Good Booms, Bad Booms*

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Abstract

Credit booms usually precede financial crises. However, some credit booms end in a crisis (bad booms) and others do not (good booms). We document that, while all booms start with an increase of Total Factor Productivity (TFP) and Labor Productivity (LP), such growth falls much faster subsequently for bad booms. We then develop a simple framework to explain this. Firms finance investment opportunities with short-term collateralized debt. If agents do not produce information about the collateral quality, a credit boom develops, accommodating firms with lower quality projects and increasing the incentives of lenders to acquire information about the collateral, eventually triggering a crisis. When the average quality of investment opportunities also grows, the credit boom may not end in a crisis because the gradual adoption of low quality projects is not strong enough to induce information about collateral. Finally, we also test the main predictions of the model.

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1 Introduction

The recent financial crisis poses challenges for macroeconomists. To understand crises and provide policy advice, models which display crises are needed. And these models must also be consistent with the stylized fact that credit booms precede crises.[1] In this paper we study 34 countries over 50 years and show that credit booms are not rare; the average country spends over half its time in a boom and a boom is, on average, ten years long. This suggests that the seeds of a crisis are sewn a decade before the boom ends in a financial crash. But, not all credit booms end in a crisis; some do (bad booms) while other do not (good booms).[2] In this paper, we provide some empirical evidence on credit booms and then analyze a model consistent with booms sometimes ending in a crisis and sometimes not. Finally, we test several predictions from the model.

The finding that credit booms start long before a financial crisis suggests a different time frame than that used in current macroeconomic models. Current macroeconomics views fluctuations as deviations from a trend and separates the growth component from the deviation based on the Hodrick and Prescott (1997) filter. Hodrick and Prescott analyzed U.S. quarterly data over 1950-1979, a period during which there was no financial crisis. The choice of the smoothing parameter in the filter comes from this period. Separating the growth component from the deviation led to the view that the growth component is driven by technological change, while deviations are due to technological "shocks". Over the short sample period of U.S. data, Prescott (1986) argues that technology shocks (measured by the Total Factor Produc-

[1]For example, see Jorda, Schularick, and Taylor (2011) study fourteen developed countries over 140 years (1870-2008). Laeven and Valencia (2012) study 42 systemic crises in 37 countries over the period 1970 to 2007: "Banking crises are . . . often preceded by credit booms, with pre-crisis rapid credit growth in about 30 percent of crises." Desmirguc-Kunt and Detragiache (1998) use a multivariate logit model to study the causes of financial crises in a panel of 45-65 countries (depending on the specification) over the period 1980-1994. They also find evidence that lending booms precede banking crises. Their results imply, for example, that in the 1994 Mexican crisis, a 10 percent increase in the initial value of lagged credit growth would have increased the probability of a crisis by 5.5 percent. Other examples of relevant studies include Gourinchas and Obstfeld (2012), Claessens, Kose, and Terrones (2011), Schularick and Taylor (2012), Reinhart and Rogoff (2009), Borio and Drehmann (2009), Mendoza and Terrones (2008), Collyns and Senhadji (2002), Gourinchas, Valdes, and Landerretche (2001), Kaminsky and Reinhart (1999), Hardy and Pazarbasioglu (1991), Goldfajn and Valdez (1997), and Drees and Pazarbasioglu (1998).

[2]We are not the first to note this. Mendoza and Terrones (2008) argue that "not all credit booms end in financial crises, but most emerging markets crises were associated with credit booms." This is also found by Dell'Ariccia et al. (2012).

tivity, TFP) are highly procyclical and "account for more than half the fluctuations in the postwar period."[3]

In analyzing our panel of countries, we do not use the H-P filter. Rather, we propose a definition of a "credit boom" that is very agnostic. It does not rely on future data or on detrending. As we show, using the H-P filter misses important features of the data in the larger, longer, sample.[4] The phenomena of interest happen at lower frequencies and it seems difficult to separate trend changes from fluctuations. Changes in technology seem important for the gestation of a financial crisis, but not because of the traditional contemporaneous *negative shock*.

