Credit Booms: the Good, the Bad, and the Ugly*

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Abstract

In recent years a number of emerging markets experienced rapid expansions in domestic credit. Though financial deepening is greatly beneficial to economic growth, it is feared that credit booms increase the likelihood of banking crises. This paper establishes that credit booms are indeed associated with episodes of banking system distress, and that the effect is highly nonlinear in both credit growth itself and the in the impact of other variables during credit booms. We find that larger and more prolonged booms and those coinciding with higher inflation and, to a lesser extent, low economic growth are more likely to end in crisis. By contrast, external factors such as real exchange overvaluation or the current account do not seem to consistently affect the crisis probability. Better banking supervision and greater trade openess seem to reduce the crisis probability.

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1 Introduction

The past 20 years witnessed a global trend towards increased financial deepening. Financial intermediation has grown and in that context bank credit has risen dramatically in relation to GDP. Given the positive relationship between financial development and economic growth, this trend has been a beneficial one. However, the process has not always been smooth. While in some countries financial deepening has followed an even path, in others it has been a bumpy process with sharp accelerations in aggregate credit, or credit booms, sometimes followed by episodes of financial distress and banking crises. This has contributed to the widespread belief that credit booms are at best dangerous, and at worst a recipe for financial disaster.[1] Yet, historically, only a fraction of booms ended in crashes, while many soft-landed without causing major disruption.

There is a disconnect between the literature that establishes the strong positive effect of financial development on growth (see Levine, 2005, for a survey), and the arguments linking credit booms to crises. After all, the two phenomena are measured using the same variable: in the growth literature financial development is proxied by private credit as a share of GDP, while a credit boom is identified by an abnormally high growth rate in that same variable. This raises three important questions. First, what are the real effects of credit booms and, hence, the implicit costs associated with stopping them? In other words, are credit booms financial development? Second, are all credit booms alike or can we tell in advance the healthy from the dangerous ones? Finally, based on the answers to these two questions, can we provide some guidance on what booms need to be stopped and what it is worth to let to continue? In this paper we investigate all three questions.

We first identify credit boom episodes by examining whether the actual rate of growth of credit in an economy, as measured by the credit-to-GDP ratio, appears abnormally high (as defined below). Then, we look at how credit growth interacts with several macroeconomic, institutional, and banking-sector specific factors in determining the probability of banking crises, while allowing for a break in the relationship during boom episodes. In particular,

[1] See Gourinchas, Valdes, and Landerretche (2001).

we run a logit model in which we interact several variables commonly used in the empirical literature on banking crises with the various measures of credit booms. Importantly, in our estimation we only use information available to policy makers and market participants at the time of each boom episode.

In the second part of this paper, we plan to examine the real effects of credit booms, following the difference-in-differences approach first introduced by Rajan and Zingales (1998). [This is still work in progress]. The idea is that if credit booms have positive real effects, these should be disproportionately larger in sectors that are highly reliant on bank finance. In that context, the difference between the growth performance during booms and during tranquil times of sectors highly dependent on external finance and of sectors primarily relying on internal finance can be used as a proxy for the real benefits associated with the boom itself. Further, we can do the same exercise for booms ending in crises, by looking at the overall growth differential over the boom-bust cycle.

Finally, we will employ the methodology of Wurgler (2000) to see whether credit booms improve the allocation of capital in the economy. Wurgler uses industry-level data to regress the growth rate of investment on the growth rate of value added. The idea is that at short lags, without financial constraints capital would be allocated to the fastest-expanding sectors. Combining this approach with credit boom data, we determine whether credit booms on average improve the flow of investment to the most appropriate sectors. Based on this methodology, we can also divide booms into good and bad according to whether they have an overall positive real effect or not.

The results in this manuscript are to be considered preliminary and will likely be revised in later versions of the paper. We find that, while it is not possible to fully discriminate between "good" and "bad" (or "ugly") credit booms, several macroeconomic variables help to predict whether a boom is heading for some form of financial distress. Not surprisingly, larger and longer-lasting booms and those coinciding with higher inflation and, to a lesser extent, low growth are more likely to end in crisis. By contrast, external factors such as real exchange overvaluation or the current account do not seem to consistently affect the crisis probability. Better banking supervision and greater trade openness seem to reduce the crisis probability.

We also find some evidence that booms which start from a higher level of financial development have a higher chance of ending in crisis. This captures the notion that countries starting from a low base are less vulnerable during credit booms.

This paper makes two substantial contributions to the literature. First, it establishes that there are different types of credit booms, associated with different levels of financial sector risk and having different real effects. Second, it shows that it is to some extent possible to identify these booms ex-ante and possibly to intervene to avoid major financial problems.

A large empirical literature on banking crises finds a positive, but often small and not always significant, link between credit growth and financial crises. Demirguc-Kunt and Detragiache (2002) and Kaminsky and Reinhart (1999) find evidence that fast credit growth increases the probability of banking crises. Gourinchas et al. (2001) examine a large number of episodes characterized as lending booms and find that the probability of having a banking crisis increases after such episodes and that the conditional incidence of having a banking crisis depends critically on the size of the boom. However, they find that the increase is not statistically significant, and that, as with this paper, and consistent with Tornell and Westermann (2001), most lending booms are not followed by crises. Mendoza and Terrones (2004) reach, instead, the conclusion that lending booms are typically bad. However, their definition of boom may entail a bias as their trend is estimated over the entire sample period. Hilbers et al. (2005) compare the behavior of several macroeconomic variables around booms and find evidence consistent with the results in this paper, in particular with regard to inflation and the current account balance. Borio and Lowe (2002) find that fast credit growth accompanied by rapid increases in asset prices is often associate with episodes of financial instability. Kraft and Jankov (2005) examine the recent boom in Croatia and find that fast credit growth has been associated with an increased probability of loan quality deterioration and a worsening current account balance. Ranciere, Tornell, and Westermann (2006) focus on the dual effect of financial liberalization on growth and the probability of financial crises.

