
	All	**Bad**	**Good**	**All**	**Bad**	**Good**	**All**	**Bad**	**Good**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
p	2.258$^{+,c}$	2.159$^{+,c}$	2.479$^{+,i}$	2.262$^{+,c}$	2.167$^{+,c}$	2.407$^{+,i}$	2.162$^{+,c}$	2.067$^{+,c}$	2.285$^{+,c}$
	(0.183)	(0.370)	(0.275)	(0.205)	(0.378)	(0.238)	(0.205)	(0.378)	(0.283)
Δp	-0.209**			-0.231**			-0.178*		
	(0.104)			(0.115)			(0.104)		
p+Δp	2.048$^{+,c}$			2.031$^{+,c}$			1.984$^{+,c}$		
	(0.178)			(0.196)			(0.202)		
Credit/Dep	-0.029***	-0.058**	-0.007	-0.029***	-0.059**	-0.008	-0.029***	-0.059**	-0.006
	(0.010)	(0.026)	(0.020)	(0.010)	(0.025)	(0.019)	(0.010)	(0.025)	(0.020)
CapInflows	0.005*	0.048**	0.004	0.061***	0.107**	0.088	0.058***	0.107**	0.083
	(0.003)	(0.025)	(0.005)	(0.019)	(0.043)	(0.066)	(0.019)	(0.043)	(0.066)
RGDPgr	-0.134***	-0.201***	-0.161**	-0.128***	-0.234***	-0.151**	-0.121***	-0.234***	-0.139**
	(0.042)	(0.064)	(0.070)	(0.045)	(0.076)	(0.070)	(0.045)	(0.076)	(0.071)
Inflation	-0.004	0.002	-0.008**	-0.004*	0.001	-0.007*	-0.004	0.001	-0.006
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
CurrAccount	0.076***	0.075	0.082***	0.078***	0.046	0.092***	0.080***	0.046	0.096***
	(0.026)	(0.050)	(0.031)	(0.026)	(0.051)	(0.035)	(0.025)	(0.051)	(0.034)
ApprecREER	-2.302*	2.667	-4.081***	-2.205*	3.345*	-3.815***	-2.115*	3.345*	-3.949***
	(1.186)	(1.887)	(1.378)	(1.189)	(1.812)	(1.391)	(1.225)	(1.812)	(1.422)
ExchRateFlex	-0.057	-0.302	-0.014	0.020	-0.061	0.041	-0.001	-0.061	-0.011
	(0.108)	(0.300)	(0.128)	(0.116)	(0.303)	(0.138)	(0.121)	(0.303)	(0.140)
BefElect2	0.364*	-0.004	0.311	0.339	-0.627	0.376	0.225	-0.627	0.226
	(0.217)	(0.549)	(0.294)	(0.258)	(0.774)	(0.304)	(0.277)	(0.774)	(0.325)
Left	0.136	-0.045	0.288	0.149	0.201	0.214	0.139	0.201	0.191
	(0.225)	(0.600)	(0.276)	(0.242)	(0.607)	(0.298)	(0.250)	(0.607)	(0.322)
Centre	-0.758*	-2.285***	0.237	-0.859*	-2.323***	0.108	-0.967**	-2.323***	0.087
	(0.411)	(0.663)	(0.554)	(0.458)	(0.715)	(0.575)	(0.485)	(0.715)	(0.642)
MajGov	0.602**	1.254	0.521*	0.529**	1.087	0.499	0.553*	1.087	0.510
	(0.250)	(0.932)	(0.310)	(0.264)	(0.822)	(0.348)	(0.284)	(0.822)	(0.359)
PartyTenure	-0.002	-0.009*	0.001	-0.002	-0.008	-0.001	-0.002	-0.008	0.001
	(0.002)	(0.005)	(0.004)	(0.003)	(0.006)	(0.004)	(0.003)	(0.006)	(0.004)
ParlSys	-0.332	-1.405*	-0.058	-0.417	-1.383*	-0.188	-0.400	-1.383*	-0.062