Our evidence suggests that credit booms start with a *positive shock* to TFP and labor productivity (LP), but that in bad booms the shock dies off rather quickly while this is not the case for good booms. The role of technology over such a longer horizon has been noted by economic historians and growth economists. Indeed, in the long-term, technology has played a central role in understanding growth. The historical time series of TFP growth has been linked to periods of growth due to technological innovation, such as the steam locomotive, telegraph, electricity or IT (see Kendrick (1961), Abramovitz (1956), Field (2009), Gordon (2010) and Shackleton (2013)).

Our finding that credit booms average ten years, and that positive shocks to TFP and LP occur at the start of the boom, is closely related to studies of "Medium-Term Business Cycles," which are also about ten years. Comin and Gertler (2006) find that TFP moves procyclically over the medium term (in U.S. quarterly data from 1948:1-2001:2 – a period without a systemic financial crisis).[5] They do not analyze credit variables however. Drehmann, Borio, and Tsatsaronis (2012) use an analysis of turning points (as well as frequency-based filters) to study six variables for seven countries over the period 1960-2011. In particular, they analyze credit to the private non-financial sector and the ratio of credit to GDP, which is the measure we study. Their main finding is the existence of a medium-term component in credit fluctuations. Also, see Claessens, Motto and Terrones (2011a and 2011b). We show that there is a difference in the productivity growth over credit booms that end in a financial crisis.

[3]Band pass filters are an alternative to the H-P filter (e.g., see Baxter and King (1999) and Christiano and Fitzgerald (2003)). Band pass filters with frequencies between two and 32 quarters essentially produce cycles that are very similar to those produce by the H-P filter.

[4]We are by no means the first to note this problem with the H-P filter. See, e.g., Comin and Gertler (2006).

[5]The U.S. S&L crisis never threatened the solvency of the entire financial system; it was not *systemic*.

We then develop a simple framework to understand how *positive productivity shocks* can lead to credit booms which sometimes end with a financial crash. The model begins with the arrival of a new technology. Firms are financed with short-term collateralized debt (e.g. repo). Lenders can at a cost learn the quality of the collateral, but it is not always optimal to do this. If information is not produced, then a credit boom can develop in which more and more firms obtain financing and gradually adopt new projects. Here there is a link between the credit boom and the diffusion of the technology. In booms that end in a crisis, firms that obtain financing are adopting lower quality projects. This provides an incentive for lenders to acquire information at some point after the original technological innovation, and then finding out that much of the collateral was bad – a crisis. When the technological growth persists, however, the effects of a gradual decline in the quality of adopted projects because of the credit boom may not be large enough to induce a crisis. The credit boom and the diffusion of the technology are linked.

The model is an extension of Gorton and Ordonez (2014), a macroeconomic model based on the micro foundations of Gorton and Pennacchi (1990) and Dang, Gorton, and Holmström (2013). These authors argue that short-term debt, in the form of bank liabilities or money market instruments, is designed to provide transactions services by allowing trade between agents without fear of adverse selection, and then improving credit. This is accomplished by designing debt to be "information-insensitive," that is, such that it is not profitable for any agent to produce private information about the assets backing the debt, the collateral. Adverse selection is avoided in trade.

As in Gorton and Ordonez (2014), for simplicity we abstract from including financial intermediaries in the model and instead we have households lending directly to firms. The debt we have in mind is short-term debt like sale and repurchase agreements ("repo") or other money market instruments. In these cases, the collateral is either a specific bond or a portfolio of bonds and loans. The backing collateral is hard to value as it does not trade in centralized markets where prices are observable. But, we can also think of the debt as longer term. For example, Chaney, Sraer, and Thesmar (2012) show that firms, in fact, do use land holdings as the basis for borrowing. In 1993, 59 percent of U.S. firms reported landholdings and of those holding land, the value of the real estate accounted for 19 percent of their market value. Firms use their land as pledgeable assets for borrowing. Chaney, Sraer, and Thesmar (2012) review the related literature.