A few recent theoretical papers have provided explanations for why lending booms can lead to financial crises, especially in emerging economies. Here we provide a brief and far from exhaustive review of this literature. According to the Kiyotaki and Moore (1997) "financial accelerator" model, an increase in value of collateralizable goods releases credit constraints. This leads to an increase in the volume of lending, which in turn fuels further increases in asset values, raising the overall exposure of the banking system. Under Berger and Udell's (2004) "institutional memory" view, in periods of fast credit expansion it is difficult for banks to recruit enough experienced loan officers (especially if there has not been a crisis for a while). This leads to a deterioration of loan portfolios, which reduces bank profitability and increases the probability of a crisis. Dell'Ariccia and Marquez (2006) propose a model of "adverse selection and the business cycle:" during the expansionary phase of the cycle, adverse selection is less severe and banks find it optimal to reduce borrower screening and lending standards to trade quality for market share. This leads to deteriorated portfolios, lower profits, and an increased probability of a crisis.

The rest of this paper is organized as follows: Section 2 describes how we identify credit boom episodes; Section 3 examines the relationship between credit booms and banking crises; Section 4 concludes.

2 Identifying Credit Booms

As with recessions and economic expansions there is a fair amount of arbitrariness in how to identify credit booms. For robustness we consider two different methodologies and, following Gourinchas et al. (2001), we apply them to two separate definitions of credit growth. The first is a simple threshold rule. We classify a country-year as experiencing a credit boom if Bank Credit to the Private Sector (hereafter BCPS) as a share of GDP grows at more than 10 percent. We also vary this numerical threshold to check robustness.

The second methodology identifies credit booms by examining whether the actual rate of growth of credit in an economy – as measured by BCPS ratio – appears abnormally high relative to its previous trend. Since credit is a stock variable measured at year-end, the BCPS ratio is constructed with the geometric average of GDP in years t and t+1. This measure has two main advantages. First, it can be built using readily available data with widespread country and time-series coverage. Second, it does not consider the financial sector in isolation, but relates it to the size of the economy, while at the same time correcting for the procyclicality of bank lending. That said, because of the positive relationship between financial development and growth, bank lending follows a positive trend, even when measured in relation to GDP. Therefore, credit booms need to be isolated as definite events separate from normal increments in the volume of credit.

We apply the methodology developed in Gourinchas et al. (2001) and define a lending boom as an episode where the BCPS ratio deviates from a rolling, backward-looking, country-specific trend (estimated by a non-linear trend). This means that credit growth in each year x will be compared with a trend estimated over the period 1980-x. The idea is that the trend represents the historically "normal" pace of credit growth for each particular country. Furthermore, the estimated trend summarizes the information about past credit growth available to policy makers and market participants at the time of the boom.[2]

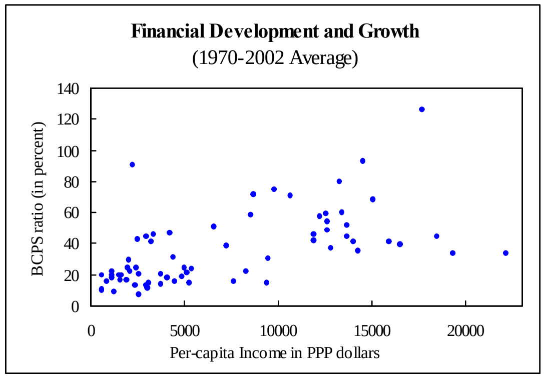
Based on this approach, an episode of fast credit growth becomes a boom if its deviation from the trend exceeds a certain threshold. As in Mendoza and Terrones (2004), this paper employs country- and path-dependent thresholds, based on the standard deviation of the historical deviations of the BCPS ratio from its estimated trend. More specifically, an episode becomes a boom if the BCPS ratio exceeds or meets either of the following two conditions:

i) The deviation from trend is greater than 1.5 times its historical country-specific standard deviation and the annual growth rate of the BCPS ratio exceeds 10 percent.

ii) The annual growth rate of the BCPS ratio exceeds 20 percent.

This definition takes into account country-specific conditions and reflects both the relative level and the speed of the BCPS ratio. A country-specific threshold is needed since what may seem like a large deviation in countries with a historically smooth credit growth

[2] Alternatively, a trend could be estimated over the entire sample period, as in Mendoza and Terrones (2004). However, this approach would have two drawbacks. First, it would tend to overestimate bad credit booms because of the bias introduced by the subsequent crisis. Second, it would make use of information not available at the time of the boom, and hence, would make the estimates difficult to apply operationally.



may be the norm in a country with an experience of uneven growth. The growth rate of the BCPS ratio is included to control for cases in which, because of a relatively smooth acceleration in credit, extremely fast credit growth may occur while the actual BCPS ratio falls close to its trend.