	(0.281)	(0.785)	(0.368)	(0.291)	(0.792)	(0.359)	(0.313)	(0.792)	(0.416)
OECD	-0.406	-0.435	-0.617*	-0.512*	-0.816	-0.557	-0.475	-0.816	-0.565
	(0.272)	(0.648)	(0.346)	(0.289)	(0.715)	(0.343)	(0.319)	(0.715)	(0.393)
Dec80	0.145	-0.847	0.456	0.265	-1.017	0.538	0.126	-1.017	0.328
	(0.353)	(0.956)	(0.412)	(0.372)	(1.081)	(0.433)	(0.412)	(1.081)	(0.487)
Dec90	-0.735***	-1.131**	-0.498	-0.594**	-0.849*	-0.463	-0.706**	-0.849*	-0.619
	(0.272)	(0.499)	(0.336)	(0.292)	(0.497)	(0.364)	(0.298)	(0.497)	(0.377)
Dec00	-0.988***	-1.149**	-1.136***	-1.081***	-1.186	-1.235***	-1.118***	-1.186	-1.277***
	(0.271)	(0.556)	(0.355)	(0.299)	(0.757)	(0.389)	(0.303)	(0.757)	(0.396)
Dec10	0.378		0.668	0.744		0.963	1.144		1.332
	(0.866)		(1.003)	(0.856)		(1.016)	(0.842)		(1.042)
Const	-2.623***	-1.889	-3.368***	-2.899***	-2.652*	-3.513***	-2.640***	-2.652*	-3.175***
	(0.582)	(1.497)	(0.773)	(0.642)	(1.562)	(0.823)	(0.649)	(1.562)	(0.825)
#Obs.	983	374	609	915	353	562	861	353	508
#Spells	112	35	77	102	31	71	96	31	65
LogL	-290.1	-84.30	-187.7	-265.3	-74.54	-174.7	-251.2	-74.54	-161.1
SBIC	725.0	281.2	503.7	673.8	260.5	476.0	644.4	260.5	446.8

Notes: See Tables 2 and 3. Here *Δp* is the estimated difference in the duration dependence parameter between "bad" and "good" credit booms; *p+Δp* is the value of the duration dependence parameter for credit booms that ended in a banking crisis (hard landing or "bad" credit booms). For each threshold are reported the results for the estimations with "All", "Bad" and "Good" credit booms, respectively. All economic variables are lagged one period to avoid simultaneity problems.

Table 6: The role of Central Bank independence

	All sample		OECD	Non-OECD	Bad	Good
	(1)	(2)	(3)	(4)	(5)	(6)
p	$2.237^{+,C}$	$2.267^{+,C}$	$2.372^{+,C}$	$2.512^{+,I}$	$3.142^{+,I}$	$2.493^{+,I}$
	(0.182)	(0.182)	(0.365)	(0.307)	(0.501)	(0.281)
Credit/Dep	-0.029***	-0.029***	-0.023	-0.036**	-0.042*	-0.012
	(0.010)	(0.010)	(0.061)	(0.015)	(0.025)	(0.022)
CapInflows	0.003	0.003	0.007	0.003	0.024	0.004
	(0.004)	(0.004)	(0.018)	(0.006)	(0.035)	(0.005)
RGDPgr	-0.119***	-0.105**	-0.189***	-0.115	-0.235***	-0.169**
	(0.041)	(0.042)	(0.073)	(0.072)	(0.071)	(0.077)
Inflation	-0.003	-0.003	-0.003	-0.003	0.004	-0.008**
	(0.003)	(0.003)	(0.016)	(0.004)	(0.003)	(0.004)
CurrAccount	0.097***	0.107***	0.123***	0.098**	0.103*	0.089***
