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Duration dependence and change-points in the likelihood of credit booms ending

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Abstract

Whether the likelihood of credit booms ending is dependent on its age or not, or whether the respective behaviour is smooth or bumpy are important issues to which the economic literature has not given attention yet. This paper tries to fill that gap in the literature, exploring those issues with a proper duration analysis. Credit booms are identified considering two criteria well established in the literature: (i) the Mendoza-Terrones criteria; (ii) and the Gourinchas-Valdes-Landarretche criteria. A continuous-time Weibull duration model is employed over a group of 71 countries for the period 1975q1-2010q4 to investigate whether credit booms are duration dependent or not. Our findings show that the likelihood of credit booms ending increases over its duration and that these events have become longer over the last decades. Additionally, we extend the baseline Weibull duration model in order to allow for change-points in the duration dependence parameter. The empirical findings support the presence of a change-point: increasing positive duration dependence is observed in booms that last less than eight to ten quarters, but it becomes decreasing or even irrelevant for longer events. Analogous results are found for those credit boom episodes that are followed by systemic banking crisis (bad credit booms). Our findings also show that credit booms are, on average, longer in Industrial than in Developing countries.

Keywords: Credit booms, duration analysis, Weibull model, duration dependence, change-points
JEL Codes: C41,E32, E51

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1. Introduction

The rapid build-up in domestic credit can have deleterious effects on economic activity. Understanding the dynamics of credit is important to evaluate not only the behaviour of the economic activity but also the financial system. The literature argues that recessions are more likely, the longer an economy builds up booms in financial markets —more specifically, booms in credit markets (Brunnermeier and Sannikov, 2012). In addition, there is evidence that the probability of banking distress increases the longer the duration of credit booms are (Barajas, Dell'Ariccia and Levechenko, 2009).

The empirical literature shows that credit expansions can lead to higher growth (Levine, 2005) but also heighten aggregate volatility and the likelihood of banking crisis (Reinhart and Kaminsky, 1999; Demirguc-Kunt and Detragiache, 2002). Credit booms are typically the result of result of surges in private capital inflows (Bruno and Shin, 2012; Calderón and Kubota, 2012; Obstfeld, 2012). These surges lead to a rapid build-up of leverage which, in turn, may lead to financial fragility (Borio and Disyatat, 2011; Gourinchas and Obstfeld, 2012). A massive rising of inflows of foreign capital may lead to excessive monetary and credit expansions (Sidaoui et al., 2011), increase the vulnerability associated to currency and maturity mismatches (Akyuz, 2009), create distortions in asset prices (Agnello and Sousa, 2011; Agnello et al., 2012a) and, consequently, bubbles in stock and market prices and overvaluation of the real exchange rate (Magud et al., 2012).

Duration analysis has been widely used to examine the length of business cycle phases. Diebold and Rudebusch (1992) conduct a duration analysis to evaluate the stabilization process of the economic activity during the post war period. In the same line, Vilasuso (1995) employs nonparametric change-point tests to examine the duration of the business cycle in the United States. Castro (2010) also conducts a duration analysis over a panel of industrial countries and finds evidence that supports that the longer an expansion or contraction, the more likely it is for that phase of the cycle to come to an end. Claessens, Kose and Terrones (2011) apply the Weibull duration model to financial cycles and find that the longer a financial downturn (as measured by the length of peak-to-trough phases in credit, housing prices and equity prices), the more likely this downturn is likely to end.

Hence, understanding the duration of credit boom is of crucial importance given its consequences on the financial sector and economic activity. For instance, Barajas, Dell'Ariccia and Levchenko (2009) and Dell'Ariccia et al. (2012) examine whether the duration of credit booms is important in predicting future financial crisis or not. In fact, the literature finds that the duration (as well as the amplitude) of the credit booms is a robust predictor of those booms that end up in a systemic banking crisis.

The main goals of this paper are: first, to investigate whether the likelihood of credit boom episodes ending depends on its own length of time, i.e. whether they are duration dependent or not; and, second, to analyse whether there are breaks in its behaviour employing a Weibull duration model with change-points. Castro (2012) adapts the Weibull model with change-points proposed by Lara-Porras et al. (2005) to examine the duration of the business cycle phases. Therefore, we follow his strategy in employing a continuous-time Weibull model with change-points to analyze the duration of credit booms.

Our paper uses the quarterly gross capital flows data for 71 countries from 1975q1 and 2010q4. Following Rothenberg and Warnock (2011), Forbes and Warnock (2011), and Calderón and Kubota (2012a, 2012b), we argue that the dynamics of capital flows and credit markets along the business cycles are better captured using quarterly data.

The identification of credit boom episodes follows the work undertaken by Calderon and Kubota (2012b). Given that there is no single criterion to identify credit booms, they use: (i) the Mendoza and Terrones (2008) criteria (MT-criteria) and (ii) and the Gourinchas, Valdes and Landarretche (2001) criteria (GVL-criteria). The first criterion identifies a credit boom when the deviation of the real credit per capita from its trend exceeds 1.75 times its standard deviation, whilst the second one considers that a credit boom takes place if the deviation of the ratio of credit to GDP from its trend exceeds 1.5 times its standard deviation or the (year-on-year) growth in the credit-GDP ratio exceeds 20 percent. The paper also differentiates regular booms vis-a-vis those that end up in a systemic bank crisis or *bad* credit booms. Empirical evidence shows that not all credit booms end in a full-blown banking crisis and that a large share of them are followed by a soft landing (Tornell and Westermann, 2002; Barajas et al. 2009; Calderón and Servén, 2011). Consequently, we define bad credit booms as credit booms followed by a systemic banking crisis (Barajas et al., 2009; Calderón and Kubota, 2011).

We start by estimating a basic continuous-time Weibull model to investigate whether the likelihood of credit booms ending depends on its own age and concluded that, in fact, it does depend: credit booms are affected by positive duration dependence. We then extend the baseline Weibull duration model to allow for change-points in the duration dependence parameter —as implemented in Lara-Porras et al. (2005) and Castro (2012). The basic Weibull model assumes that the behaviour of duration dependence is smooth (i.e. either constant, increasing or decreasing) over time, whereas the degree of likelihood of a credit boom ending as it gets older may change after certain duration. The empirical findings indeed support the presence of a change-point: increasing positive duration dependence is observed in booms that last less than eight to ten quarters, but it becomes decreasing or even non-relevant for longer events (according to the GVL-criteria). This evidence is robust to the criteria used to define credit booms (MT or GVL-criteria) and the sub-group of countries (Industrial or Developing) or time period (pre or post-1990) considered. Analogous results are found for those credit booms that end up in a systemic banking crisis (bad credit booms).

The main messages of this paper are: first, that the evidence of true duration dependence is helpful in predicting credit boom episodes. The evidence of positive duration dependence implies that the risk of a credit boom ending in any particular time increases over time. If credit booms are characterised by positive duration dependence, then the duration analysis provides information which is useful in predicting turning points in the economy. Consequently, our finding of duration dependence provides evidence of predictability of credit booms. Second, our results with change-points suggest the presence of a breaking-point in credit boom episodes. The predictability of credit booms can be improved if they last less than 2 to 2 ½ years, according to the MT-criteria and GVL-criteria, respectively. However, the longer the credit boom persists – more than 2 or 2 ½ years – less predictable its end becomes, because the likelihood of their end is no longer dependent on its age, but probably depends on other time-varying random factors. Finally, we also find robust evidence of positive duration dependence for bad credit booms. In this case, the risk of a credit boom ending up in a banking crisis increases over time. Additionally, the analysis with change-points also suggests the presence of a breaking-point in credit boom episodes followed by systemic banking crisis.

Thus, our findings indicate the ending of credit booms depends positively on the length of its life span. For the MT-criteria they also show that the mean duration of credit booms is higher in industrial countries than in developing countries, therefore, credit boom episodes are more persistent, on average, in industrial countries than in developing countries. The empirical evidence provided by the estimation of the Weibull model with change-points also supports the presence of (increasing) positive duration dependence. These results imply that, on average, the duration of credit booms lasts within 2 to 2 ½ years in the last decade for MT-criteria and GVL-criteria, respectively. Specifically, the duration with the MT-criteria lasts within 2.5 years for all and developing countries in the pre-1990 period while within 3 ¾ years for industrial countries for the post-1990 period. The case of GVL-criteria duration becomes slower: 2.5 to 3 ¾ years.

All these results represent remarkable new findings in this field of the research and an important contribution to the literature and to a better understanding of the credit booms behaviour.

The rest of the paper is organized as follows. Section 2 reviews the existing literature on credit booms and duration analysis. Section 3 presents the econometric models. Section 4 describes the data and the methodology. The empirical analysis and the discussion of the results are presented in Section 5. Finally, Section 6 concludes.

2. Literature Review

This section reviews the theoretical and empirical literature of the drivers and consequences of credit booms and their duration. We first outline some empirical facts and theoretical arguments about the creation of credit booms. Then we review the few existing papers on the importance of the duration of credit booms when predicting financial and economic downturns. Finally, we review some of empirical applications of duration analysis in the Economics literature.

Rapid growth of domestic credit can take place in an economy due to the deepening of financial intermediaries (Levine, 2005), upswings in credit demand during normal output recoveries, and excessive cyclical fluctuations —or the so-called credit booms (Elekdag and Wu, 2011). In turn, credit booms are triggered, according to the literature, by (positive) productivity shocks, financial reforms, and surges in capital inflows (Dell'Ariccia et al. 2012). In fact, Mendoza and Terrones (2012) find that 20-50 percent of the peak of credit booms in industrial and emerging market economies is preceded by productivity surges, financial reforms, and massive capital inflow episodes. Elekdag and Wu (2011) add that loose monetary policy in industrial and emerging economies may have contributed to the build-up of credit booms prior to the 2008-9 global financial crises. They also corroborate the findings in the literature that longer credit booms are related to lower credit standards, deteriorating balance sheets among banks and corporations, and warning signs of overheating —such as, strong domestic demand, widening current account deficits, massive inflows of foreign finance and rising asset prices.

Minsky (1986) suggested that a benign economic environment —characterized by high growth and low output volatility— would increase speculative investor euphoria and lead to excess risk taking. Debt would exceed what agents can pay-off from their proceeds, thus leading to a financial crisis. As the credit bubble bursts, banks will curtail credit not only to sub-prime borrowers but also to those that can afford to borrow, and the economy will subsequently enter into a spiral of recession.