Once a credit boom is identified, its starting point is defined according to a similar criterion, that is the earliest year in which: (i) the BCPS ratio exceeds its trend by more than three-fourths of its historical standard deviation and its annual growth rate exceeds 5 percent; or (ii) its annual growth rate exceeds 10 percent. A boom ends as soon as either of the two following conditions is met: (i) the growth of the BCPS ratio turns negative; (ii) the BCPS ratio falls within three-fourths of one standard deviation from its trend and its annual growth rate is lower than 20 percent.

2.1 A Few Stylized Facts

A positive relationship between financial development and growth has been long established (Figure 1). Furthermore, a more recent literature based on industry-level data has shown that financial development is not just the result but also a determinant of economic growth. Fast credit growth is, then, a positive development to the extent that it reflects fast financial deepening.However, excessively fast credit has also been associated with increased financial fragility and banking crises. Most major banking crises in the past 25 years have occurred in the wake of periods of extremely fast credit growth. This regularity is not limited to emerging markets, but extends to advanced economies as well: for example, the Scandina-

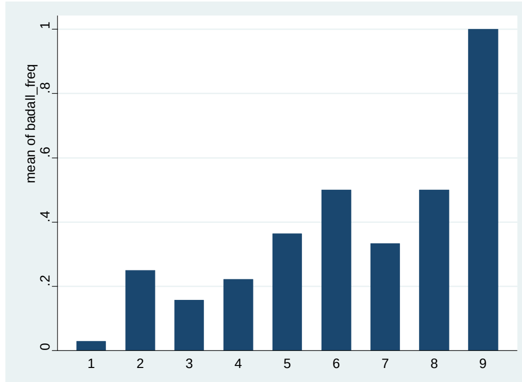


Figure 1: Proportion of Bad Booms by Duration

vian banking crisis of the early 1990s followed a period of extreme credit growth. Other notable examples include Argentina in 1980, Chile in 1982, Mexico in 1994, and the Asian crisis of 1997. All these crises involved heavy macroeconomic losses and were followed by prolonged periods of sluggish credit growth.

That said, only a minority of credit booms has led to episodes of financial distress. Out of 137 credit booms identified in this paper, only 23 precede systemic banking crises (about 16 percent), with that proportion rising to 31 (about 23 percent) if non-systemic episodes of financial distress are included.[3]

As Figures 2 and 3 illustrate, the duration and magnitude of boom episodes seems correlated with the probability they will end up badly. In particular, there are size and duration thresholds above which no boom has ended without a crisis.Booms are the most dangerous in emerging markets (18 out of 50) and the least in developing countries (8 out of 72), lending some support to the idea that in the latter fast credit growth is likely to reflect healthy financial deepening rather than a speculative bubble.[4] Regionally, Latin America appears to be a risky place to have booms with almost 40 percent ending up in crises.

[3] The proportion of booms ending in crises and episodes of financial distress is remarkably stable across identifying criteria. Of the 209 booms identified by a crude 10 percent threshold in relative growth of the credit-to-GDP ratio, 34 end up in systemic crises and 50 in some form of financial distress.

[4] That said, the possibility that banking crises series have apoorer coverage for poorer economies has to be aknowledged.

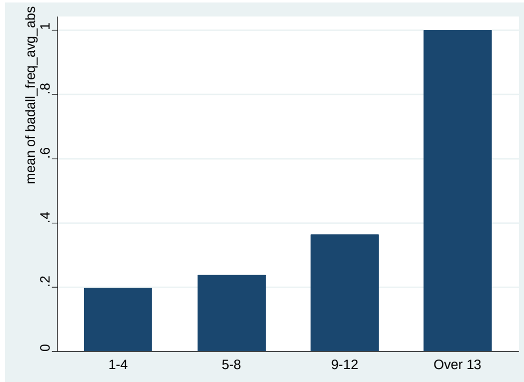


Figure 2: Proportion of Bad Booms by Avg. Absolute Credit-to_GDP Growth

3 Credit Booms and Banking Crises

In this section we examine the relationship between credit booms and banking crises. We expand on the existing empirical literature by explicitly allowing credit growth to have a differential impact on the probability of a crisis based on its own level and on several macroeconomic, institutional, and bank-specific variables. We follow two approaches. First we focus on the credit boom episodes in isolation. Essentially, we consider each boom as one observation. To each boom event is associated the average of various macroeconomic and banking variables during the boom period. Second, we follow the logit approach of Demirgüç-Kunt and Detragiache (1998, henceforth DD). Namely, we use data on banking crisis episodes in a large sample of countries to estimate the probabilities of crises based on a set of macroeconomic and banking system variables. We pay special attention to the issue of whether, and how, past credit growth in particular affects the likelihood of banking system distress. Our preferred specification builds in a large amount of nonlinear effects of credit growth on the likelihood of banking distress, both directly and interacted with other explanatory variables. Allowing for these nonlinearities improves the predictive power of the empirical model substantially.

In the first approach, two versions of a dummy variable, BAD, are constructed taking value one for booms followed within two years from their end by episodes of financial distress and by full-fledged banking crises, respectively. Then, the panel dataset is collapsed into a simple cross-section of credit booms. The country-specific mean value over each boom period of several macroeconomic and structural variables, such as inflation, the current account balance, GDP growth, boom duration, and BCPS ratio growth are associated with each observation. Finally, the following basic model is estimated with a logit regression:

$$BAD_i = \alpha + \beta DUR_I + \gamma SIZE_i + \delta INFL_i + \zeta GROWTH_i + \xi CA_i + \chi OPENNESS + \varepsilon_i.$$

where DUR is the duration of the boom in years, $SIZE$ is the average change in the BCPS ratio during the boom, $INFL$ is the average inflation rate, $GROWTH$ is the average real per capita income growth, and CA is the current account balance. This parsimonious specification allows the broadest coverage. We also run specifications including structural banking variables, such as bank concentration, quality of bank supervision, and a liberalization index, as controls, but at the cost of a reduction in sample size.