In the setting here, the basic dynamics are as follows. The economy receives a set of technological opportunities. Then starting from a situation of "symmetric information," in which all agents know the quality of all collateral, the economy evolves over time towards a regime that we call of "symmetric ignorance" – that is a situation in which agents do not acquire costly information about the quality of the underlying collateral. Without information, agents view collateral as of average quality. If average quality is high enough, then over time more and more assets can successfully be used as collateral to obtain loans supporting production. However, with decreasing marginal productivity of projects in the economy, as more firms obtain credit, the average quality of the projects in the economy declines.

When the average productivity of firms drops, the incentives to produce information rise. Once those incentives grow large enough, there is a sudden wave of information acquisition, the system transits to a "symmetric information" regime, and there is a crash in credit and output. Immediately after the crash fewer firms operate, average productivity improves and the process restarts. We characterize the set of parameters under which the economy experiences this endogenous credit cycle, which is not triggered by any fundamental shock. We also show that, as the set of opportunities also improves over time, the endogenous decline in average productivity during a credit boom can be compensated by an exogenous improvement in the quality of projects such that information acquisition is not triggered. Then credit booms do not end in crises.

We differ from Gorton and Ordonez (2014) in two very important ways in order to show the links between TFP and LP growth and credit booms and crashes. First, we introduce decreasing marginal returns and changes to the set of technological opportunities. High quality projects are scarce, so as more firms operate in the economy they increasingly use lower quality projects. Gorton and Ordonez (2014) have a fixed technology. Secondly, in contrast to Gorton and Ordonez (2014) who focus on one-sided information production (only lenders could produce information), here we allow two-sided information production: both borrowers and lenders can acquire information. This extension is critical for generating crashes, not as a response to "shocks" but just as a response of endogenous TFP growth. In contrast, in Gorton and Ordonez (2014) crashes arise because of an exogenous "shock."

Although there is nothing irrational about the booms and crashes in the model, still there is an externality because of the agents' short horizons, as in Gorton and Ordonez

(2014). Here it is also true that a social planner would not let the boom go on as long as the agents, but would not eliminate it either. So, thinking of a boom as an "asset bubble," the perceived bubble could be a good boom, but even if it was a bad boom, still the social planner would not eliminate it. If policymakers could observe TFP or LP growth with a very short lag, then, on average, they could tell whether a boom is good or bad and take action.

In our setting there is arrival of a set of technological opportunities which is exogenous for simplicity. In reality innovation is an endogenous process, but still subject to sudden discoveries. There is news that a new set of technological opportunities as arrived. It is an improvement in technology, but may have the feature that the quality of the projects becomes low as the boom proceeds. The diffusion of technology takes time because firms need financing. As the credit boom develops, more firms get financing and the technology diffuses. The crisis occurs if the lower and lower quality projects diffuse. The innovation runs out of steam (so to say). As in Gorton (1985), Dang, Gorton, and Holmström (2013) and Gorton and Ordonez (2014) the crisis is an information event. Here, however, this information event may be purely endogenous and arise in the absence of shocks. For a recent paper that revives the discussion of purely endogenous and deterministic cycles see Beaudry, Galizia, and Portier (2015). In their case cycles are determined by complementarities between aggregate employment and consumption, which induce smooth deterministic cycles. In our case there are complementarities between the volume of credit and the incentives for information acquisition. Since this complementarity is not relevant unless it makes information constraints to bind, our model displays crises that end booms.

Conceptually, the phenomena we find empirically, model, and test suggests that viewing aggregate fluctuations as deviations around a trend is too stark (see Lucas (1977)). As far as financial crises are concerned (and these are not rare; see Laeven and Valencia (2012)), the trend, the credit boom, and the crisis are intimately related. Credit booms seem related to technological growth and can end in financial crises, but these dynamics happen at lower frequency then are typically studied.