Recent theoretical efforts show that financial frictions can severely affect real economic activity. Brunnermeier and Sannikov (2012) build a dynamic stochastic general equilibrium model where shocks are amplified and propagated through leverage and asset prices. Their model introduces a mechanism through which agents respond to exogenous declines in macroeconomic risk by increasing leverage (i.e. rapid increase in credit). Consequently, low exogenous risk environment (a feature of the Great Moderation period) would be conducive to a greater build-up of systemic risk. In this setting, low fundamental risks (as signalled by low output volatility) leads to higher leverage (that is, longer and sharper credit expansions). In turn, the leverage build-up will lead to abrupt macroeconomic contractions. To put it simply, they argue that financial crises and, hence, recessions are more likely to take place, the longer an economy builds up booms in financial markets —and, more specifically, booms in credit markets.

Understanding the genesis and drivers of financial booms is important due to their devastating consequences on real economic activity. Claessens, Kose and Terrones (2012) provide an analysis of the linkages between real and financial cycles and, more specifically, the influence of financial booms (either in credit or asset prices) on the duration and amplitude of recessions and recoveries in real economic activity. They find that boom-bust financial cycles are highly synchronized with real cycles and, consequently, affect the duration and strength of recessions and recoveries. In particular, recessions associated with financial disruptions —that is, credit crunches and/or housing price busts— tend to be longer and deeper, and their ensuing recoveries are slightly shorter and stronger when combined with booms in financial markets. As financial disruptions are associated with longer and deeper recessions, recoveries associated with credit or housing price booms are associated with stronger output growth. Levine (2005) shows that credit expansions can lead to higher growth although these expansions may heighten aggregate volatility and the likelihood of banking crisis (Reinhart and Kaminsky, 1999; Demirguc-Kunt and Detragiache, 2002).

Barajas, Dell'Ariccia and Levchenko (2009) examine empirically the nature of credit booms —especially those that end up in a full blown banking crisis. They suggest that the probability of banking distress will increase the longer a credit boom in an economy is. Gourinchas and Obstfeld (2012) argue that financial crises in advanced and emerging market economies over the last century have been preceded by financial booms —that, typically, take the form of rapid growth of domestic credit and large appreciation of the domestic currency. Schularick and Taylor (2012) confirm this result for 14 advanced countries over the period 1870-2008. They argue that failures in the operation, regulation and/or supervision of the financial system have led to recurrent episodes of financial instability. In turn, these episodes are the outcome of "credit booms gone wrong." Barajas et al. (2009), in addition, show that it is not only the amplitude of the credit boom but also its duration that help predict future systemic banking crisis. In sum, understanding the duration of credit boom is of crucial importance given its consequences on the financial sector and economic activity.

The literature argues that credit booms do not always end up in systemic crises. For instance, Tornell and Westermann (2002) that the probability of a systemic banking crisis in a given country *i* at time *T*, conditional on a lending boom, is around 6 percent. Barajas et al. (2009) find that approximately 16 percent of lending booms have preceded systemic banking crises and that this likelihood will rise to 23 percent if non-systemic episodes of financial distress are included. In addition, they find that there are size and duration thresholds above which credit booms inevitably are followed by a crisis —approximately 40% of credit booms that last between 9 and 12 years end up in a crisis, whereas all credit booms over 13 years will invariably are followed by financial turmoil. These findings suggest that hard landing does not necessarily follow a boom in credit markets —especially so for shorter booms. However, longer booms (especially those over 12 years) may reflect either excessive risk taking or cronyism. In the light of these empirical findings, it might be important to distinguish whether the effects of surging capital inflows may be differ when explaining the incidence of credit booms that end up in a crisis (i.e. bad credit booms) from those credit booms followed by a soft landing (which we can denote as "good" credit booms).

Capital inflows and credit booms. Capital flows play an important role in driving credit booms —with the probability of credit booms being preceded by surges in capital inflows being larger among emerging market economies than among industrial countries (Elekdag and Wu, 2011). In particular, the sharp movements in capital flows – as a result of the recent globalization process – have put the emphasis of the analysis on the link between those flows and developments in domestic financial markets. Recent theoretical research has modelled the linkages between capital flows and banking leverage through the mechanisms that leads to rising gross flows of foreign financing in the banking sector (Bruno and Shin, 2012). They tend to show that gross capital flows move in the opposite direction of risk premia in capital markets, reflecting the sensitivity of bank leverage to risk premia.

Furceri et al. (2011) examine the relationship between capital inflows and credit in a dynamic perspective. They calculate the dynamic response (IRFs) of domestic credit to capital inflow shocks using an annual data from 1970 to 2007 for developed and emerging market economies and show that in the event of a capital inflow shock, the ratio of credit to GDP tends to increase during the first two years following the shock but the effect is reversed in the medium-term. They also find that the macroeconomic policy stance of the country may help mitigate the short-term effect of these shocks.

Calderon and Kubota (2012) use quarterly data for a wide array of countries to examine the dynamic relationship between gross inflows and credit booms. They find that an increase in gross capital inflows is more likely to predict subsequent credit booms. They also show that not all types of gross inflows have the same predictive ability: while surges in equity-type flows have no relationship or, at best, reduce the probability of build-ups in credit, a massive inflow of debt-type securities would raise the likelihood of credit booms.

On the other hand, the literature shows that these surges in capital inflows lead to a rapid build-up of leverage which, in turn, may lead to financial fragility (Borio and Disyatat, 2011; Gourinchas and Obstfeld, 2012). A massive rising inflows of foreign capital may lead to excessive monetary and credit expansions (Sidaoui et al., 2011), increase the vulnerability associated to currency and maturity mismatches (Akyuz, 2009), create distortions in asset prices (Agnello and Sousa, 2012a; Agnello et al., 2012a) and, consequently, lead to stock and housing price bubbles as well as an overvaluation of the real exchange rate (Magud et al., 2012). Recent empirical efforts show that the flexibility of the exchange rate arrangement may act as counteract the impact of gross inflows on credit expansions. Magud et. al (2012) show that surges of capital inflows in countries with less flexible monetary arrangements lead to a more rapid credit expansion and to a shift towards foreign currency. As shown in Calvo et. al (2004, 2008), the vulnerability to capital inflow reversals is greater in countries with more inflexible exchange rate regimes. These reversals, in turn, could potentially trigger credit busts and asset price deflation with deleterious effects on real economic activity.

These studies explore deeply the links between credit booms, capital flows, crises and the respective outcomes, but neglect the issue of their duration, which is another important dimension to understand the credit booms behaviour. Moreover, as the historical analysis shows the presence of several events of credit booms, with similar outcomes but different durations, the issue of their duration analysis gains even more relevance.

Having flourished in the engineering and medical fields, the duration analysis rapidly spread out to other sciences. In economics, it started to be employed in labour economics to assess the duration of periods of unemployment.[1] It has also been widely used in the analysis of the duration of the business cycle phases.[2] A basic Weibull model is usually employed in those studies with the aim of finding duration dependence in the phases of the business cycle, i.e. whether the likelihood of expansions and recessions ending is dependent on its age or not. However, this model assumes that the behaviour of duration dependence is smooth over the entire duration of the event, which may not be true. Given this limitation, Castro (2012) adapts the Weibull model with change-points proposed by Lara-Porras et al. (2005) to the analysis of the duration of the business cycle phases. This author shows that positive duration dependence in expansions is no longer present when they last more than ten years, which proves the presence of a change-point in the duration of economic expansions.

Other studies also show the presence of duration dependence in different dimensions of the economy. For instance, Bracke (2011) and Cunningham and Kolet (2011) show that the likelihood of housing booms and busts ending is positively dependent on their age. More recently, Agnello et al. (2012b) provide some evidence indicating that fiscal consolidations are also duration dependent.

Due to its properties, this kind of analysis is also suitable for studying the duration of credit booms. Hence, we employ a continuous-time Weibull model to investigate the presence of duration dependence in a large group of countries over the last decades. Additionally, we also control for the presence of change-points in the structure of the model. In the next section, we describe the aplication of these models to the study of the duration of credit booms. This analysis represents an important contribution to the economic literature in this field and it intends to contribute to a better understanding of the credit booms behaviour.

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[1] See Allison (1982) and Kiefer (1988) for a review of the literature on duration analysis.

[2] See, for example, Sichel (1991), Zuehlke (2003), Davig (2007) and Castro (2010, 2012).

3. Econometric models

This section describes the duration analysis techniques conducted in our empirical paper – more, specifically, the basic Weibull model and a Weibull model with change-points.

3.1. Duration analysis

We start by assuming that the duration variable is defined as the number of periods (quarters) a credit boom is taking place. If T measures the time span between the beginning of a credit boom and its end, then $t_1, t_2, \ldots, t_n$ will represent its observed duration. The probability distribution of the duration variable, T, can be specified by the cumulative distribution function, $F(t)=Pr(T<t)$, and the corresponding density function is $f(t)=dF(t)/dt$. Alternatively, the distribution of T can be characterized by the survivor function, $S(t)=Pr(T\geq t)=1-F(t)$, which measures the probability that the duration of a credit boom phase is larger or equal to t.

A particularly useful function for duration analysis is the hazard function such as:

$$h(t) = f(t)/S(t) \tag{1}$$

which 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 state in moment t conditional on the length of time in that state. This function helps characterizing the path of duration dependence. For instance: (i) if $dh(t)/dt>0$ for $t=t^*$, there is positive duration dependence in t^*; (ii) if $dh(t)/dt<0$ for $t=t^*$, then there is negative duration dependence in t^*; and (iii) if $dh(t)/dt=0$ for $t=t^*$, there is no duration dependence. Therefore, when the derivative of the hazard function with respect to time is positive, the probability of a credit boom ending in moment t, given that it has reached t^*, increases with its age. Thus, the longer the credit boom is, the higher the conditional probability of its end will be.

From the hazard function, we can derive the integrated hazard function such that:

$$H(t) = \int_0^t h(u)du \tag{2}$$

and compute the survivor function as follows:

$$S(t) = exp[-H(t)] \tag{3}$$

While different parametric countinuous-time duration models can measure the magnitude of duration dependence and the impact of other time-invariant variables on the likelihood of an event ending, the most commonly used functional form of the hazard function is the proportional hazard model as:

$$h(t, x) = h_0(t)exp(\beta' x) \tag{4}$$

where $h_0(t)$ is the baseline hazard function that captures the data dependence of duration and represents an unknown parameter to be estimated, $\boldsymbol{\beta}$ is a (K×1) vector of parameters that need to be estimated and **x** is a vector of covariates. The proportional hazard model can be estimated without imposing any specific functional form to the baseline hazard function (the so called "Cox model"). Given the inappropriateness of this procedure (in particular, for studying duration dependence), a popular alternative imposes a specific parametric form for the function $h_0(t)$ (i.e. the "Weibull model").