	(0.026)	(0.027)	(0.044)	(0.043)	(0.057)	(0.034)
ApprecREER	-2.023	-2.006	-5.395**	-1.279	1.768	-4.424***
	(1.273)	(1.306)	(2.509)	(1.578)	(1.838)	(1.495)
ExchRateFlex	0.039	0.020	0.350	-0.047	0.074	0.022
	(0.111)	(0.109)	(0.221)	(0.186)	(0.255)	(0.128)
AftElect4	-0.691**	-0.725**	-0.933*	-0.718	-0.972*	-0.740*
	(0.281)	(0.283)	(0.477)	(0.460)	(0.524)	(0.386)
Left	0.061	-0.076	0.035	0.212	-0.147	0.205
	(0.222)	(0.566)	(0.363)	(0.336)	(0.644)	(0.290)
Centre	-1.268***	0.522	-1.346**	-1.545**	-2.907***	0.184
	(0.370)	(1.126)	(0.655)	(0.616)	(0.892)	(0.713)
MajGov	0.599**	0.564**	0.905*	0.201	0.896	0.582
	(0.266)	(0.272)	(0.516)	(0.363)	(1.040)	(0.360)
PartyTenure	-0.001	-0.002	0.002	-0.001	-0.008	-0.001
	(0.003)	(0.002)	(0.006)	(0.004)	(0.005)	(0.004)
ParlSys	-0.240	-0.202	0.389	-0.346	-1.337	-0.055
	(0.294)	(0.308)	(0.726)	(0.389)	(0.966)	(0.392)
CBIndep	1.570***	1.758**	3.191***	0.480	4.907***	0.285
	(0.562)	(0.764)	(1.153)	(0.814)	(1.599)	(0.662)
CBIndepLeft		0.195				
		(0.896)				
CBIndepCentre		-2.783*				
		(1.698)				
OECD	-0.246	-0.276			0.292	-0.498
	(0.267)	(0.274)			(0.804)	(0.354)
Dec80	0.215	0.248	0.377	0.384	-0.598	0.695
	(0.412)	(0.421)	(0.724)	(0.659)	(1.164)	(0.502)
Dec90	-0.686**	-0.808***	-0.351	-0.903**	-0.225	-0.399
	(0.277)	(0.286)	(0.497)	(0.397)	(0.582)	(0.348)
Dec00	-1.059***	-1.063***	-0.513	-1.492***	-1.501**	-1.002***
	(0.285)	(0.283)	(0.473)	(0.374)	(0.620)	(0.380)
Dec10	0.074	0.068	-0.434	1.206		0.535
	(0.858)	(0.864)	(1.084)	(1.101)		(1.022)
Const	-3.711***	-3.784***	-6.884***	-2.867***	-6.846***	-3.522***
	(0.776)	(0.806)	(2.095)	(1.076)	(2.578)	(0.894)
#Obs.	952	952	420	532	367	585
#Spells	106	106	46	60	33	73
LogL	-270.1	-268.2	-112.1	-145.3	-71.51	-176.0
SBIC	684.3	694.2	345.0	416.2	261.1	485.8

Notes: See Tables 2 and 3. Estimations using Gourinchas et al. (2001) criteria with threshold equal to 1.5. Columns 1 and 2 present results for all sample; separate samples for OECD and Non-OECD are presented in columns 3 and 4; and separate regressions for bad and good credit booms are reported in columns 5 and 6. All economic variables are lagged one period to avoid simultaneity problems. *CBIndep* is the Central Bank independence index developed by Garriga (2016); this index is also multiplied by the dummies *Left* and *Centre* to generate the variables *CBIndepLeft* and *CBIndepCentre*, respectively.