The model has a number of predictions that we confirm in the data. First, firms become riskier during bad booms as compared to good booms. Second, booms started with a burst of innovation. Third, estimated TFP is significantly composed of a measure of firm fragility during booms, and more so in bad booms.

In the next section we introduce the dataset and analyze TFP growth, LP growth, credit booms, and crises. Then in Section 3 we describe and solve the model, focusing on the information properties of debt. In Section 4 we study the aggregate and dynamic implications of information, focusing on endogenous cycles. We test the main predictions of the model in Section 5. In Section 6, we conclude.

2 Good Booms, Bad Booms: Empirical Evidence

Not all credit booms end in a financial crisis. Why do some booms end in a crisis while others do not? To address this question empirically we investigate productivity (total factor productivity and labor productivity) trends during booms. Even though not all growth of credit may stem from movements in TFP or LP, we study their role as a primary driver of credit growth. In this section we produce some stylized facts about credit booms, productivity and crises. We define a "credit boom" below and analyze the aggregate-level relations between credit growth, TFP and LP growth and the occurrence of financial crises. We do not test any hypotheses but rather organize the data to develop some preliminary stylized facts.

2.1 Data

There are clearly important data decisions to be made to study credit booms. The stylized facts of business cycles developed by focusing solely on the U.S., starting with Kydland and Prescott (1990) who looked at U.S. quarterly data over 1954-1989, using the H-P filter. While the literature by now is very large, it continues to use the H-P filter and typically does not include credit variables. Over the last 25 years or so, longer time series have been used. But, these are only available for a smaller panel of countries. Backus and Kehoe (1992), for example, study ten developed countries where there is at least 100 years of data. They H-P filter and do not look at credit variables. More typical is Stock and Watson (2003) who study seven developed countries over the period 1960-2002. Aguiar and Gopinath (2007) study thirteen middle-income and thirteen developed countries with at least 40 quarters of data; they H-P filter and do not study credit aggregates. Since the financial crisis, credit variables have been a focus.[6] Schularick and Taylor (2012) study 14 developed countries over the period

[6]Many of these studies were cited in footnote 1.

1870-2008. They do not detrend and look at credit aggregates as well as macroeconomic variables.

There is a trade-off between breadth of countries and length of series and, it seems, between nosier data on emerging economies versus developed economies. Focusing solely on developed countries provides better data and longer time series. We choose to focus on a cross section that includes emerging countries at the cost of time series length, as do Mendoza and Terrones (2008) and Herrera, Ordonez, and Trebesch (2014). The data we use seem nosier because of IMF data revisions that mostly seem to focus on emerging countries. See Ley and Misch (2014). Nevertheless we want to include emerging countries because our view is that what we are studying should occur in all market economies. Our choice of data set is not only different in terms of looking at a larger cross section, but we as mentioned we do not H-P filter and we focus on credit variables. We analyze a sample of 34 countries (17 advanced countries and 17 emerging markets) over a 50 year time span, 1960-2010. A list of the countries used in the analysis, together with a classification of the booms (based on the definition given below), is provided in the Appendix.

As a credit measure, we use domestic credit to the private sector over GDP, from the World Bank Macro Dataset. Domestic credit to the private sector is defined as the financial resources provided to the private sector, such as loans, purchases of nonequity securities, trade credit and other account receivables, that establish a claim for repayment. For some countries these claims include credit to public enterprises

Gourinchas, Valdes, and Landerretche (2001) and Mendoza and Terrones (2008) measure credit as claims on the non-banking private sector from banking institutions. We choose domestic credit to the private sector because of its breadth, as it includes not only bank credit but also corporate bonds and trade credit.

For total factor productivity (TFP), we obtain measured aggregate TFP constructed by Mendoza and Terrones (2008). The data source is IMF Financial Statistics. TFP is computed through Solow residuals. Mendoza and Terrones back out the capital stock from investment flows using the perpetual inventory method, and use hours-adjusted employment as the labor measure. We also use labor productivity, computed as hours-adjusted output-labor ratio, obtained from the Total Economy Database (TED).