This cross-sectional approach makes it easy to treat boom episodes as different from periods of regular credit growth, but has two main shortcomings. First, it does not make use of available information. Second, it looks at each boom as a concluded episode, while during a boom it will be impossible to determine whether the boom is ending or it will continue. We, then, turn to the logit approach of DD (1998). We, first, estimate the following multivariate logit model:

$$\begin{aligned} BD_{ct} &= \alpha + \beta_1 Growth_{ct} + \beta_2 REER_{ct} + \beta_3 r_{ct} + \beta_4 \pi_{ct} + \beta_5 Credit/GDP_{ct} + \\ &\quad \beta_6 CreditGrowth_{ct-1} + \beta_7 Concentration_c + \varepsilon_{ct} \end{aligned} \tag{1}$$

where c denotes country and t year. The dependent variable is an indicator which takes on a value of 1 when a country begins experiencing banking system distress in a given year, and zero otherwise.[5] The first four explanatory variables are the standard macro controls: growth, real exchange rate appreciation, real interest rate, and inflation.[6] The specification

[5] Most crises coded by DD last for multiple years. The dependent variable in the regression specification takes on the value of 1 only in the first year of the crisis. The observations for which the crisis is ongoing are dropped from the sample.

[6] The set of macro controls is somewhat more parsimonious than in the standard DD specification, reflecting the fact that many other possible controls turn out to be insignificant in most specifications. We experimented with including income per capita, the current account, M2/Reserves, and the results were unaffected as these variables, which, perhaps surprisingly, are usually not significant. We also experimented with alternative measures of inflation and exchange rate changes, and the results were unchanged.

includes the value of private credit as a share of GDP, and the lagged value of real credit growth. We include one banking system indicator, banking system concentration, as it has been shown to have a strong effect on the likelihood of crises.[7]

As the focus of this study is on credit growth, we pay special attention to its evolution, and in particular to episodes of credit booms. We control for lagged growth in private credit, and its level as a share of GDP. However, we believe that there are strong nonlinearities that exist in episodes of credit booms. In particular, each explanatory variable, be it credit growth, real interest rate, or exchange rate appreciation, is likely to affect banking crisis probabilities differently depending on whether or not a country is in the middle of a credit boom, as well as its duration to date.

In order to exploit the nonlinearities inherent in episodes of credit booms and banking distress, we start with the sample of credit booms identified in the previous section. We then construct a variable which captures the duration of a credit boom. $Duration_{ct}$ takes on the value of zero if there is no credit boom. It takes the value of 1 in the first year of the boom, 2 in the second year, etc. We then include that variable as the main effect on our regression, and also interact it with all of the other explanatory variables. This is how we arrive at the following estimation equation:[8]

[7] We experimented with a variety of other banking system characteristics, such as existence of a deposit insurance scheme, dollarization of deposits, and state and foreign ownership. By and large, we do not find a significant effect of these characteristics on the likelihood of banking crises, and thus we omit them from the final specification. It must be noted that all of these, including the banking system concentration, do not have a time series dimension. Thus, their role in explaining the time variation in estimated probability of distress is limited to interacted terms with time-varying variables.

[8] We experimented with a variety of boom definitions and thresholds, and with a variety of empirical specifications. The one we use delivers the most explanatory power, but the results are broadly unchanged for alternative specifications. For instance, we estimated alternative specifications in which *Duration* is replaced by a zero-one indicator of whether there is a boom in that year. We also used the cumulative growth in private credit/GDP during the boom episode instead of *Duration*. The results were similar.

$$
\begin{aligned}
BD_{ct} = {} & \alpha + \beta_1 Growth_{ct} + \beta_2 REER_{ct} + \beta_3 r_{ct} + \beta_4 \pi_{ct} + \beta_5 Credit/GDP_{ct} + \\
& \beta_6 CreditGrowth_{ct-1} + \beta_7 Concentration_c + \beta_8 Duration_{ct} \\
& + \beta_9 Duration * Growth_{ct} + \beta_{10} Duration * REER_{ct} + \beta_{11} Duration * r_{ct} \\
& + \beta_{12} Duration * \pi_{ct} + \beta_{13} Duration * Credit/GDP_{ct} \\
& + \beta_{14} Duration * CreditGrowth_{ct} + \beta_{15} Duration * Concentration_c + \varepsilon_{ct}
\end{aligned} \tag{2}
$$

The Data Appendix presents the country sample along with the crisis episodes documented by DD (2005), as well as detailed descriptions of variable definitions and sources. The macro variables and the private credit data come from IFS and World Development Indicators. Banking system concentration comes from the World Bank Financial Development Database, described in Beck, Demirgüç-Kunt, and Levine (2000). The sample is a yearly panel of 100 countries for the period 1980-2004. During this time, DD (2005) document 77 episodes of banking crises. Thus, as a "control group" we include some countries that did not experience any banking distress over the sample period.