ANNEX

Table A.1: Sensitivity analysis: political variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
p	2.128[+,c]	2.121[+,c]	2.126[+,c]	2.124[+,c]	2.139[+,c]	2.135[+,c]	2.130[+,c]
	(0.165)	(0.162)	(0.163)	(0.161)	(0.164)	(0.165)	(0.165)
Credit/Dep	-0.033***	-0.034***	-0.034***	-0.034***	-0.034***	-0.033***	-0.034***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
CapInflows	0.004	0.004	0.004	0.004	0.004	0.005	0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
RGDPgr	-0.128***	-0.127***	-0.128***	-0.126***	-0.120***	-0.120***	-0.125***
	(0.041)	(0.040)	(0.040)	(0.040)	(0.040)	(0.041)	(0.038)
Inflation	-0.004	-0.004	-0.004	-0.004	-0.003	-0.004	-0.004
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
CurrAccount	0.080***	0.079***	0.081***	0.080***	0.080***	0.079***	0.074***
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
ApprecREER	-2.006*	-1.890	-2.003*	-1.815	-1.696	-1.780	-1.785
	(1.141)	(1.178)	(1.123)	(1.199)	(1.193)	(1.182)	(1.227)
ExchRateFlex	-0.073	-0.066	-0.074	-0.062	-0.054	-0.054	-0.055
	(0.109)	(0.110)	(0.109)	(0.109)	(0.108)	(0.108)	(0.110)
BefElect4	0.187						
	(0.220)						
ElectQ		-0.783					
		(0.576)					
ElectYr			0.083				
			(0.223)				
AftElect2				-0.441			
				(0.351)			
AftElect4					-0.602**	-0.547**	-0.620**
					(0.271)	(0.277)	(0.269)
BefElect2						0.254	
						(0.255)	
Left	0.081	0.103	0.111	0.084	0.065	0.057	0.096
	(0.223)	(0.219)	(0.223)	(0.219)	(0.221)	(0.221)	(0.223)
Centre	-1.054***	-1.074***	-1.075***	-1.085***	-1.084***	-1.057***	-1.148***
	(0.336)	(0.337)	(0.336)	(0.336)	(0.340)	(0.342)	(0.343)
MajGov	0.688***	0.672***	0.696***	0.673***	0.650**	0.648**	0.630**
	(0.257)	(0.258)	(0.255)	(0.258)	(0.257)	(0.256)	(0.261)
PartyTenure	-0.002	-0.002	-0.002	-0.002	-0.002	-0.003	
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	
LeaderTenure							-0.002
							(0.010)
ParlSys	-0.382	-0.363	-0.383	-0.366	-0.357	-0.372	-0.291
	(0.279)	(0.282)	(0.283)	(0.282)	(0.282)	(0.282)	(0.267)
OECD	-0.387	-0.379	-0.403	-0.368	-0.332	-0.331	-0.377
	(0.271)	(0.269)	(0.271)	(0.271)	(0.277)	(0.276)	(0.268)
Dec80	0.043	0.012	0.039	0.010	0.011	0.042	0.022
	(0.351)	(0.348)	(0.351)	(0.347)	(0.350)	(0.354)	(0.349)
Dec90	-0.797***	-0.807***	-0.801***	-0.815***	-0.808***	-0.799***	-0.815***
	(0.268)	(0.269)	(0.268)	(0.269)	(0.271)	(0.270)	(0.271)
Dec00	-0.946***	-0.983***	-0.969***	-0.973***	-0.945***	-0.922***	-0.979***
	(0.273)	(0.267)	(0.266)	(0.267)	(0.270)	(0.272)	(0.262)
Dec10	0.343	0.227	0.294	0.224	0.257	0.325	0.224
	(0.865)	(0.855)	(0.863)	(0.853)	(0.841)	(0.848)	(0.835)
Const	-2.420***	-2.336***	-2.375***	-2.331***	-2.324***	-2.376***	-2.326***
	(0.564)	(0.552)	(0.555)	(0.550)	(0.556)	(0.563)	(0.582)
#Obs.	983	983	983	983	983	983	1002
#Spells	112	112	112	112	112	112	112
LogL	-292.6	-291.8	-292.9	-292.1	-290.0	-289.5	-291.5
SBIC	723.0	721.4	723.5	722.0	717.8	723.8	721.2

Notes: See Tables 2 and 3. Estimations using Gourinchas et al. (2001) criteria with threshold equal to 1.5. All economic variables are lagged one period to avoid simultaneity problems. *BefElect4* is equal to 1 in the 4 quarters before the election quarter, and 0 otherwise; *ElectQ* is equal to 1 in the election quarter, and 0 otherwise; *ElectYr* is equal to 1 in the election year quarters, and 0 otherwise; *AftElect2* and *AftElect4* are equal to 1 in the 2 and 4 quarters after the election, respectively, and 0 otherwise; *LeaderTenure* measures number of quarters that the current party leader has been in control of the government office.