3.2. The basic Weibull model

The Weibull model is characterized by the following (baseline) hazard function as:

$$h_0(t) = \gamma p t^{p-1} \tag{5}$$

where p parameterizes the duration dependence, t denotes time, γ is a constant, $p>0$ and $\gamma>0$. 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 $p=1$. In this last case, the Weibull model is equal to an Exponential model. Therefore, by estimating p, we can test for duration dependence in credit boom phases.

If we plug the Weibull specification for the baseline hazard function as expressed by equation (5) in the proportional hazard function denoted by (4), we get:

$$h(t,x) = \gamma p t^{p-1} \exp(\beta' x) \tag{6}$$

Hence, the corresponding survivor function can be written as:

$$S(t,x) = exp[-H(t,x)] = exp[-\gamma t^{p} \exp(\beta' x)] \tag{7}$$

This model can be estimated by Maximum Likelihood, and the log-likelihood function for a sample of i=1,…,n boom episodes is given by:

$$\begin{aligned} \ln L(\cdot) &= \ln \prod_{i=1}^{n} f(t_i, x_i) = \ln \prod_{i=1}^{n} h(t_i, x_i)^{c_i} S(t_i, x_i) = \sum_{i=1}^{n} [c_i \, ln \, h(t_i, x_i) + ln \, S(t_i, x_i)] \\ &= \textstyle\sum_{i=1}^{n} [c_i(\ln \gamma + \ln p + (p-1) \ln t_i + \beta' x_i) - \gamma t_i^{p} \, exp(\beta' x_i)] \end{aligned} \tag{8}$$

where c_i indicates when observations are censored. If the sample period under analysis ends before the turning point has been observed, then observations will be censored (i.e. c_i=0); when the turning points are observed in the sample period, the observations are not censored (in which case, c_i=1).

3.3. *A Weibull model with change-points*

While the basic structure of the log-likelihood function for the Weibull model allows us to analyze the presence of duration dependence in credit boom phases, we also move a step further in that we assess the extent to which the likelihood of a boom ending as it gets older changes after a certain duration. Thus, we allow for the possibility of a structural break in the Weibull model and conjecture that the parameters of the baseline hazard function (p and γ) can change at a certain point (i.e. the "change-point") in time. In particular, we expect that the degree of duration dependence, p, changes after the event has lasted more than a certain time. Consequently, we do not only expect that the likelihood of a credit boom phase ending increases over time, but also that if it has lasted more than a certain time, the likelihood of ending may change significantly after that point, that is, the magnitude of duration dependence may decrease or increase from that point onwards.

We propose a Weibull model for credit boom phases with change-points that follows the general model framework developed by Lara-Porras et al. (2005) and Castro (2012) for cases where the Weibull distribution, or the respective parameters characterizing the baseline hazard function, varies over time for different intervals, but remain constant within each interval. For simplicity, let us re-write equation (5) as:

$$h_0(t) = \gamma p t^{p-1} = \lambda p (\lambda t)^{p-1} \tag{9}$$

where $\gamma=\lambda^p$. Hence, the survival function becomes:

$$S(t,x) = exp[-H(t,x)] = exp[(\lambda t)^p \exp(\beta' x)] \tag{10}$$

Denoting $g(t)=lnH(t)$ and considering a change point, τ_c, and two intervals, $t_0<t\leq\tau_c$ and $\tau_c<t\leq t_T$, $g(t)$ can be expressed as:

$$g(t) = \ln(\lambda_j t)^{p_j} \tag{11}$$

with j=1,2. Due to the fact that the continuity of $g(t)$ in the change-point, τ_c has to be verified, we must impose that:

$$\ln(\lambda_1 \tau_c)^{p_1} = \ln(\lambda_2 \tau_c)^{p_2} \tag{12}$$

Solving this equation with respect to p_2, we get:

$$p_2 = p_1 \frac{\ln(\lambda_1 \tau_c)}{\ln(\lambda_2 \tau_c)} \tag{13}$$

Consequently, in the case of the survival time ending in the first interval, we have that:

$$g(t) = p_1 \ln(\lambda_1 t) \tag{14}$$

and, similarly, for the following survival time ending in the second interval:

$$g(t) = p_2 \ln(\lambda_2 t) = p_2 \ln(\lambda_2 t) \frac{\ln(\lambda_1 \tau_c)}{\ln(\lambda_2 \tau_c)} \tag{15}$$

Considering the *i*-th spell (or individual), we get:

$$g(t_i) = d_i p_1 \ln(\lambda_1 t_i) + (1 - d_i) p_1 \ln(\lambda_2 t_i) \frac{\ln(\lambda_1 \tau_c)}{\ln(\lambda_2 \tau_c)} \tag{16}$$

where d_i=1 if $t_0<t\leq\tau_c$, d_i=0 if $\tau_c<t\leq t_T$, and i=1,2,...,n (i.e. the number of spells).

For $H(t_i,\mathbf{x}_i)=exp[g(t_i)+\boldsymbol{\beta}'\mathbf{x}_i]$, the hazard function is given by:

$$h(t_i, x_i) = dH(t_i, x_i)/dt_i = g'(t_i)H(t_i, x_i) = \left[d_i \frac{p_1}{t_i} + (1 - d_i) \frac{p_1}{t_i} \frac{\ln(\lambda_1 \tau_c)}{\ln(\lambda_2 \tau_c)}\right] H(t_i, x_i) \tag{17}$$

and the corresponding survivor function can be expressed as:

$$S(t_i, x_i) = exp[-H(t_i, x_i)] \tag{18}$$

Therefore, the log-likelihood function can be written as:

$$\ln L(\cdot) = \sum_{i=1}^{n} \{c_i [\ln g'(t_i) + g(t_i) + \beta' x_i] - exp[g(t_i) + \beta' x_i]\} \tag{19}$$

where $g'(t) = d_i \dfrac{p_1}{t_i} + (1 - d_i) \dfrac{p_1}{t_i} \dfrac{\ln(\lambda_1 t_c)}{\ln(\lambda_2 t_c)}$. This model is estimated by Maximum Likelihood, given a particular change-point τ_c. The relevance of the change-point is evaluated by testing whether there is a statistically significant difference between p_1 and p_2, i.e. whether the duration dependence parameter changes significantly between the two sub-periods.

4. Data and Methodology

This section describes the definition and sources of the data for our empirical assessment and the strategy to identify credit booms. Then we show the descriptive statistics for the episodes and duration of credit booms and identify the duration of credit booms.

To proceed with the duration analysis, we collected quarterly data for 71 countries (23 industrial economies and 48 emerging market economies) from 1975q1 to 2010q4 on real credit. The measure of credit considered in our analysis is the deposit money bank claims on the private sector taken from the line 22d of the IMF's International Financial Statistics (IFS). We express the amount of credit in real terms by dividing the nominal credit by the CPI index (at the end of the quarter). Other measures of credit considered in this study are the ratio of real credit to GDP and the leverage of the banking system. The latter indicator is computed as the ratio of private credit to bank deposits where deposits are measured as the sum of demand and time deposits (IFS lines 24 and 25, respectively).

However, our aim is to identify credit booms to compute the respective duration. Defining a credit boom is not easy because there is no consensus in the literature on the best methodology to identify them. Some studies use the amount of real credit provided by the banking system; others use the bank lending normalized by either total population or the amount of goods produced in the real economy. In this study we decided to focus on the criteria used by Calderón and Kubota (2012) for their analysis on the effects of surges in private capital inflows over credit booms. In their paper they consider the following criteria from the literature on credit booms: (i) Mendoza and Terrones (2008) or MT-criteria; and (ii) Gourinchas, Valdes and Landarretche (2001) or GVL-criteria, which is later implemented and updated by Barajas, Dell'Ariccia and Levchenko (2009).

In the criteria defined by Mendoza and Terrones (2008) to identify credit booms, an episode of credit boom takes place whenever the amount of credit extended by the banking system to the private sector grows by more than its experience during a typical cyclical expansion. The amount of real credit per capita, l_{it}, is the key variable to identify a boom in lending. They denote $\tilde{l}_{it}$ as the deviation of (the log of) real credit per capita from its long-run trend (or its cyclical component), and $\sigma\left(\tilde{l}_{it}\right)$ as its corresponding standard deviation. In this study, we follow Mendonza and Terrones' (2008) strategy in computing the long-run trend of real credit per capita using the Hodrick-Prescott (HP) filter.

A country is considered to have experienced a credit boom if it has one or more subsequent quarters where the condition $\tilde{l}_{it} > \varphi\sigma\left(\tilde{l}_{it}\right)$ holds. The factor φ is a threshold factor set by Mendonza and Terrones (2008) at 1.75. We adopted this factor as a basis for our analysis, but we also consider other values of φ (1.5 and 2.0) to evaluate the robustness of our results. Note that the peak date of the credit boom, $\hat{t}$, takes place in the quarter that maximizes the deviation $\left\{\tilde{l}_{it} - \varphi\sigma\left(\tilde{l}_{it}\right)\right\}$ from the set of contiguous quarters while it satisfies the condition stated above. Once $\hat{t}$ has been determined, the starting period of the credit boom t^S is such that $t^S < \hat{t}$ and it yields the smallest value for $\left\{\tilde{l}_{it} - \varphi^S\sigma\left(\tilde{l}_{it}\right)\right\}$ while the final period of the boom t^F is such that $t^F < \hat{t}$ and also yields the smallest value for $\left\{\tilde{l}_{it} - \varphi^F\sigma\left(\tilde{l}_{it}\right)\right\}$ where $\varphi^S = \varphi^F = 1$.

For robustness, we also consider the GVL-criteria to identify credit booms. This method identifies a credit boom by looking at the growth of credit in the economy as 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 determined threshold. In particular, a credit boom takes place if the ratio of private credit to GDP meets either of the following two conditions: (i) the deviation of *L/y* from its estimated trend, say *L/y*, is greater than 1.5 times its standard deviation and the year-on-year growth rate of *L/y* exceeds 10 percent, and/or (ii) the year-on-year growth rate in the ratio *L/y* exceeds 20 percent.[3] We also adopted this procedure but, like in the MT-criteria, we considered other thresholds in a robustness analysis: 1.75 and 2.0.