Once we have computed credit booms and TFP and LP growth over booms, we look for the presence of financial crises at the end of the boom. For this we rely on the classification in Laeven and Valencia (2012), who identify financial crises worldwide since 1960.[7] Their definition of a crisis is given below.

2.2 Definition of Credit Booms

There is no consensus in the literature about the definition of a "credit boom" and the definitions are quite different. A boom is usually defined by the ratio of credit growth -to-GDP relative to a trend, so there is the issue of how the trend is determined. This will determine whether the booms are short or long. Theory is silent on this issue.

Detrending raises the issue of whether all the data should be used, or only retrospective data. Using a retrospective trend allows for recent changes in the financial system (e.g., financial liberalization) to have more weight, relative to using all the data to determine the trend. A Hodrick-Prescott filter uses all the data. Gourinchas, Valdes, and Landerretche (2001) define a boom as the deviation of the credit-to-GDP ratio from a rolling retrospective stochastic trend. They use data for 91 countries over 36 years and find that credit booms are associated with booms in investment and current account reversals, and are often followed by slowdowns in GDP growth. Mendoza and Terrones (2008) focus instead on pure credit and define a boom as a deviation from the trend of credit obtained through an HP-filter. The threshold that defines a boom is set to identify booms as the episodes that fall in the top 10% of the credit growth distribution. Dell'Ariccia et al. (2012) compare the credit-to-GDP ratio to a retrospective, rolling, country-specific cubic spline and then classify booms based on a threshold.

The boom definitions differ in how the cyclical component, $c_{i,\widehat{t}}$, is obtained, i.e., how the data are detrended. A boom in country i at time t is an interval $[t^s, t^e]$ containing dates in the interval, $\widehat{t}$, such that credit growth is high when compared to the time series standard deviation:

$$c_{i,\widehat{t}} \geq \phi\sigma(c_i). \tag{1}$$

[7]Laeven and Valencia (2012) start in 1970, while our data starts in 1960. Under our definition of a boom, we have only five booms that end prior to 1968 (Japan 1967, Costa Rica 1966, Uruguay 1965, the Philippines 1968, and Peru 1968). For these episodes there is no evidence of subsequent financial crises (based on GDP growth). These episodes start close to the beginning of the Laeven and Valencia data set and they do not classify these countries as being in distress in 1970. The exclusion of these episodes does not affect the results.

The start (s) and the end (e) are selected to minimize a credit intensity function:

$$|c_{i,\widehat{t}} - \phi^i \sigma(c_i)|$$

for $i = \{s, e\}$ where $t^s < \widehat{t} < t^e$. The thresholds ϕ and ϕ^i are chosen to match the desired average boom frequency and length. The start and end thresholds are implicitly determined by the smoothness of the detrending procedure.

The approach we take is different. We do not detrend the series for each country, but define booms as periods in which credit growth is above a given threshold. We want to impose as few preconceptions as possible. There are several reasons for our approach, defined below.

We do not want to implicitly set an upper bound on the length of the boom. Using deviations from a trend implies that a boom has predetermined maximum length, because a protracted boom would be included in the trend component. We want to avoid this. Even a retrospective detrending method slowly adjusts to sudden changes. We want to allow for sudden increases in credit as well as a slower process of financial innovation. So, we will not impose a trend-cycle decomposition on the data. The data will inform us as to whether crises are associated with longer or shorter booms.

Also, the data on credit exhibit very large heterogeneity across countries. Sometimes there are strong increases in credit that appear as structural breaks, while other times there are large sudden movements. We do not take a stand on which of these events are more likely to be the relevant events for studying "credit booms." This is an open question.

We define a credit boom as starting whenever a country displays three years of credit growth that averages more than x^s and positive growth in each of the three years. The boom ends whenever a country experiences at least two years of credit growth not higher than x^e. In our baseline experiments we choose $x^s = 5\%$ and $x^e = 0\%$. The choice of thresholds is based on the average credit growth in the sample. Changes in thresholds do not alter the results qualitatively. Later we will compare the results using this classification procedure to one which uses Hodrick-Prescott filtering.