Table A.2: Sensitivity analysis: economic variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
p	$2.156^{+,c}$	$2.083^{+,c}$	$2.029^{+,c}$	$2.147^{+,c}$	$2.146^{+,c}$	$2.145^{+,c}$	$2.149^{+,c}$
	(0.214)	(0.165)	(0.167)	(0.191)	(0.190)	(0.191)	(0.166)
Credit/GDP	-0.047						
	(0.073)						
Credit/GDPgr		-0.190					
		(0.605)					
Credit/Pop			0.002				
			(0.002)				
Credit/Dep				-0.033***	-0.033***	-0.033***	-0.034***
				(0.010)	(0.010)	(0.010)	(0.010)
CapInflows	0.007**	0.006*	0.006*				0.004
	(0.003)	(0.003)	(0.004)				(0.004)
PortfInflows				-0.235			
				(0.313)			
OtherInflows					-0.190		
					(0.475)		
TotInflows						-0.057	
						(0.265)	
RGDPgr	-0.091*	-0.053	-0.073**	-0.101**	-0.100**	-0.101**	-0.123***
	(0.054)	(0.036)	(0.037)	(0.044)	(0.044)	(0.044)	(0.040)
Inflation	-0.002	-0.001	-0.002	-0.002	-0.002	-0.002	-0.003
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)
CurrAccount	0.053*	0.060**	0.053**	0.085***	0.084***	0.085***	0.084***
	(0.030)	(0.024)	(0.025)	(0.027)	(0.027)	(0.026)	(0.026)
ApprecREER	-3.404**	-1.503	-1.247	-2.592*	-2.575*	-2.572*	-1.703
	(1.736)	(1.309)	(1.250)	(1.564)	(1.563)	(1.562)	(1.214)
ExchRateFlex	-0.166	-0.039	-0.067	-0.083	-0.088	-0.086	
	(0.141)	(0.107)	(0.110)	(0.113)	(0.113)	(0.113)	
ExchRateFlexF							-0.031
							(0.027)
AftElect4	-0.659**	-0.590**	-0.617**	-0.750**	-0.755**	-0.755**	-0.596**
	(0.305)	(0.270)	(0.275)	(0.302)	(0.302)	(0.302)	(0.271)
Left	0.181	0.188	0.230	-0.101	-0.099	-0.100	0.083
	(0.252)	(0.222)	(0.223)	(0.233)	(0.234)	(0.233)	(0.222)
Centre	-1.306***	-0.900**	-0.892**	-1.150***	-1.128***	-1.129***	-1.109***
	(0.421)	(0.355)	(0.348)	(0.376)	(0.367)	(0.368)	(0.340)
MajGov	0.461**	0.415*	0.426**	0.779***	0.787***	0.782***	0.645**
	(0.204)	(0.234)	(0.213)	(0.287)	(0.287)	(0.287)	(0.254)
PartyTenure	-0.001	-0.001	-0.001	-0.004	-0.004	-0.004	-0.002
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)
ParlSys	-0.717*	-0.571*	-0.534*	-0.342	-0.348	-0.343	-0.375
	(0.351)	(0.298)	(0.282)	(0.294)	(0.293)	(0.294)	(0.288)
OECD	0.242	0.057	0.032	-0.197	-0.191	-0.194	-0.338
	(0.301)	(0.271)	(0.278)	(0.293)	(0.292)	(0.293)	(0.280)
Dec80	-0.395	-0.078	-0.059	-0.147	-0.143	-0.146	0.068
	(0.506)	(0.367)	(0.363)	(0.456)	(0.457)	(0.456)	(0.357)
Dec90	-0.938***	-0.885***	-0.868***	-0.833***	-0.836***	-0.836***	-0.805***
	(0.305)	(0.280)	(0.281)	(0.290)	(0.290)	(0.290)	(0.273)
Dec00	-0.822***	-0.881***	-0.901***	-0.853***	-0.838***	-0.844***	-0.952***
	(0.309)	(0.276)	(0.274)	(0.286)	(0.286)	(0.286)	(0.269)
Dec10	0.377	0.211	0.416	-0.124	-0.131	-0.129	0.159
	(0.901)	(1.094)	(0.802)	(1.206)	(1.209)	(1.208)	(0.850)
Const	-2.444***	-2.781***	-2.605***	-2.378***	-2.374***	-2.370***	-2.203***