[3] According to Barajas et al. (2009), the starting and final quarter of the identified credit boom is defined accordingly. The beginning of the episode is the earliest year in which *L/y* is greater than ¾, its standard deviation and the annual growth rate of *L/y* exceeds 5 percent, or the annual growth rate of *L/y* exceeds 10

These methodologies offer some differences. The MT-criteria uses the real credit per capita to identify booms in credit markets whereas the GVL-criteria use the ratio of credit to GDP. Both criteria use the HP-filter to compute the trend in credit and apply a rolling variant of the filter that takes information up to the moment where the deviation is computed. Thresholds are country-specific rather than based on the cross-sectional distribution of countries. Like Calderón and Kubota (2012), we use quarterly information on credit, which, as they argue, is more appropriate to assess cyclical movements and volatility associated to crisis episodes.[4]

We collect quarterly information on real credit provided by the banking system to the private sector for 71 countries from 1975q1 to 2010q4 to identify the credit boom episodes according to the two criteria outlined above. Table 1 presents some descriptive statistics for the number of episodes identified (Obs.), their mean duration (Mean), standard deviation (S.D.), minimum (Min.) and maximum (Max.). Industrial and Developing countries and different periods of time are also considered in this analysis.

<Insert Table 1 around here>

Using the MT-criteria we are able to identify 123 credit boom episodes over our entire time dimension -- of which 32 episodes took place in Industrial economies and 91 in Developing countries. Over time, most episodes of lending booms occur in the 1990s (50). On the other hand, when we use the GVL-criteria, we are able to identify a larger number of episodes (231), especially in the period 2000-2010 (98).[5] Most of them also occur in the group of Developing countries (180).

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percent. Analogously, the end quarter of the boom is determined if either the year-on-year growth rate of *L/y* becomes negative, or *L/y* falls below ¾ times its standard deviation and its growth rate is lower than 20 percent.

[4] 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) rather than the value of 100 used in the MT-criteria to decompose the annual data.

[5] This means that the GVL criteria allow us to identify many episodes of credit booms in the run-up to the recent global financial crisis.

By organizing the data in spells – where a spell represents the number of years that a credit boom lasts and it is denoted by *Dur* – we are able to compute their mean duration.[6] According to the MT-criteria, credit booms last on average around 6.1 quarters, but they last longer in the group of Industrial countries (7.5) than in the group of Developing countries (5.6) – see Table 1. According to the GVL-criteria they tend to last a bit more (about 8.5 quarters), either for Industrial or Developing countries. Whether there is any significant difference or not in the duration of credit booms between these groups of countries is something that we will test below in the empirical analysis. In particular, we will test whether there is a significant difference in the average duration of credit booms, as well as in the duration dependence parameter (*p*) between these two groups of countries. This will be done by including the dummy *D_Indus* in the model, which takes the value of 1 for Industrial countries and 0 otherwise. Moreover, some separate regressions for each of these groups will also be considered.

Additionally, we observe in Table 1 that the average duration of credit booms has increased over the last decades, independently of the criteria used. Whether this evidence is statistically solid is another issue that we will explore in the empirical analysis using dummies for each decade (*Dec70*, *Dec80*, *Dec90*, *Dec00*). Following Castro (2012), we also consider a kind of a trend variable for the credit boom spells, labelled as Event, to check whether their duration has become gradually longer or shorter over time. This variable reports the order or observation number of each event over time and for every single country: it is equal to 1 for the first event, 2 for the second, and so on. If the coefficient on this variable is significantly smaller (larger) than zero, phase durations get longer (shorter) over time or, better, from spell to spell.

5. Empirical Analysis

This section investigates whether there is positive duration dependence in credit boom episodes using quarterly data from 1975q1 to 2010q4 for both industrial and developing countries (23 and 48, respectively). We also conduct a test whether there is positive duration

[6] The variable Dur corresponds to t_{i} in the model described in the previous Section.

dependence in bad credit booms followed a systemic banking crisis. We analyse the results from the basic Weibull duration model and the model with change-points. Finally, we conduct a series of robustness checks.

5.1. The baseline model

The empirical evidence that emerges from the estimation of the basic Weibull model presented in sub-Section 3.2 is summarized in Tables 2 and 3. These tables are divided in two blocks, one for each criterion used to define credit booms: the MT-criteria and the GVL-criteria. We start by recalling that the estimate of p measures the magnitude of the duration dependence and γ corresponds to the estimate of the constant term. A one-sided test is used to detect the presence of positive duration dependence (i.e. whether $p>1$) and the sign '+' indicates significance at a 5% level.

The results reported in Table 2 provide strong evidence of positive duration dependence for credit booms, either using the MT-criteria or the GVL-criteria. This means that the likelihood of a credit boom ending increases as the time goes by. This is robust for all regressions presented in this table although significant differences arise in the dynamic path of this likelihood between the MT-criteria and the GVL-criteria. the probability of credit booms ending at time *t*, provided that they lasted until that period grows over time at an increasing rate according to the MT-criteria, but at a decreasing rate according to the GVL-criteria.[7] For instance, p is in most of the cases statistically greater than 2 when the MT-criteria is used, therefore, the statistical analysis of the second-order derivative of the baseline hazard function indicates the presence of constant positive duration dependence in credit booms. On the other hand, *p* is lower than 2 in most cases when the GVL criteria is used; that is, there is evidence of a decreasing duration dependence in the GVL-defined credit booms. Our result is in line with the shorter mean duration of the credit booms identified by the MT-criteria, as observed above in the descriptive statistics. Nevertheless, we should emphasize that positive duration dependence is present in the duration of credit booms independently of the criteria used to identify them.

[7] See Castro (2010, 2012) for details on the analysis of the second-order derivative of the baseline hazard function.

<Insert Table 2 around here>

We assumed that credit booms may have a length from one quarter to the maximum observable in our sample although, according to our characterization, their minimum duration is higher than one (it is two – see Table 1). Therefore, our duration analysis evaluates whether truncating the booms at their minimum duration affects the results or not. Consequently, the hazard rate must be identically zero for the first quarter and some non-zero value thereafter. Truncation is made at the minimum observable durations: $d_0 = min(d_i)$-1, where min(d_i) is the shortest boom observed in the sample (two, in our case). This means that the survival function is now:

$$S(t_i, x_i) = exp\left[-\gamma\left(t_i^p - d_0^p\right)exp(\beta' x_i)\right] \tag{20}$$

Truncation is allowed for in the regressions presented in Column 2 of Table 2, but the results are not affected by this "small" truncation. This implies that positive duration dependence is still present in credit booms regardless the criteria used to define these booms. In general, results in the duration research are generally not sensitive to the choice of this minimum observable duration and the qualitative conclusions tend to be identical in any case.[8] Thus, we will carry on with our analysis without taking into account this intricacy in the model.

In the regressions presented in column 1, we also assume that the population of individual spells is homogeneous, i.e. each credit boom is under the same risk of ending. Given that this may not represent the reality, the regressions in column 3 allow for the presence of unobserved heterogeneity or frailty. In statistical terms, a frailty model is similar to a random-effects model for duration analysis: it represents an unobserved random proportionality factor that modifies the hazard function of an individual spell and accounts for heterogeneity caused by unmeasured covariates or measurement errors. In order to include

[8] See, for example, Sichel (1991), Layton and Smith (2007) and Castro (2010, 2012).

frailty in the Weibull model, the hazard function expressed by equation (6) is modified as follows:

$$h(t,x|v) = vh(t,x) \tag{21}$$

where *v* is an unobserved individual-spell effect that scales the no-frailty component. The random variable *v* is assumed to be positive with unity mean, finite variance (θ) and independently distributed from *t* and **x**. The survival function becomes:

$$S(t,x|v) = [S(t,x)]^{v} \tag{22}$$

Since the values of v are not observed, we cannot estimate them. Therefore, we follow Lancaster (1990) and assume v follows a Gamma distribution with unity mean and variance θ. Consequently, the frailty survival function can be written as:

$$S(t,x|\beta,\theta) = [1-\theta \ln S(t,x)]^{-(1/\theta)} \tag{23}$$

the frailty hazard function becomes:

$$h(t,x|\beta,\theta) = h(t,x)[S(t,x|\beta,\theta)]^{\theta} \tag{24}$$

and the corresponding log-likelihood function can be expressed as:

$$\ln L(\cdot) = \sum_{i=1}^{n} \left\{c_i[\ln \gamma + \ln p + (p-1)\ln t_i + \beta' x_i] - \left(c_i + \frac{1}{\theta}\right)\ln\left[1+\gamma t_i^{p} exp(\beta' x_i)\right]\right\} \tag{25}$$

The variance parameter (θ), which measures the presence (or absence) of unobserved heterogeneity, is an additional parameter that needs to be estimated. As θ is always greater than zero, the limiting distribution of the maximum-likelihood estimate of θ is a normal distribution that is halved or chopped-off at the zero-bound. Therefore, the likelihood ratio test (*LR test*) used to detect its presence is a `boundary' test that takes in account the fact that the null distribution is not the usual chi-squared with one degree of freedom, but rather a mixture of a chi-squared with no degrees of freedom and a chi-squared with one degree of freedom (Gutierrez et al., 2001). The results show some evidence of unobserved heterogeneity, as corroborated by the *p-value* of the *LR test* reported at the bottom of column 3: at a 5% level we do not reject the presence of frailty either using the MT-criteria or GVL-criteria. This can be due to the omission of some relevant conditionings. According to Jenkins (2005, p. 81) omitted variables are one reason for the presence of frailty in the model. Hence, in the next regressions we will control for that problem including some additional regressors in the equation.[9]

In particular, frailty can be linked to the presence of individual country-specific effects in the model. Therefore, in the regressions in column 4 we add country-dummy variables to the equation. In this case, the test for pooling, i.e. the *LR test*, is used to assess whether the model controlling for country-specific effects is preferred to simple pooling. The *p-value* of the *LR test* reported at the bottom of column 4 supports the existence of those effects. However, Claessens et al. (2011, p.17) points out that having only a limited number of observations/spells per country – which is our case – fixed effects may have to be ruled out. In fact, we had some difficulties in achieving convergence when country-dummies are included in the model, especially when other regressors are used. Hence, we decided to simplify the analysis considering only two sets of countries that present some homogeneity inside each group, but that are heterogeneous between then: Industrial and Developing countries. This procedure (partially) solves the problems faced with the use of country-dummies – controlling for eventual individual or group heterogeneity – and allow us to test for differences in the mean duration of credit booms between those two groups of countries.

Thus, in Column 5, we add the dummy variable *D_Indus* to the model. We observe that the coefficient associated to this variable is negative and statistically significant when the MT-criteria is considered. This suggests that, on average, credit booms tend to last longer in

[9] We should stress that when we tried to control for frailty with those additional regressors the model did not achieve convergence. Therefore, we conduct our analysis with the more parsimonious structure for the Weibull model.

the group of Industrial countries.[10] However, when the GVL-criteria is used no significant differences are found in the mean duration of credit booms between Industrial and Developing countries. These two findings are well in line with what we have observed in the descriptive statistics (see Table 1).