Our definition imposes no restrictions based on detrending. Since the threshold is fixed and financial deepening grows over the sample period, we have booms clustered in the second half of the sample period. This is not inconsistent with what we are studying and, again, we will later compare the results to the other procedure.

We say that a credit boom is accompanied by a financial crisis whenever Laeven and Valencia (2012) classify a crisis in a neighborhood of two years of the end of the boom.[8] Their database covers the period 1970 to 2011. They define a systemic banking crisis as occurring if two conditions are met: (1) there are "significant signs of financial distress in the banking system (as indicated by significant bank runs, losses in the banking system, and/or bank liquidations) and (2) if there are "significant banking policy intervention measures in response to significant losses in the banking system." Significant policy interventions include: (1) extensive liquidity support (when central bank claims on the financial sector to deposits exceeds five percent and more than double relative to the pre-crisis level); (2) bank restructuring gross costs are at least three percent of GDP; (3) significant bank nationalizations; (4) significant guarantees are out in place; (5) there are significant asset purchases (at least five percent of GDP); (6) there are deposit freezes and/or bank holidays.

By our definition, there are 87 booms in the sample, of which 33 ended in a financial crisis. The complete list of booms and crises is in the Appendix. There are very long booms; the longest is in Australia from the 1983 to 2010 (28 years). The definition also results in booms being relatively frequent. Of the 1695 years in the sample, 929 were spent in a boom, 55% of the time. On average, over 50 years, a country spent 27 years in a boom and, on average, 9 of those years were spent in a boom that ended in a crisis.[9] This is our first result. Booms are not rare.

Table 1 provides an overview of the booms, showing average credit growth, average TFP and LP growth, average real GDP growth, average investment growth and the average duration of the booms. The last column shows the t-statistic for the null hypothesis that the mean for each variable is the same for booms that end in a crisis and those that do not. There is no statistical difference between any of these variables. In fact, the means of credit growth, TFP growth and LP growth are essentially the same. Table 2 shows advanced economies and Table 3 shows emerging economies.[10]

[8] In the modern era, dating the start and end of a crisis is typically based on observing government actions. This makes it difficult to precisely date the end dates of crises (and the start dates), so we use a two year window. See Boyd, De Nicolo, and Loukoianova (2011).

[9] The data are very noisy and are constantly being revised. We remove sample points where the growth rate is greater than 5 percent in absolute value.

[10] The subsamples for crisis and non-crisis booms are small, as shown in Table 1, so there may be

In emerging economies TFP growth and LP growth are faster in booms that do not end in a crisis.[11]

One difference between advanced and emerging economies is that emerging economies had more booms and more booms that ended in a crisis: half and half. Average credit growth is higher in emerging economies for booms that end with a crisis. TFP and LP growth are notably higher in booms that do not end in a crisis, for emerging economies. For advanced economies TFP and LP growth appear the same statistically.

The fact that only 8 booms of the 39 booms in advanced economies were booms that ended in a crisis makes this sample quite noisy. And this contributes some noise to Table 1. Our analysis focuses on the differences in productivity over booms that end in a crisis and those that do not, both the path differences and the mean differences. Our results are consistent with previous literature that finds an asymmetry between boom episodes in emerging and advanced countries. Gourinchas, Valdes, and Landerretche (2001) find that emerging markets are more prone to credit booms. Mendoza and Terrones (2008) find that countries with fixed or managed exchange rates are more subject to credit booms and that in these countries credit booms are more likely to end in a crisis. Herrera, Ordonez, and Trebesch (2014) find that in emerging economies credit booms are usually accompanied by an increase in government's popularity.