	(0.817)	(0.532)	(0.554)	(0.634)	(0.632)	(0.634)	(0.532)
#Obs.	840	996	999	861	861	861	983
#Spells	90	112	114	93	93	93	112
LogL	-235.3	-296.9	-300.8	-243.9	-244.4	-244.5	-289.4
SBIC	605.3	731.9	739.7	623.0	623.9	624.1	716.7

Notes: See Tables 2 and 3. Estimations using Gourinchas et al. (2001) criteria with threshold equal to 1.5. All economic variables are lagged one period to avoid simultaneity problems. *Credit/GDP* is the ratio of private credit to GDP and *Credit/GDPgr* is the respective growth rate; *Credit/Pop* is the ratio of private credit to the population; *PortfInflows* and *OtherInflows* represent, respectively, portfolio investment and other investment liability flows as percentage of GDP; *TotInflows* measures the total gross capital inflows as percentage of GDP(FDI, portfolio investment and other investment); *ExchRateFlexF* is an alternative fine classification for the exchange rate flexibility ranging from 0 to 15 (see Reinhart and Rogoff, 2004; and Ilzetzky et al., 2009).

Table A.3: Robustness checks: additional controllers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
p	$2.121^{+,c}$	$2.187^{+,c}$	$2.093^{+,c}$	$2.255^{+,c}$	$2.209^{+,c}$	$2.209^{+,c}$	$2.278^{+,c}$
	(0.168)	(0.208)	(0.286)	(0.215)	(0.232)	(0.228)	(0.245)
Credit/Dep	-0.034***	-0.036***	0.004	-0.033***	-0.029***	-0.034***	-0.033***
	(0.010)	(0.012)	(0.058)	(0.011)	(0.011)	(0.012)	(0.012)
CapInflows	0.004	0.005	0.001	-0.002	-0.002	-0.003	-0.002
	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)	(0.007)	(0.006)
RGDPgr	-0.115***	-0.167***	-0.263***	-0.154***	-0.130**	-0.136**	-0.136**
	(0.041)	(0.050)	(0.062)	(0.056)	(0.060)	(0.058)	(0.058)
Inflation	-0.003	-0.001	0.003	-0.005	-0.004	-0.005	-0.006
	(0.003)	(0.006)	(0.005)	(0.003)	(0.003)	(0.004)	(0.004)
CurrAccount	0.082***	0.068**	0.024	0.072***	0.075**	0.081***	0.082***
	(0.025)	(0.030)	(0.041)	(0.028)	(0.029)	(0.030)	(0.030)
ApprecREER	-1.568	-1.926	-1.679	-3.299**	-3.182*	-3.420**	-2.773*
	(1.227)	(1.537)	(2.627)	(1.658)	(1.689)	(1.743)	(1.634)
ExchRateFlex	-0.040	-0.124	-0.041	-0.046	-0.054	-0.031	-0.028
	(0.107)	(0.131)	(0.156)	(0.132)	(0.145)	(0.146)	(0.142)
WorldIntRate	-2.929						
	(5.565)						
IntRateSpread		-0.006					
		(0.005)					
CapAccOpen			-0.063				
			(0.667)				
TradeOpen				0.716**	0.666*	0.625*	0.745**
				(0.327)	(0.347)	(0.358)	(0.372)
RiskAversion					0.007		
					(0.014)		
CompRiskRating						-0.008	
						(0.006)	
EcoRiskRating							-0.014
							(0.012)
FinRiskRating							-0.016**
							(0.008)
PolRiskRating							-0.001
							(0.007)
AftElect4	-0.600**	-0.525*	-0.605*	-0.608*	-0.563*	-0.521	-0.556*
	(0.270)	(0.289)	(0.367)	(0.311)	(0.318)	(0.322)	(0.326)
Left	0.019	0.145	0.037	0.024	0.070	0.051	0.112