Another issue that can be analysed here is whether the duration dependence parameter is the same for Industrial and Developing countries or not. To analyze this issue, we start by replacing the parameter p by $p+\Delta pD\_Indus$ in the regressions presented in column 6 to directly estimate that difference (i.e. Δp); in column 7, we also include the dummy *D_Indus*. When the MT-criteria is used, we observe a significant difference in the the duration dependence parameter between those two groups of countries (column 6), however, that difference becomes statistically insignificant when the dummy *D_Indus* is added to the equation (see column 7). This means that the main difference between them is in the mean duration of credit booms and not in the duration dependence parameter: evidence of positive duration dependence is found for both groups of countries, as shown in the regression in column 7 or even in the separate regressions for Industrial and Developing countries presented in columns 8 and 9, respectively. However, despite the duration dependence parameter begin statistically similar, our findings indicate the presence of increasing duration dependence in the first group and constant duration dependence in the second. Hence, the rate at which credit booms end in the group of industrial countries is slightly higher, even though the difference is not statistically significant.

When we employ the GVL-criteria, no significant differences are observed either in the duration dependence parameter or in the mean duration of credit booms between those groups of countries. Nevertheless, we should note that: (i) like in the MT-criteria, the rate at which credit booms end in the group of Industrial countries is slightly higher than in the group of Developing countries (even though this difference is not significant); (ii) but, unlike the MT-criteria, we observe constant positive duration dependence in the first group (instead of increasing) and decreasing (instead of constant) positive duration dependence in the second. This conclusion is corroborated in the separate regressions presented in columns 8 and 9.

[10] Note that a negative coefficient means a lower probability of the event ending over time, i.e a longer duration.

In sum, our findings show that credit booms are duration dependent. In particular, they show that the likelihood of these events ending increases over time, at an increasing rate if they are defined using the MT-criteria, but at a decreasing rate if the GVL-criteria is used instead. Moreover, with the MT-criteria we also observe that the mean duration of credit booms is higher in the group of Industrial countries than in the group of Developing countries.

As we are using a continuous-time duration model, there is no scope to include regressors that vary over time, but it is possible to consider a few that remain constant over each spell. The dummy *D_Indus*, included in some regressions above, is one example. Other possible regressors are the trend variable *Event* for spells and the dummies for the decades (*Dec80*, *Dec90*, *Dec00*). These additional regressors are included in the first two regressions presented in Table 3 to collect for possible time effects. The results confirm the presence of positive duration dependence (increasing with the MT-criteria and decreasing with the GVL-criteria) and a lower likelihood of credit booms ending for Industrial countries (with the MT-criteria). Moreover, the negative coefficient on *Event* shows that credit booms have become longer from spell to spell, but its effect has not proved to be statistically significant, When controlling for time-effects using dummies for the decades, however, we are able to unveil significant effects. The results indicate that the likelihood of a credit boom ending indeed decreases over time, especially in the 1900s and 2000s. To collect this effect more precisely, we created another dummy to group these two decades: *D*90_10. This dummy takes the value of one for the period between 1990 and 2010, and zero otherwise. Both regressions presented in column 3 confirm that, on average, credit booms have indeed become longer after 1990.[11] This implies that longer credit booms may be associated to increasing financial globalization. The rapid expansion of global asset trade —as observed by the increased financial globalization over the last 25 years— has led to rising gross inflows and higher levels of activity in credit markets. Claessens et al. (2012) show that greater financial openness reduces the duration of downturns in credit markets and that it may also increase the duration of credit booms. Hence, we can infer that the greater duration dependence can be perceived as a

[11] These findings are also in line with what we have observed in the descriptive statistics (see Table 1)

consequence of the increasing globalization process, deeper integration and liberalization of some markets and economies and higher capital mobility observed since the 1990s.

<Insert Table 3 around here>

Similarly to what we did above for the groups of Industrial and Developing countries, we also analyze here whether the duration dependence parameter is the same or not before and after 1990. Hence, we replace the parameter p by $p+\Delta pD90\_10$ in the regressions presented in column 4 to directly estimate that difference (i.e. Δp); in column 5, we also include the dummy $D90\_10$. We observe a significant difference in the duration dependence parameter between those two periods (column 4) and that difference remains significant when the dummy $D90\_10$ is included, especially in the GVL-criteria (see column 5). However, the coefficient on the dummy looses its statistical significance. Hence, the main difference between these two periods is more in the duration dependence parameter than in the mean duration of credit booms. In fact, separate regressions in columns 6 and 7 for the pre- and post-1990 periods, respectively, show that the difference in the constant parameter γ is negligible while the difference in the duration dependence parameter is substantial, especially when the GVL-criteria is considered. This might mean that this second criteria is more sensitive to the higher duration of credit booms in the last few years. In fact, the GVL-criteria allow us to identify many episodes of credit booms in the run-up to the recent global financial crisis as well as booms that have occurred during the recovery that followed the recent crisis. Moreover, with these criteria we observe the presence of constant positive duration dependence in the pre-1990 period and decreasing duration dependence in the post-1990 period, which reflects the higher propensity for longer credit booms in the recent years.[12] As a result, the recent financial globalization leads to longer trough-to-peak cycles in credit —and more specifically, longer credit booms, especially in industrial countries.

[12] However, this evidence is not so clear when the MT-criteria is used: both duration dependence parameters (for pre- and post-1990 periods) present evidence of increasing duration dependence and their difference is not statistically significant (see columns 5 to 7).

Are all credit booms alike? Looking at the duration dependence of bad credit booms.

We test whether there is a positive duration dependence in bad credit booms. It is clear from the literature that not all credit booms end in crisis —most of them are followed by soft landing (Tornell and Westermann, 2002; Barajas et al. 2009; Calderón and Servén, 2011). More specifically, it is likely that one out of four credit boom episodes will end with a currency or a banking crisis (Mendoza and Terrones, 2012). Table 4 provides these results for bad credit booms followed a systemic banking crisis.

Independently of the criteria used, we robustly find the presence of positive duration dependence for bad credit booms —which evolves at a constant pace over time. Consequently, bad credit booms have a greater propensity to end over time. This evidence is even more robust when we estimate the model with a change-point. Here, our findings show that the likelihood of bad credit booms ending increases at a faster pace for those that last less than 10 quarters. For those episodes with longer duration, their respective likelihood increases at a decreasing rate. This implies that they tend to persist for a bit longer once they pass that threshold. The difference between the parameters (p_2-p_1) is also statistically significant which supports the suitability of the change-points Weibull model to the analysis of the duration of bad credit booms.

Regarding the effect of the additional regressors, we are not able to find any significant impact. The coefficients on D_Indus, Event and D90_10 fail to be statistically significant. Hence, there are not significant differences in the level of the duration dependence coefficient between industrial and developing countries (column 2) or pre- vis-à-vis after 1990 (column 4).[13]

Thus, our results show the presence of positive duration dependence and of a change-point in the duration of bad credit booms, independently of the criteria used to define them (MT or GVL) and the sub-group of countries (Industrial or Developing) or time period (pre- or post-1990) considered. Therefore, we robustly find that bad credit booms also tend to die out within two years and a half.

[13] We also controlled for decade dummies. The estimated coefficients for these dummies were not statistically significant.

<Insert Table 4 around here>

5.2. The model with change-points in duration dependence

The results presented in Tables 2 and 3 rely on the assumption that the magnitude of the duration dependence parameter is invariant whatever the duration of the credit booms spells is. In Figure 1, we plot the survivor functions for credit booms for all countries, Industrial and Developing countries and pre- and post-1990 periods, regarding the two concepts to define credit booms (the MT and GVL-criteria). It is clear that the probability (or proportion) of a credit boom surviving after duration t_i substantially decreases as they become older. This sharp decline is consistent with the existence of positive duration dependence. Moreover, the survivor functions quickly fall until t_i=8 – for all the cases considering the MT-criteria – and until t_i=10 (for all and Developing countries and for the pre-1990 period) or t_i=15 (for the Industrial countries and for the post-1990 period) – for the cases considering the GVL-criteria – but, and these evolve at a slower pace. This highlights the possibility of breaks in duration dependence and it is necessary to have a more flexible framework allowing for change-points in the Weibull distribution at τ_c=8 (MT-criteria) and τ_c=10 or τ_c=15 (GVL-criteria). In fact, Figure 1 suggests that the magnitude of duration dependence parameter might be lower when credit booms are longer than those values and the likelihood of their ending can significantly change above those thresholds.[14] Thus, there is significant evidence to suspect that change-points in the duration of credit booms may indeed exist.

<Insert Figure 1 around here>

[14] Another signal of the existence of a break-point in duration dependence for credit booms is provided by the slope of the survivor functions. For example, in the case of the full sample, our computations show that the average slope, considering the MT-criteria (GVL-criteria), is equal to -0.128 (-0.090) for booms that are shorter than 8 (10) quarters and -0.020 (-0.013) for those that last longer than 8 (10) quarters. Putting it differently, when credit booms have a duration shorter than 8 (10) quarters, each additional quarter of duration, on average, increases the likelihood of they ending by about 12.8 (9.0) percentage points. In contrast, when they have a length longer than 8 (10) quarters, each additional quarter of duration rises the likelihood of they ending by only 2.0 (1.3) percentage points. Similar conclusions were reached for the sub-samples. The respective computations are available upon request.

In order to test for the presence of differences in the duration dependence parameter, we consider a Weibull model with change-points. For each criterion, we estimate two dependence duration parameters, one for the first duration-period (p_1) and another one for the second duration-period (p_2), and evaluate the statistical significance of the difference between the two (p_2-p_1).[15,16] The results are reported in Table 5.

In column 1, we estimate a simple equation without covariates. In column 2, we control for differences in the average duration of credit booms between Industrial and Developing countries and to account for the possibility of their duration change over time. Columns 3 and 4 present the results of separate regressions for Industrial and Developing countries, respectively, controlling for time-effects. In column 5, the dummies for the time-effects are replaced by the dummy for the post-1990 period.[17] Finally, columns 6 and 7 present separate regressions for the pre- and post-1990 periods, respectively, controlling for group-effects.

<Insert Table 5 around here>

As expected, the results presented in Table 5 show that the duration dependence parameter indeed varies with the duration of the credit boom spells. In particular, the magnitude of the duration dependence parameter is always significantly lower when credit booms are longer than 8 or 10 quarters, considering they are defined by the MT-criteria or GVL-criteria, respectively. Remarkably, the difference between the parameters after and before the respective change-point (p_2-p_1) is always negative and statistically significant,

[15] The estimates for the two constant terms are $\gamma_1=\lambda_1^{p_1}$ and $\gamma_2=\lambda_2^{p_2}$.