The methodology we use to arrive at our estimates is a standard and well accepted one in the literature. First introduced by DD (1998), the logit approach has been used to analyze a wide variety of potential determinants of banking system distress (the literature to date is surveyed in DD, 2005). While quite standard, the approach we take in this paper has some limitations. Perhaps the most significant is that because it requires large cross-country and time series coverage, not many micro-level banking sector variables can be included in the specifications. Doing so would be desirable because these variables – banking system profitability, non-performing loan ratios, sectoral distribution and currency composition of lending and the like – may have a great deal of influence over the soundness of a banking system. Another concern is endogeneity. This approach does not allow us to establish whether a given independent variable has a causal effect on precipitating banking distress. It can only show under what kinds of circumstances banking distress tends to occur. The advantage of this methodology, on the other hand, is that it allows analysis based on a large set of country experiences. Furthermore, just as studies based on bank-level data may be informative about how bank-level variables are associated with individual bank failure, the macro approach is informative about how macro shocks are associated with systemic bank failure.

3.1 Results

Starting from the cross-section model, we first report the results for a parsimonious specification limited to macroeconomic variables available for most countries and years in our sample (booms coinciding with episodes of hyperinflation are excluded). For robustness, table 1 reports the estimates for credit booms defined according to our two alternative criteria, plus a set of boom defined relative to a HP filtered estimated over the entire sample (as in Mendoza and Terrones, 2004). While the coefficients change in size and significance, the results appear relatively robust to the boom definition. All the coefficients have the expected sign. Boom duration and size, inflation, and openness (measures as the sum of imports and exports divided by GDP) are significant, or almost significant in all three samples. GDP growth and the current account balance do not seem to have a consistent impact on the probability of a crisis. Finally, as in previous paper the fit of the model is relatively poor, with the psuedo-R^2 between 0.1 and 0.2.

In Table 2, we include an index measuring the quality of bank supervision in the regression. This vasty improves the fit of the model, but at the cost of country coverage. Results are consistent with those in Table 1. However, openness is no longer significant, partly due to the reduced sample size. Supervisory quality has the expected effect of reducing the probability of a crisis and is significant in two out of three boom samples. For further robustness, we also estimated these specifications for a sample of developing countries and emerging markets only, obtaining similar results (not reported).

The estimated marginal effects are remarkably stable across boom samples. Prolonging a boom by one year increases the probability of crisis by about 4 percentage points. Increasing its size by 1 percentage point relative to GDP raises the probability of crisis by 5 percentage points.

Turning to the panel regressions, Table 4 presents the results of estimating the empirical model. Column 1 reports a parsimonious version of the DD specification (equation 1), which is linear and does not include any interaction terms. Most of the explanatory variables are significant and have the expected signs, including the growth of private credit. We then estimate a specification with a rich set of interaction terms: all of the explanatory variables are allowed to affect the dependent variable differentially depending on the duration of the credit boom (equation 2). The explanatory power of the empirical model is almost doubled, judging from the increase in the pseudo-R^2, which admittedly is still low. Many variables do indeed affect crisis probabilities differentially depending on the credit boom duration.

We then estimate the model on a subsample of countries similar to those which are currently experiencing a credit boom: those belonging to the Emerging Markets (EM) group of countries as classified by the IMF's World Economic Outlook.[9] It is likely that credit booms and banking crises are of a fundamentally different nature in both developed countries and poorer ones with smaller financial systems and no access to international financial markets. Column 3 reports the results. As we can see, the sample size is decreased more than three-fold, but the pseudo-R^2 doubles, providing a better fit for the data and the estimated probabilities. As we can see, most of the explanatory variables are significant in both the main effect and interacted with duration. In particular, credit growth on its own significantly increases the probability of an episode of banking distress. Furthermore, the effect is much stronger as the duration of credit boom increases.

We next calculate the marginal effect of a change in each independent variable on the probability of banking distress. This probability can be evaluated at any point in the distribution of the independent variables, usually the median. The coefficients reported in Table 4 are not useful for establishing the relative magnitude of the effect of various explanatory variables on the probability of observing banking system distress. Because this is a logit regression, the coefficients do not have the usual interpretation of being the partial derivative of the left-hand side variable with respect to the regressor.

We report the results in Table 5. It reports the change in the estimated probability of banking system distress which results from a one standard deviation change in each

[9] The countries in the EM sample are given in the Appendix Table.

explanatory variable. Since the effect of a change in each variable differs depending on the duration of the possible ongoing credit boom, the columns report the marginal effects in each year of the credit boom. The estimates in this Table are based on the specification in Column 3 of Table 4, that is, the Emerging Markets sample.

The key result is that different variables affect the marginal probabilities of distress very differently depending on the duration of the boom. It is clear from Column 1 that in the absence of a credit boom, growth is the strongest predictor of the likelihood of banking system distress. A one standard deviation increase in growth is associated with the probability of banking distress that is 3.2 percent lower. Lagged credit growth is the second most important determinant of distress probability, though its effect is three times lower, raising that probability by just over 1 percent. The effect of other variables is negligible in the absence of a credit boom, none topping 1 percent.

It turns out that the positive effect of growth becomes weaker as the boom goes on: higher growth late in the credit boom lowers the probability of banking distress by less than in the absence of a credit boom (see columns 2 through 6, which trace out the evolution of the marginal effects of the explanatory variables during an ongoing credit boom). By contrast, the effect of credit growth increases significantly in a lasting credit boom. In a boom which has lasted 5 years, a one standard deviation increase in the growth of private credit raises the probability of distress by 12.2 percent. This is 12 times larger than the effect of an identical shock to credit growth in the absence of a boom, and almost 4 times larger (and of the opposite sign), as the effect of growth in the absence of a boom.