It is instructive to compare our results to results obtained when the HP-filter is used (using a parameter of 100). Tables 4-6 constitute a summary of the results for this boom definition. In this case, there are 44 booms, 21 of which end in a crisis. Of the 1651 years in the sample, only 202 are spent in a boom, 12 percent. The average country spends 6 years in a boom, of which three are in a boom that ends in a crisis. From this point of view, booms are not central to aggregate economic activity. Booms without a crisis have higher labor productivity, but TFP growth is negative, whether

concerns about the power of the test. Resampling by randomly selecting pairs (a bootstrap) and repeating the test shows that the null is rejected with more confidence, confirming that the differences in the data do indeed exist.

[11]The classification of countries into advanced or emerging comes from http://www.imf.org/external/pubs/ft/weo/2008/01/weodata/groups.htm#oem. Advanced countries include the U.S., U.K., Austria, Belgium, Denmark, France, the Netherlands, Japan, Israel, Finland, Greece, Ireland, Portugal, Spain, Australia, Sweden and New Zealand. Emerging countries are: Turkey, Argentina, Brazil, Chile, Colombia, Costa Rica, Ecuador, Mexico, Peru, Uruguay, Egypt, India, Korea, Malaysia, Pakistan, the Philippines and Thailand.

Table 1: Descriptive Statistics - All Economies

	Whole Sample	Booms	Booms with a Crisis	Booms without a Crisis	t-Statistic for Means
Avg. Credit growth (%)	3.83	8.96	10.23	8.34	1.66
Avg. TFP growth (%)	0.83	0.87	0.79	0.91	-0.55
Avg. Pnts Gnt growth (%)	8.01	7.81	7.25	8.09	-0.24
Avg. LP growth (%)	2.52	2.57	2.24	2.70	-1.78
Avg. Duration (years)		10.68	9.59	11.31	-1.01
Avg. Time spent in boom		27.32	9.03	18.29	
Number of Booms		87	32	55	
Sample Size (years)	1695	929	307	622	

Table 2: Descriptive Statistics - Advanced Economies

	Whole Sample	Booms	Booms with a Crisis	Booms without a Crisis	t-Statistic for Means
Avg. Credit growth (%)	4.26	7.37	5.00	7.99	-2.15
Avg. TFP growth (%)	0.74	0.73	0.86	0.69	0.53
Avg. Pnts Gnt growth (%)	4.41	4.56	4.48	4.58	-0.03
Avg. LP growth (%)	2.77	2.69	2.97	2.62	1.27
Avg. Duration (years)		13.38	13.50	13.35	0.05
Avg. Time spent in boom		29.00	6.00	23.00	
Number of Booms		39	8	31	
Sample Size (years)	834	522	108	414	

the boom ends in a crisis or not. Not much is going on in advanced economies. TFP growth is quite different in emerging economies, but not statistically so.

Table 7 compares the results of using the HP-filter to detect booms to our results with the agnostic definition of a boom. The first line of the table shows that of the 161 boom-years detected using the HP-filter, 80% of those boom years are in our sample of boom-years. Line 2 shows that of the 40 booms detected with the HP- filter, we detected 91 percent of those boom. The bottom part of the table looks at the overlap of the booms detected with both methods. When do the HP-filter booms start compared to our starting date? The table shows that 63 percent of the HP-filter booms started more than three years after our starting point. This, of course, is not surprising because the HP-filter is constraining the data and pushed more of the boom into the trend. So, the HP-filter booms are essentially occurring in the middle of our booms. The average duration of our booms is ten years while the average duration of an HP-filter boom is five years.