[16] The delta method is used to compute the respective standard-errors.

[17] As it very complex to control, at the same time, for change-points and different duration dependence parameters for the pre- and post-1990 periods, we use instead the dummy *D*90_10 and estimate separate regressions for both periods to control for those time differences.

independently of the criteria used to define credit booms.[18] In particular, considering the MT-criteria, increasing positive duration dependence is observed in credit booms that last less than 8 quarters, while decreasing (or constant) duration dependence characterizes those booms that last more than that threshold. Consequently, our findings show that there is significant evidence of credit boom episodes ending within two years. With the GVL-criteria, even though increasing duration dependence is observed for booms that last less than 10 quarters, when their length is longer, duration dependence is no more present, i.e. the likelihood of ending is no longer dependent on their age. Indeed, while the parameter p_1 is statistically significant in all specifications, p_2 does not seem to exhibit statistical significance. As a result, independently of the criteria used, we robustly find that there is a change-point in the duration of credit booms. Moreover, all these results hold even when country/group-effects and time-effects are controlled for.

After controlling for change-points, we are still observing that the average duration of credit booms is significantly higher in the group of Industrial countries and that its duration has increased over the last two decades (see, in particular, columns 2 and 5). As our final exercise, we control for the presence of change points in each group of countries (columns 3 and 4) and time-periods (columns 6 and 7) separately. Independently of the criterion or subgroups used, all results show the presence of a change-point, therefore, this confirms our simple plotted charts in Figure 1. Overall, the results are similar to the ones obtained with the full sample except for developing countries. When the MT-criteria is used for developing countries (column 4), we confirm the presence of (increasing) duration dependence for credit booms that last less than 8 quarters, however, duration dependence is no longer present for those booms that last more than that threshold.

Thus, our results conclude that there is strong evidence supporting the presence of a change-point in the duration of credit booms, independently of the criteria used to define them (MT or GVL) and the sub-group of countries (Industrial or Developing) or time period (pre-

[18] Even though Figure 1 is clear about the location of the change-points, we tried other quarters as change-points, but unsurprisingly this difference was never statistically significant in those cases. Those additional results are not reported here to save space but they are available upon request.

or post-1990) considered. Therefore, our findings show strong evidence that the life of credit booms dies out within two years regardless of any criteria, sub-group of countries and time period used.

5.3. Robustness checks

The MT-criteria identifies a credit boom when the deviation of the real credit per capita from its trend exceeds 1.75 times its standard deviation. The GVL-criteria considers that a credit boom takes place if the deviation of the ratio of credit to GDP from its trend exceeds 1.5 times its standard deviation or the (year-on-year) growth in the credit-GDP ratio exceeds 20 percent. For robustness purposes, we consider different and reasonable values for those parameters and check whether our findings are robust to those changes or not. Accordingly, for the MT-criteria, we replace the parameter φ=1.75 by φ=1.5 and φ=2.0 and for the GVL-criteria, we consider φ=1.75 and φ=2.0 instead of φ=1.5. Table 6 presents the results of these robustness checks for both criteria with different parameters. For this analysis, we select the more representative equations from the regressions presented above for both the basic Weibull model and the Weibull model with change-points.

<Insert Table 6 around here>

Starting with the MT-criteria and considering the basic Weibull specification (columns 1 and 3 in Table 6), the results support our empirical findings: there is evidence of increasing duration dependence using either the 1.5 or 2.0 thresholds. These results also confirm that industrial countries are characterized by longer credit booms and that their length has increased over the last couple of decades. This evidence is also supported by the Weibull specifications with change-points (columns 2 and 4). Most importantly, we corroborate the presence of a change-point in credit booms at the same 8 quarters threshold as increasing positive duration dependence is found for shorter booms while their duration dependence is constant for longer ones. Consequently, the difference in the duration dependence parameters is statistically significant either at φ=1.5 or φ=2.0.

The results for the GVL-criteria are not different from the ones obtained above: (i) the basic Weibull specifications (regressions 5 and 7) confirm the evidence of decreasing duration dependence; (ii) there are no significant differences between industrial and developing countries; (iii) credit booms became longer over the last decades; (v) the presence of a change-point is confirmed (the difference p_2-p_1 is statistically significant either for φ=1.75 or φ=2.0); (vi) increasing duration dependence is observed for those booms that last less than 10 quarters although, once again, no duration dependence is found for longer events. As a result, our robustness analysis confirms our empirical findings.

6. Conclusions

This paper analyses whether the credit booms are duration dependent and investigates the presence of change-points in the likelihood of they ending. It represents an avenue of research that, to the best of our knowledge, remains vastly unexplored in the empirical literature of credit booms. We employ a continuous-time duration model over a group of 71 countries from 1975q1 to 2010q4 to investigate whether the likelihood of credit booms ending indeed depends on its own age and to check the presence of change-points in its behaviour. The credit booms considered in this analysis were identified using two criteria well established in the literature: the Mendoza-Terrones and the Gourinchas-Valdes-Landarretche criteria.

The main message of this paper is that there is robust evidence of positive duration dependence in credit booms. This finding provides information of the predictability of credit boom episodes. It implies that the risk of credit booms coming to an end in a particular year increases over time.

Our results also show that these events have become longer over the last decades, which means an increase in the persistence of credit boom phases over time. Moreover, the findings provided by this study also indicate that credit booms are, on average, longer in Industrial than in Developing countries.

Additionally, the baseline Weibull duration model was extended to allow for breaks or change-points in the duration dependence parameter. While the basic Weibull model assumes that the behaviour of duration dependence is smooth (i.e. either constant, increasing or decreasing) over time, the degree of likelihood of a credit boom ending as it gets older may change after a given duration. The empirical findings indeed support the presence of a change-point: increasing positive duration dependence is observed in booms that last less than eight to ten quarters, but it becomes decreasing or even non-relevant for longer events (according to the GVL-criteria). This evidence is robust to the criteria used to define credit booms (MT or GVL criteria) and the sub-group of countries (Industrial or Developing) or time period (pre- or post-1990) considered. This represents a striking finding in this field of the literature that certainly contributes to a better and deeper understanding of the credit booms behaviour. Moreover, it can also contribute to a timely formulation of policies that can help fine-tuning the trade-off between credit and economic growth.

Additionally, we also show that those credit booms that end up in a crisis (bad credit booms) also exhibit evidence of positive duration dependence and the presence of a change-point: the likelihood of bad booms ending increases at an increasing rate for those that last less than 10 quarters; for those that last longer the respective likelihood also increases but at a decreasing rate.

While providing valuable information on the duration of credit booms, the present paper opens new avenues for further work. For instance, given that the selection of the change-point is exogenously determined by a sensible graphical analysis of the survivor function, an interesting extension of this piece of research would be to incorporate a discrete latent variable in the standard Weibull model. This would make the selection of the change-point endogenous, thereby, representing a challenging and promising approach to be considered in the future.

Finally, we observed that longer credit booms tend to be less dependent on its age – as shown by the Weibull model with change-points. Hence, it is likely that other time-varying factors might be considered to explain its duration. This means that the study of the duration of credit booms can also be extended with the application of discrete-time duration models that allow for the inclusion of those time-varying covariates. That is another dimension of the problem that is beyond of the scope of this paper but to which the authors are carefully addressing in another paper.

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List of Tables

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

Dur	Obs.	Mean	S.D.	Min.	Max.
MT (2008) criteria					
All countries	123	6.05	2.8	2	17
Industrial countries	32	7.44	2.83	4	16
Develping countries	91	5.56	2.63	2	17
D_Indus	123	0.26	0.44	0	1
Event	123	1.52	0.77	1	5
1975-1979	12	4.67	2.31	2	8
1980-1989	30	5.63	2.22	2	10
1990-1999	50	6.46	3.23	2	17
2000-2010	31	6.32	2.61	2	12
GVL (2001) criteria					
All countries	231	8.53	5.88	2	35
Industrial countries	51	8.51	5.28	2	27
Develping countries	180	8.54	6.05	2	35
D_Indus	231	0.22	0.42	0	1
Event	231	2.23	1.24	1	7
1975-1979	16	5.69	2.89	2	12
1980-1989	41	5.98	3.05	2	16
1990-1999	76	8.93	5.42	2	27
2000-2010	98	9.77	6.95	2	35

Notes : This table reports the number of episodes (Obs.), the mean duration (Mean), the standard deviation (S.D.), the minimum (Min.) and the maximum (Max.) duration for credit boom spells. The data are quarterly and comprises 79 countries over the period 1975q1-2010q4. Credit booms are identified using the works of Mendoza and Terrones (2008) and Gourinchas et al. (2001). The MT-criteria identifies a credit boom when the deviation of the real credit per capita from its trend exceeds 1.75 times its standard deviation. The GVL-criteria considers that a credit boom takes place if the deviation of the ratio of credit to GDP from its trend exceeds 1.5 times its standard deviation or the (year-on-year) growth in the credit-GDP ratio exceeds 20 percent. Note that this criteria was more recently applied and updated by Barajas, Dell'Ariccia and Levchenko (2009).