The effect of the level of private credit as a share of GDP on the likelihood of distress increases throughout the boom as well. Without a boom, the effect of this variable is negligible. However, as the boom progresses it goes from virtually zero to 10 percent, once again a sizeable effect. This shows that banking distress is less likely after a credit boom if the level of financial intermediation nonetheless remains low (due, for instance, to starting from a low base). Overall, the credit variables, both in growth rates and in levels, are by far the most important ones in the presence of a boom.

The other variables, which have a negligible effect without a credit boom, become progressively more important during a boom as well. For instance, higher inflation raises the probability of distress by 3.4 percent if the boom has been going on for 5 years, while banking concentration lowers it by 3.6. The other variables which matter are growth (-2.2 percent), and the real interest rate (almost 1 percent). Perhaps surprisingly, exchange rate changes have a very modest effect, no matter whether or not there is a boom. This conclusion remains unchanged even when this variable is interacted with dollarization in the banking system.

To summarize, our estimates show that credit booms have an important effect on the likelihood of banking system distress in a large sample of countries we consider. In addition, it appears that the impact of credit booms is highly nonlinear, both in credit growth itself, as well as in how other macro variables affect the likelihood of a crisis.

4 Conclusions

This paper examined the relationship between credit booms and banking crises. It found that contrary to widespread belief only a minority of credit booms end in some form of financial distress. That said, these episodes are associated with a higher probability of crisis than "normal" times. Larger more prolonged booms and those associated with high inflation rates and, to a lesser extent, low economic growth are more likely to end up in a crisis. Trade openness and good bank supervision, instead, are associated with lower crisis probabilities. Finally, there is only weak evidence that external imbalances have a consistent effect on the link between booms and crises.

A few caveats about the interpretation of the results: First, while there is strong evidence that the variables considered in this paper are useful to forecast whether or not a boom will end up in a crisis, the fit of the estimated models is relatively poor. Several additional variables may be useful to predict dangerous credit booms, and hence improve the fit of the model: information on real estate and asset bubbles, bank market structure variables, information on the health of the banking system. Unfortunately, many of these variables are available only for a small set of countries and years. We are currently working to increase the coverage of our sample in that direction. Second, since our interest was primarily in being able to tell bad from good booms, no attempt was made in this paper to address the potential endogeneity of some of our regressors. It follows that, while the results are helpful in that direction, they should not be taken at face value to do policy analysis. Finally, even booms that may end up in banking crises might be welfare enhancing if their benefits (greater access to credit, cheaper loans etc.) overwhelm their costs. That will be the focus of future work for the second part of this paper.

References

Berger, A., and G. Udell, 2004, "The Institutional memory Hypothesis and the Procyclicality of Bank Lending Behavior," *Journal of Financial Intermediation*, Vol. 13, pp. 458-495.

Borio, C., and P. Lowe, 2002, "Asset Prices, Financial and Monetary Stability: Exploring the Nexus," BIS Working Paper No. 114.

Caballero, R., and A. Krishnamurthy, 2001, "International and Domestic Collateral Constraints in a Model of Emerging Market Crises," *Journal of Monetary Economics,* Vol. 48, pp.513-548.

Caprio, G. and D. Klingebiel, 2003, "Episodes of Systemic and Borderline Financial Crises," World Bank mimeo.

Dell'Ariccia, G., and R. Marquez, 2006, "Lending Booms and Lending Standards," *Journal of Finance,* Vol. 61, pp. 2511-2545.

Demirguc-Kunt, A., and E. Detragiache, 2002, "Does Deposit Insurance Increase Banking System Stability? An Empirical Investigation," *Journal of Monetary Economics*, Vol. 49, pp. 1373-1406.

Gourinchas, P.O., R. Valdes, and O. Landerretche, 2001, "Lending Booms: Latina America and the World," *Economia*, Spring Issue, pp. 47-99.

Hilbers, P., I. Otker-Robe, C. Pazarbasioglu, and G. Johnsen, 2005, "Assessing and Managing Rapid Credit Growth and the Role of Supervisory and Prudential Policies," IMF Working Paper 05/151.

Kaminsky, G., and C. Reinhart, 1999, "The Twin Crises: The Causes of Banking and Balance-of-Payments Problems," *American Economic Review*, Vol. 89, pp. 473-500.

Kiyotaki, N., and J. Moore, 1997, "Credit Cycles," *Journal of Political Economy*, Vol. 105, pp. 211-248.

Kraft, E., and L. Jankov, 2005, "Does Speed Kill? Lending Booms and their Consequences in Croatia," *Journal of Banking and Finance,* Vol. 29, pp. 105-121.

Laeven, L., Klingebiel, D., and R. Krozner, 2006, "Financial Crises, Financial Dependence, and Industry Growth," *Journal of Financial Economics,* forthcoming.

Levine, R. 2005. "Finance and growth: theory and evidence." In: Philippe Aghion and Steven Durlauf (eds.) Handbook of Economic Growth. Elsevier Science, The Netherlands, pp. 865-934.

Rajan, R., 1994, "Why Bank Credit Policies Fluctuate: A Theory and Some Evidence," *Quarterly Journal of Economics*, Vol. 109, pp. 399-441.

Rajan, R. and L. Zingales, 1998, "Financial Development and Growth," *American Economic Review,* Vol. 88, pp. 559-586.