	(0.227)	(0.256)	(0.314)	(0.245)	(0.260)	(0.262)	(0.259)
Centre	-1.083***	-1.097***	-2.351***	-1.692***	-1.599***	-1.621***	-1.598***
	(0.342)	(0.413)	(0.786)	(0.438)	(0.461)	(0.439)	(0.460)
MajGov	0.628**	0.805**	1.293**	0.676**	0.586*	0.619*	0.659**
	(0.260)	(0.318)	(0.509)	(0.320)	(0.326)	(0.319)	(0.327)
PartyTenure	-0.002	-0.002	0.013	-0.003	-0.002	-0.002	-0.003
	(0.003)	(0.003)	(0.014)	(0.003)	(0.003)	(0.003)	(0.004)
ParlSys	-0.337	-0.472	-0.105	-0.746**	-0.684*	-0.601	-0.723*
	(0.284)	(0.321)	(0.531)	(0.358)	(0.379)	(0.386)	(0.389)
OECD	-0.316	-0.248	-0.362	-0.110	-0.030	0.013	-0.038
	(0.280)	(0.324)	(0.349)	(0.320)	(0.334)	(0.349)	(0.350)
Dec80	0.077	-0.232	0.027	-0.052	-0.525	-0.654	-0.550
	(0.355)	(0.452)	(0.561)	(0.507)	(0.669)	(0.648)	(0.663)
Dec90	-0.767***	-0.890***	-0.477	-0.700**	-0.732**	-0.773**	-0.770**
	(0.285)	(0.313)	(0.453)	(0.310)	(0.336)	(0.326)	(0.333)
Dec00	-0.956***	-0.977***	-0.849**	-0.809**	-0.895***	-0.880***	-0.864**
	(0.270)	(0.299)	(0.387)	(0.321)	(0.329)	(0.334)	(0.338)
Dec10	-0.216	-0.031	-1.398	0.362	0.388	0.282	0.415
	(1.204)	(0.969)	(1.053)	(0.878)	(0.881)	(0.888)	(0.907)
Const	-2.200***	-2.263***	-3.171***	-2.946***	-3.073***	-2.398***	-2.093**
	(0.617)	(0.685)	(1.124)	(0.821)	(0.886)	(0.905)	(0.965)
#Obs.	981	827	501	824	785	782	782
#Spells	111	90	56	88	83	82	82
LogL	-288.3	-233.2	-140.7	-223.8	-213.5	-210.3	-209.6
SBIC	721.4	607.4	412.0	588.6	573.6	567.2	579.2

Notes: See Tables 2 and 3. Estimations using Gourinchas et al. (2001) criteria with threshold equal to 1.5. All economic variables are lagged one period to avoid simultaneity problems. *WorldIntRate* is the world real interest rate proxied by the money market rate of the US as suggested by Di Giovanni and Shambaugh (2008) and collected from the IFS; *IntRateSpread* is the interest rate spread (lending rate minus deposit rate, in percentage; Source: IFS); *CapAccOpen* is an index measuring a country's degree of capital account openness (the Chinn and Ito's (2008) index); *TradeOpen* measures trade openness: exports plus imports over GDP (Source: IFS); *RiskAversion* is a measure for global risk aversion proxied by the VXO index, which is a measure of implied volatility computed using 30-day S&P 100 index at the money options (higher values of this index indicate rising global risk aversion); *EcoRiskRating*, *FinRiskRating*, *PolRiskRating* and *CompRiskRating* are measures for economic, financial, political and composite risk ratings from the International Country risk Guide (ICRG): higher values mean lower risk; *CompRiskRating* is a composite measure of the other three dimensions.

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