Table 2: Duration dependence in credit booms: basic Weibull model estimation

MT-criteria	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
γ	0.0113 ***	0.0137 **	0.0048 **	0.0056	0.0118 **	0.0105 **	0.0148 **	0.0027	0.0148 **
	[0.0042]	[0.0058]	[0.0021]	[0.0060]	[0.0047]	[0.0044]	[0.0067]	[0.0018]	[0.0068]
p	2.320 +,i	2.236 +,c	2.903 +,i	4.724 +,i	2.387 +,i	2.431 +,i	2.275 +,c	2.784 +,i	2.275 +,c
	[0.189]	[0.209]	[0.235]	[0.390]	[0.218]	[0.235]	[0.245]	[0.326]	[0.245]
Δp						-0.212 **	0.510		
						[0.111]	[0.403]		
p+Δp						2.219 +,c	2.784 +,i		
						[0.202]	[0.321]		
θ			0.337 **						
			[0.147]						
D_Indus					-0.564 **		-1.701 **		
					[0.237]		[0.805]		
LogL	-84.78	-288.72	-81.96	-18.15	-80.81	-287.31	-285.42	-15.28	-64.66
LR test			0.022	0.000					
SBIC	179.18	587.07	178.36	397.21	176.07	589.05	590.08	37.50	138.35
Spells	123	123	123	123	123	123	123	32	91
GVL-criteria									
γ	0.0245 ***	0.0338 ***	0.0033 **	0.0269 **	0.0241 ***	0.0243 ***	0.0263 ***	0.0177 **	0.0263 ***
	[0.0043]	[0.0073]	[0.0013]	[0.0124]	[0.0042]	[0.042]	[0.0049]	[0.0077]	[0.0049]
p	1.627 +,d	1.513 +,d	2.931 +,i	2.348 +,i	1.627 +,d	1.621 +,d	1.593 +,d	1.772 +,c	1.593 +,d
	[0.080]	[0.092]	[0.242]	[0.130]	[0.079]	[0.081]	[0.087]	[0.187]	[0.087]
Δp						0.037	0.179		
						[0.072]	[0.203]		
p+Δp						1.657 +,d	1.772 +,c		
						[0.094]	[0.184]		
θ			1.062 ***						
			[0.215]						
D_Indus					0.056		-0.397		
					[0.171]		[0.469]		
LogL	-231.73	-667.37	-213.16	-171.29	-231.67	-673.75	-673.47	-47.90	-183.36
LR test			0.000	0.001					
SBIC	474.34	1345.62	442.64	777.97	479.67	1353.49	1368.70	103.66	377.10
Spells	231	231	231	231	231	231	231	51	180

Notes: Estimations for the duration of credit booms considering the Mendoza and Terrones (2008) criteria (first block) and Gourinchas et al. (2001) criteria (second block). Heteroscedasticity and serial autocorrelation robust standard errors clustered by country are reported in square brackets; ***, **, * - 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 and increasing positive duration dependence, respectively; Δp is the estimated difference in the duration dependence parameter between Industrial and Developing countries; $p+\Delta p$ is the value of the duration dependence parameter for the Industrial countries. The Schwartz Bayesian Information Criterion (SBIC) is computed as follows: $SBIC=2(-logL+(k/2)logN)$, where k is the number of regressors and N is the number of observations (spells). Truncation at the minimum values of *Dur* is used in the regressions presented in column 2. In column 3, the p-value of the LR test for unobserved heterogeneity/frailty gives assesses if the estimated variance (θ) is different from zero. In column 4, the *p-value* of the *LR test* analyses the statistical significance of country-specific dummy variables (pooling test), that is, $LR=-2(logL_{r}-logL_{u})$, where r and u correspond to the restricted and unrestricted models, respectively. Columns 8 and 9 present separate regression results for the Industrial and Developing countries, respectively

Table 3: Duration dependence in credit booms: basic Weibull with time-effects

MT-criteria	(1)	(2)	(3)	(4)	(5)	(6)	(7)
γ	0.0125 *	0.0171 **	0.0137 **	0.0101 ***	0.0097 *	0.0094 *	0.0103 **
	[0.0067]	[0.0073]	[0.0058]	[0.0039]	[0.0057]	[0.0056]	[0.0044]
p	2.388 +,i	2.478 +,i	2.450 +,i	2.609 +,i	2.624 +,i	2.624 +,i	2.393 +,i
	[0.215]	[0.194]	[0.204]	[0.198]	[0.273]	[0.274]	[0.237]
Δp				-0.220 **	-0.241		
				[0.100]	[0.296]		
p+Δp				2.389 +,i	2.383 +,i		
				[0.209]	[0.228]		
D_Indus	-0.576 **	-0.519 **	-0.497 **	-0.489 **	-0.489 **	-0.237	-0.579 **
	[0.235]	[0.223]	[0.234]	[0.230]	[0.229]	[0.304]	[0.289]
Event	-0.037						
	[0.179]						
Dec80		-0.357					
		[0.291]					
Dec90		-0.774 ***					
		[0.284]					
Dec00		-0.588 **					
		[0.268]					
D90_10			-0.439 **		0.046		
			[0.203]		[0.611]		
LogL	-80.78	-77.65	-78.46	-283.72	-283.72	-26.04	-51.94
SBIC	180.81	184.17	176.17	586.69	591.50	63.30	117.07
Spells	123	123	123	123	123	42	81
GVL-criteria							
γ	0.0269 ***	0.0387 ***	0.0374 **	0.0177 **	0.0167 ***	0.0152 ***	0.184 ***
	[0.0056]	[0.0104]	[0.0072]	[0.0033]	[0.0065]	[0.0057]	[0.0039]
p	1.627 +,d	1.772 +,d	1.756 +,d	2.117 +,c	2.143 +,c	2.167 +,c	1.666 +,d
	[0.080]	[0.078]	[0.082]	[0.111]	[0.202]	[0.196]	[0.088]
Δp				-0.442 ***	-0.475 **		
				[0.077]	[0.219]		
p+Δp				1.675 +,d	1.668 +,d		
				[0.080]	[0.088]		
D_Indus	0.023	0.112	0.125	0.135	0.136	0.378	0.071
	[0.176]	[0.168]	[0.164]	[0.161]	[0.161]	[0.265]	[0.0173]
Event	-0.047						
	[0.175]						
Dec80		-0.092					
		[0.224]					
Dec90		-0.876 ***					
		[0.267]					
Dec00		-1.156 ***					
		[0.246]					
D90_10			-0.962 ***		0.079		
			[0.139]		[0.434]		
LogL	-231.41	-214.90	-216.55	-656.48	-656.47	-43.36	-170.60
SBIC	484.60	462.46	454.87	1334.74	1340.16	98.85	356.68
Spells	231	231	231	231	231	57	174

Notes : See Table 2. Δp is the estimated difference in the duration dependence parameter between the pre- and post-1990 periods; hence, $p+\Delta p$ is the value of the duration dependence parameter for the the period post-1990; Columns 6 and 7 present separate regression results for the pre- and post-1990 periods, respectively.

Table 4: Duration dependence in bad credit booms

MT-criteria	(1)	(2)	(3)	(4)	(5)	(6)
γ_1	0.0156 *	0.0154	0.0108	0.0161	0.1409 ***	0.1853 ***
	[0.0076]	[0.0096]	[0.0069]	[0.0191]	[0.0098]	[0.0467]
γ_2					0.2316 ***	0.3954 ***
					[0.0763]	[0.1142]
p_1	2.086 +,c	2.141 +,c	2.147 +,c	2.272 +,c	2.457 +,c	2.491 +,i
	[0.235]	[0.313]	[0.254]	[0.515]	[0.280]	[0.276]
p_2					1.003	1.118
					[0.253]	[0.340]
Δp		-0.028		-0.127		
		[0.443]		[0.567]		
p+Δp		2.114 +,c		2.146 +,c		
		[0.314]		[0.270]		
p_2-p_1					-1.454 ***	-1.373 ***
					[0.398]	[0.445]
D_Indus		-0.427	-0.464	-0.408		-0.334
		[1.031]	[0.459]	[0.470]		[0.407]
Event			0.312			
			[0.458]			
D90_10				-0.134		-0.306
				[1.262]		[0.370]
LogL	-34.15	-108.17	-33.15	-107.68	-106.61	-105.77
SBIC	75.83	231.39	81.34	234.17	224.50	234.10
Spells	43	43	43	43	43	43

GVL-criteria	(1)	(2)	(3)	(4)	(5)	(6)
γ_1	0.0081 **	0.0093 **	0.0091	0.0101	0.1037 ***	0.4141 ***
	[0.0033]	[0.0047]	[0.0060]	[0.0123]	[0.0072]	[0.0971]
γ_2					0.1068 ***	1.2637 *
					[0.0146]	[0.6613]
p_1	2.022 +,c	1.949 +,c	2.033 +,c	2.039 +,c	2.682 +,i	2.686 +,i
	[0.150]	[0.181]	[0.155]	[0.417]	[0.344]	[0.350]
p_2					1.475 +,d	1.505 +,d
					[0.223]	[0.221]
Δp		0.339		0.014		
		[0.299]		[0.438]		
p+Δp		2.288 +,c		2.053 +,c		
		[0.239]		[0.157]		
p_2-p_1					-1.208 ***	-1.181 ***
					[0.445]	[0.450]
D_Indus		-0.683	0.147	0.249		0.212
		[0.773]	[0.374]	[0.357]		[0.326]
Event			-0.154			
			[0.399]			
D90_10				-0.404		-0.287
				[1.252]		[0.392]
LogL	-40.72	-144.15	-40.48	-144.01	-141.99	-141.66
SBIC	89.23	303.86	96.53	307.48	295.66	302.77
Spells	49	49	49	49	49	49

Notes: See Tables 2 and 3. Δp is the estimated difference in the duration dependence parameter between industrial and developing countries (column 2) and the pre- and post-1990 periods (column 4); hence, p+Δp is the value of the duration dependence parameter for industrial and the post-1990 period, respectively; p2-p1 is the estimated difference in the duration dependence parameters in the model with a change-point.
The change point is located at 10 quaters of duration for both criteria.

Table 5: Duration dependence in credit booms: basic Weibull with change-points

MT-criteria	(1)	(2)	(3)	(4)	(5)	(6)	(7)
γ_1	0.1513 ***	0.2269 ***	0.2118 ***	0.258 ***	0.2340 **	0.2969 ***	0.7370 ***
	[0.0052]	[0.0210]	[0.0743]	[0.0357]	[0.0984]	[0.0478]	[0.1291]
γ_2	0.181 ***	0.3546 ***	0.4597 *	0.4607 *	0.3800 *	0.3577 **	3.8444
	[0.0183]	[0.0412]	[0.2431]	[0.2567]	[0.2080]	[0.1439]	[4.120]
p_1	2.833 +,i	2.890 +,i	4.616 +,i	2.662 +,i	2.888 +,i	2.683 +,i	3.026 +,i
	[0.218]	[0.219]	[0.668]	[0.215]	[0.219]	[0.311]	[0.279]
p_2	1.457 +,d	1.653 +,c	1.867 +,c	1.479	1.628 +,c	2.206 +,c	1.567 +,c
	[0.232]	[0.277]	[0.387]	[0.373]	[0.278]	[0.436]	[0.313]
$p_2 - p_1$	-1.376 ***	-1.237 ***	-2.743 ***	-1.183 ***	-1.259 ***	-0.477	-1.459 ***
	[0.306]	[0.337]	[0.795]	[0.422]	[0.334]	[0.547]	[0.430]
D_Indus		-0.466 **			-0.459 **	-0.245	-0.533 **
		[0.189]			[0.190]	[0.295]	[0.229]
Dec80		-0.327	1.024 **	-0.488			
		[0.314]	[0.438]	[0.334]			
Dec90		-0.618 **	-0.088	-0.598 **			
		[0.288]	[0.302]	[0.310]			
Dec00		-0.567 *	0.267	-0.683 **			
		[0.292]	[0.384]	[0.320]			
D90_10					-0.353 *		
					[0.183]		
LogL	-283.98	-278.77	-70.66	-203.05	-279.22	-92.08	-186.57
SBIC	582.41	596.03	165.59	437.68	587.32	202.86	395.10
Spells	123	123	32	91	123	42	81