Ranciere, R., Tornell, A., and F. Westermann, 2006, "Decomposing the Effects of Financial Liberalization: Crises vs. Growth," *Journal of Banking and Finance,* Vol. 30, pp. 3331-3348.

Terrones, M. and E. Mendoza, 2004, "Are Credit Booms in Emerging Markets a Concern?," *World Economic Outlook*, pp. 148-166 (Washington: International Monetary Fund).

Tornell, A., and F. Westermann, 2002, "Boom-Bust Cycles in Middle Income Countries: Facts and Explanation" *IMF Staff Papers*, Vol. 49 Special Issue, pp. 111-153.

Wurgler, J., 2000, "Financial Markets and the Allocation of Capital," *Journal of Financial Economics,* Vol. 58, pp. 187-214.

Table 1. Predictors of Bad Credit Booms

Dependent variable: dummy =1 if crisis occurs within 2 years from boom's end	Base criterion	Credit-to-GDP growth over 10 percent	HP filter over entire sample
Duration	0.276	0.189**	0.345*
	(1.61)	(2.44)	(1.79)
Size	0.271**	0.220**	0.289***
	(2.36)	(2.5)	(2.72)
Inflation	0.015	0.021**	0.006
	(1.58)	-2.53	(0.65)
Growth (GDP percapita)	-3.647	(-2.055)	-4.186
	(-1.28)	-0.95	(-1.2)
Current Account Balance	-2.532	(-2.994)	-6.419*
	(-0.67)	-0.96	(-1.75)
Openness	-4.423***	-1.908**	-4.649**
	(-2.67)	(-2.16)	(-2.2)
Constant	-1.559	-2.293***	-1.413
	(-1.34)	(-3.00)	(-1.21)
Observations	94	152	73
Preudo R2	0.20	0.10	0.21

Episodes of hyperinflation (over 100 percent a year average) are excluded.
Logit regression. Robust z- statistics reported
* significant at percent, ** significant at percent; *** significant at percent.

Table 2. Predictors of Bad Credit Booms

Dependent variable: dummy =1 if crisis occurs within 2 years from boom's end	Base criterion	Credit-to-GDP growth over 10 percent	HP filter over entire sample
Duration	0.418*	0.193**	0.427
	(1.82)	(2.53)	(1.62)
Size	0.535**	0.354***	0.442**
	(2.24)	(2.71)	(1.98)
Inflation	0.040***	0.026***	0.034
	(2.66)	(2.68)	(1.05)
Growth (GDP percapita)	-11.056**	-3.533	-4.597
	(-2.04)	(-1.03)	(-0.83)
Current Account Balance	11.592	4.782	10.465
	(0.98)	(0.75)	(0.64)
Openness	-2.832	-1.221	-2.294
	(-1.17)	(-1.48)	(-0.81)
Quality of Supervision	-2.678***	-1.468***	-3.09
	(-3.24)	(-2.66)	(-1.17)
Constant	-2.151	-1.963***	-2.138
	(-1.46)	(-3.23)	(-0.91)
Observations	63	103	45
Preudo R2	0.36	0.19	0.36

Episodes of hyperinflation (over 100 percent a year average) are excluded.
Logit regression. Robust z- statistics reported
* significant at percent, ** significant at percent; *** significant at percent.

Table 3. Marginal Effects

Dependent variable: Probability of a crisis to occur within two years form the boom	Base criterion	Credit-to-GDP growth over 10 percent	HP filter over entire sample
Duration	0.04*	0.03**	0.06
Size	0.05**	0.05***	0.06**
Inflation	0.004***	0.004***	0.004
Growth (GDP percapita)	-1.01**	-0.53	-0.61
Current Account Balance	1.05	0.71	1.40
Openness	-0.26	-0.18	-0.31
Quality of Supervision	-0.24***	-0.22***	-0.41

Episodes of hyperinflation (over 100 percent a year average) are excluded.

Table 4: Logit Estimation Results

	(1)	(2)	(3)
Growth(GDP per capita)	-0.146***	-0.181***	-0.259***
	(0.029)	(0.031)	(0.044)
REER appreciation	-2.035*	-2.084*	-2.201*
	(1.073)	(1.126)	(1.231)
Real Interest Rate	0.067***	0.278***	0.419***
	(0.025)	(0.083)	(0.143)
Inflation	0.052	-0.13	-0.312*
	(0.045)	(0.097)	(0.160)
Priv. Credit/GDP	-0.03	-0.304	0.807
	(0.445)	(0.486)	(0.849)
Credit Growth(t-1)	1.587**	1.357	2.943*
	(0.696)	(0.826)	(1.543)
Banking System Concentration	-2.044***	-1.737**	-1.977
	(0.701)	(0.784)	(1.289)
Duration of Credit Boom		0.415	-2.385
		(0.963)	(1.731)
Priv. Credit/GDP*Duration		1.150**	2.558***
		(0.472)	(0.914)
Credit Growth(t-1)*Duration		0.284	5.783*
		(1.289)	(3.309)
Growth(GDP per capita)*Duration		0.076***	0.016
		(0.025)	(0.039)
REER appreciation*Duration		0.019	0.345
		(0.816)	(0.972)
Real Interest Rate*Duration		-0.517**	-0.801**
		(0.209)	(0.363)
Inflation*Duration		1.204**	1.915**
		(0.528)	(0.908)
Banking System Concentration*Duration		-1.564	-1.377
		(1.167)	(1.958)
Constant	-1.992***	-2.118***	-2.050**
	(0.577)	(0.663)	(0.829)
Sample	FULL	FULL	EM ONLY
Observations	1945	1945	583
Preudo R2	0.1	0.14	0.27

Robust standard errors in parentheses

* significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent

Table 5: Magnitudes of the Effect of the Independent Variables

	Duration of boom					
	none	1-year	2-year	3-year	4-year	5-year
Growth(GDP per capita)	-0.032	-0.030	-0.028	-0.026	-0.024	-0.022
REER appreciation	-0.006	-0.005	-0.004	-0.003	-0.002	-0.001
Real Interest Rate*	0.001	-0.001	-0.003	-0.005	-0.007	-0.009
Inflation*	-0.001	0.006	0.013	0.020	0.027	0.034
Priv. Credit/GDP	0.006	0.024	0.043	0.061	0.080	0.098
Credit Growth(t-1)	0.011	0.033	0.056	0.078	0.100	0.122
Banking System Concentration	-0.008	-0.013	-0.019	-0.024	-0.030	-0.036

* reports the change in probability due to moving from the 25th to the 75th percentile in the distribution of the variable

Appendix Table 1: Sample Countries and Distress Episode Dates

Country	DD banking disress dates	Country	DD banking disress dates
Algeria	1990–1992	Kenya	1993–1995
Argentina 1/	1980–1982, 1989-1990, 1995, 2001–2004*	Korea, Rep. 1/	1997–2002
Australia		Kuwait	
Austria		Lebanon	1988–1990
Bahrain		Lesotho	
Bangladesh		Libya	
Belgium		Madagascar	1988–1991**
Belize		Malawi	
Benin	1988–1990	Malaysia 1/	1985–1988, 1997–2001
Bolivia	1986–1988, 1994–1997**, 2001–2004*	Mali	1987–1989
Botswana		Mauritius	
Brazil 1/	1990, 1994–1999	Mexico 1/	1982, 1994–1997
Burkina Faso	1988–1994	Morocco 1/	
Burundi	1994–1997**	Myanmar	
Cameroon	1987–1993, 1995–1998	Nepal	1988–1991**
Canada		Netherlands	
Chad	1992	New Zealand	
Chile 1/	1981–1987	Niger	1983–1986**
China 1/		Nigeria 1/	1991–1995
Colombia 1/	1982–1985, 1999–2000	Norway	1987–1993
Congo, Rep.	1992–2002*	Oman 1/	
Costa Rica	1994–1997**	Pakistan 1/	
Cote d'Ivoire 1/	1988–1991	Panama 1/	1988–1989
Cyprus		Papua New Guinea	1989–1992**
Denmark		Paraguay	1995–1999
Dominican Republic 1/		Peru 1/	1983–1990
Ecuador 1/	1995–2002*	Philippines 1/	1981–1987, 1998–2004*
Egypt, Arab Rep. 1/		Portugal	1986–1989
El Salvador 1/	1989	Saudi Arabia 1/	
Ethiopia		Senegal	1983–1988
Finland	1991–1994	Seychelles	
France		Singapore	
Gabon		South Africa 1/	1985
Gambia, The		Spain	
Germany		Sri Lanka 1/	1989–1993
Greece		Swaziland	1995
Guatemala		Sweden	1990–1993
Guyana	1993–1995	Switzerland	
Haiti		Tanzania	1988–1991**
Honduras		Thailand 1/	1983–1987, 1997–2004*
Hong Kong, China		Togo	
India 1/	1991–1994**	Trinidad and Tobago	
Indonesia 1/	1992–1995**, 1997–2004*	Tunisia 1/	1991–1995
Iran, Islamic Rep.		Turkey 1/	1982, 1991, 1994, 2001–2004*
Ireland		United Kingdom	
Israel	1983–1984	United States	1980–1992
Italy	1990–1995	Uruguay 1/	1981–1985, 2002-2004*
Jamaica	1996–2000	Venezuela, RB 1/	1993–1997
Japan	1992–2002*	Zambia	
Jordan 1/	1989–1990	Zimbabwe 1/	

1/ Country in the EM sample
* The crisis is still ongoing as of 2005
** The end of the crisis is uncertain; a 4-year duration is assumed

Appendix Table 2: Variable Definitions and Sources

Variable Name	Definition	Source
BD	Banking Distress Indicator	Damirguc-Kunt and Detragiache (2005)
Growth	Real per capita GDP growth	World Bank WDI
REER	Real effective exchange rate appreciation	IMF
r	Ex post real interest rate=nominal interest rate minus contemporaneous inflation;	IFS: the nominal interest rate is the treasury bill rate (IFS line 60c), or if not available, the discount/bank rate (IFS line 60), or, if not available, the deposit rate (IFS line 60l); WDI: inflation is the growth rate of the GDP deflator
π	Inflation = growth rate of GDP deflator	WDI
Credit/GDP	Private credit/GDP	IFS: domestic credit to the private sector (IFS line 23d), divided by GDP in current local currency (WDI)
CreditGrowth	Growth in private credit	Growth in private credit (defined above) divided by gdp deflator (WDI)
Concentration	Banking system concentration=Assets of three largest banks as a share of assets of all commercial banks.	World Bank Financial Structure Database (http://econ.worldbank.org/staff/tbeck)
Duration	Number of years since the inception of the current credit boom; if not in a credit boom, *Duration* =0. A credit boom is defined as a year in which *CreditGrowth* >0.1	