GVL-criteria	(1)	(2)	(3)	(4)	(5)	(6)	(7)
γ_1	0.1167 ***	0.1797 ***	0.1168 ***	0.1695 ***	0.1805	0.2300 ***	0.1704 ***
	[0.0034]	[0.0197]	[0.0216]	[0.0105]	[0.1751]	[0.0368]	[0.0094]
γ_2	0.1436 ***	0.3527 ***	0.2433	0.3151 ***	0.3633	0.5584	0.4747 ***
	[0.0135]	[0.952]	[0.2089]	[0.0740]	[0.7174]	[0.4510]	[0.1588]
p_1	2.346 +,i	2.426 +,i	2.328 +,c	2.388 +,i	2.429 +,i	2.364 +,i	2.002 +,c
	[0.135]	[0.140]	[0.306]	[0.130]	[0.141]	[0.216]	[0.120
p_2	1.001	1.128	1.008	1.098	1.112	1.145	0.957
	[0.093]	[0.102]	[0.278]	[0.109]	[0.102]	[0.286]	[0.126]
$p_2 - p_1$	-1.345 ***	-1.297 ***	-1.320 ***	-1.290 ***	-1.317 ***	-1.219 ***	-1.043 ***
	[0.170]	[0.181]	[0.510]	[0.167]	[0.181]	[0.413]	[0.126]
D_Indus		0.065			0.069	0.321	0.018
		[0.140]			[0.139]	[0.277]	[0.155]
Dec80		-0.079	-0.076	-0.080			
		[0.277]	[0.593]	[0.301]			
Dec90		-0.801 ***	-1.588 ***	-0.644 **			
		[0.296]	[0.543]	[0.330]			
Dec00		-0.976 ***	-1.254 ***	-0.966 ***			
		[0.279]	[0.541]	[0.312]			
D90_10					-0.838 ***		
					[0.146]		
LogL	-650.35	-637.66	-138.88	-497.31	-638.32	-136.07	-509.91
SBIC	1317.03	1313.43	305.28	1030.98	1309.30	292.36	1040.46
Spells	231	231	51	180	231	57	174

Notes : See Tables 2 and 3. p_2-p_1 is the estimated difference in the duration dependence parameters. Columns 3 and 4 present separate regression results for the Industrial and Developing countries, respectively. Columns 6 and 7 present separate regression results for the pre- and post-1990 periods, respectively. The change-point is located at duration equal to 8 quarters in all regressions considering the MT-criteria. For the GVL-criteria, it is located at duration equal to 10 quarters, except for the Industrial countries and post-1990 period which is located at 15 quarters of duration.

Table 6: Robustness checks with different thresholds

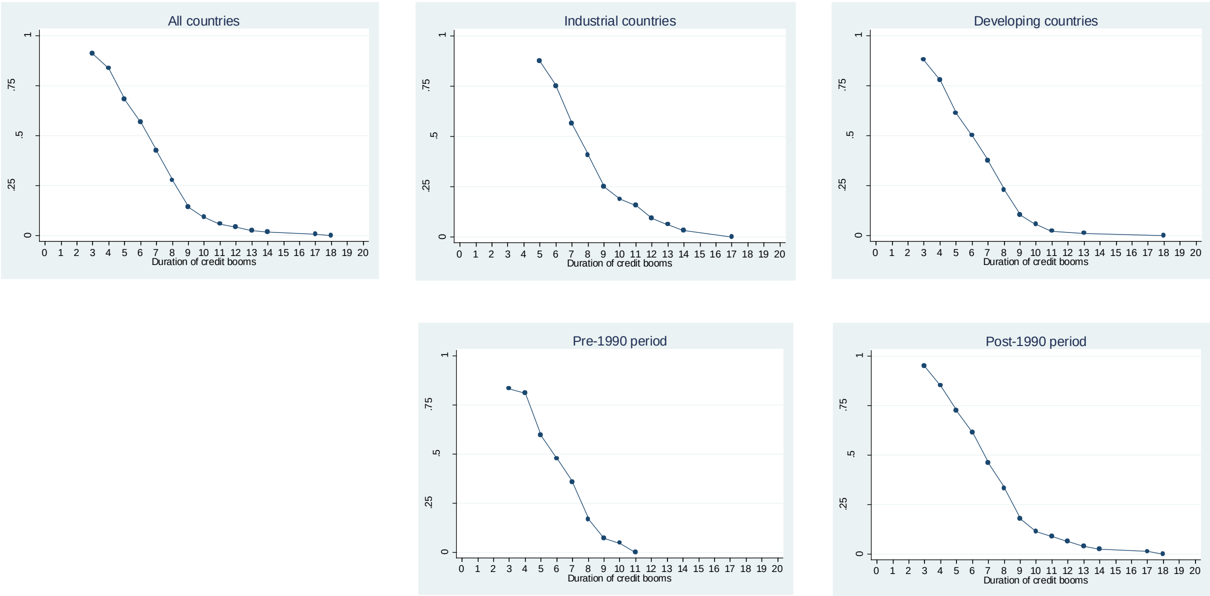
	MT-criteria				GVL-criteria			
	$\varphi = 1.5$		$\varphi = 2.0$		$\varphi = 1.75$		$\varphi = 2.0$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
γ_1	0.0223 ***	0.2641 ***	0.0140 *	0.3763 ***	0.0364 ***	0.1785 ***	0.0358 ***	0.1800 **
	[0.0078]	[0.0269]	[0.0079]	[0.0599]	[0.0095]	[0.0095]	[0.0097]	[0.0199]
γ_2		0.3972 ***		0.8366 **		0.3221 ***		0.3174 ***
		[0.0959]		[0.3314]		[0.0701]		[0.0786]
p_1	2.330 +,i	2.601 +,i	2.506 +,i	2.968 +,i	1.781 +,d	2.410 +,i	1.767 +,d	2.389 +,i
	[0.146]	[0.157]	[0.237]	[0.221]	[0.077]	[0.146]	[0.079]	[0.159]
p_2		1.683 +,c		1.720 +,c		1.193		1.216
		[0.263]		[0.317]		[0.162]		[0.196]
$p_2 - p_1$		-0.918 ***		-1.247 ***		-1.217 ***		-1.173 ***
		[0.313]		[0.393]		[0.199]		[0.212]
D_Indus	-0.475 ***	-0.434 ***	-0.557 **	-0.528 **	0.040	-0.011	0.085	0.044
	[0.181]	[0.154]	[0.253]	[0.212]	[0.186]	[0.151]	[0.198]	[0.165]
Dec80	-0.305	-0.274	-0.939	-0.347	-0.033	-0.010	-0.056	-0.039
	[0.285]	[0.304]	[0.349]	[0.376]	[0.219]	[0.268]	[0.234]	[0.279]
Dec90	-0.592 **	-0.480 *	-0.740 **	-0.542 *	-0.881 ***	-0.795 ***	-0.883 ***	-0.800 ***
	[0.261]	[0.264]	[0.352]	[0.308]	[0.273]	[0.300]	[0.264]	[0.288]
Dec00	-0.485 **	-0.464 *	-0.471 **	-0.448 *	-1.174 ***	-1.008 ***	-1.145 ***	-0.983 ***
	[0.246]	[0.262]	[0.230]	[0.255]	[0.244]	[0.274]	[0.248]	[0.276]
LogL	-109.24	-360.20	-57.48	-211.36	-193.95	-583.03	-179.82	-542.22
SBIC	248.81	755.78	142.09	454.38	419.95	1208.81	391.14	1121.21
Spells	157	157	92	92	209	209	191	191

Notes : See Tables 2, 3 and 4. Odd columns report the results from the basic Weibull model estimation, while even columns show the results from the Weibull model with a change-point; the change-point is located at duration equal to 8 and 10 quarters for the MT-criteria and GVL-criteria, respectively.

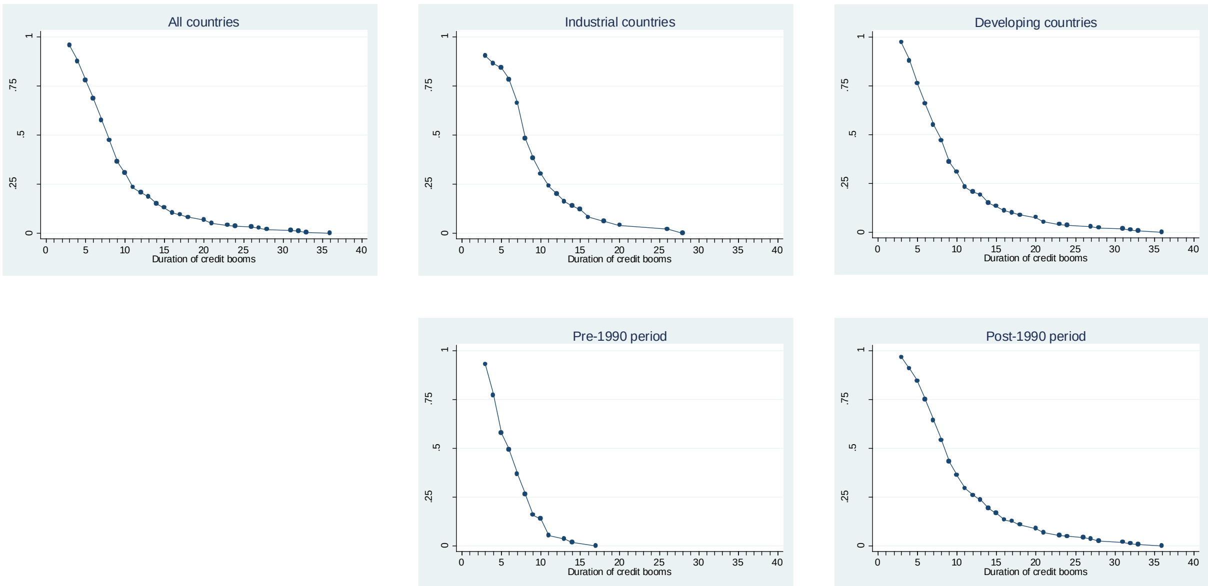
List of Figures

Figure 1. Survivor functions for credit booms according to criteria, groups and periods.

MT-criteria



GVL-criteria



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