Table 3: Descriptive Statistics - Emerging Economies

	Whole Sample	Booms	Booms with a Crisis	Booms without a Crisis	t-Statistic for Means
Avg. Credit growth (%)	3.40	11.00	13.07	9.03	3.04
Avg. TFP growth (%)	0.91	1.06	0.75	1.35	-1.77
Avg. Pnts Gnt growth (%)	12.54	13.33	9.12	18.23	-1.21
Avg. LP growth (%)	2.13	2.32	1.48	2.96	-3.19
Avg. Duration (years)		8.48	8.29	8.67	-0.21
Avg. Time spent in boom		22.61	11.06	11.56	
Number of Booms		48	24	24	
Sample Size (years)	861	407	199	208	

Table 4: Descriptive Statistics (with H-P filter) - All Economies

	Whole Sample	Booms	Booms with a Crisis	Booms without a Crisis	t-Statistic for Means
Avg. Credit growth (%)	4.12	6.38	6.82	6.17	0.41
Avg. TFP growth (%)	0.69	-0.11	-0.10	-0.11	0.04
Avg. rGDP growth (%)	1.71	1.24	0.96	1.43	-1.45
Avg. Inv growth (%)	0.58	0.69	0.80	0.62	0.43
Avg. LP growth (%)	1.75	1.15	1.00	1.24	-0.81
Avg. Duration (years)		4.59	4.62	4.57	0.14
Avg. Time spent in boom		6.31	3.03	3.28	
Number of Booms		44	21	23	
Sample Size (years)	1651	202	97	105	

Table 5: Descriptive Statistics (with H-P filter) - Advanced Economies

	Whole Sample	Booms	Booms with a Crisis	Booms without a Crisis	t-Statistic for Means
Avg. Credit growth (%)	5.19	5.65	3.62	6.12	-2.34
Avg. TFP growth (%)	0.64	-0.12	0.30	-0.25	1.32
Avg. rGDP growth (%)	1.89	1.29	1.27	1.30	-0.05
Avg. Inv growth (%)	0.65	0.35	0.07	0.41	-0.57
Avg. LP growth (%)	2.00	1.31	1.54	1.24	0.82
Avg. Duration (years)		4.58	4.50	4.61	-0.23
Avg. Time spent in boom		6.47	1.59	4.88	
Number of Booms		24	6	18	
Sample Size (years)	806	110	27	83	

Table 6: Descriptive Statistics (with H-P filter) - Emerging Economies

	Whole Sample	Booms	Booms with a Crisis	Booms without a Crisis	t-Statistic for Means
Avg. Credit growth (%)	2.51	7.96	8.79	6.41	0.86
Avg. TFP growth (%)	0.75	-0.08	-0.27	0.43	-1.30
Avg. rGDP growth (%)	1.49	1.15	0.83	2.07	-2.10
Avg. Inv growth (%)	0.49	1.30	1.15	1.63	-0.68
Avg. LP growth (%)	1.31	0.68	0.54	1.23	-1.11
Avg. Duration (years)		4.60	4.67	4.40	0.48
Avg. Time spent in boom		5.75	4.38	1.38	
Number of Booms		20	15	5	
Sample Size (years)	845	92	70	22	

Table 7: Overlap between booms using HP-filter and Gorton and Ordonez (2014)

	Number	**As a ratio of HP booms**
HP boom-years in GO	161	0.80
HP booms included in GO	40	0.91
HP booms	44	1.00
HP booms included in GO starting		
- in the same year	2	0.05
- a year later	6	0.15
- two years later	3	0.07
- three years later	4	0.10
- more than three later	25	0.63

Finally, we examine the crises in our sample. Our procedure was to start with our definition of a credit boom, apply it to each country, and examine Laeven and Valencia (2012) to see if the boom ended in a crisis. Laeven and Valencia have many more countries in their sample than we do, so overall they have more booms. We can reverse this procedure by first identifying all the crises that occur in our sample, based on Laeven and Valencia, and then seeing how they are related to our definition of a boom. Table 8 is a summary of the financial crises in our sample, based on Laeven and Valencia (2012). There are 89 crises in Laeven and Valencia that are in our sample, of which 32 are associated with a boom that ends in one of these crises. There are 57 crises that either happen during a boom that does not end with the crisis, or that do not happen during a credit boom. So, there are good booms and bad booms, but also crises unrelated to the end of booms, or with booms at all. Subsequently, in a Logit analysis of what is associated with crises, we will use all of the crises.

Table 8: Financial Crises in the Sample

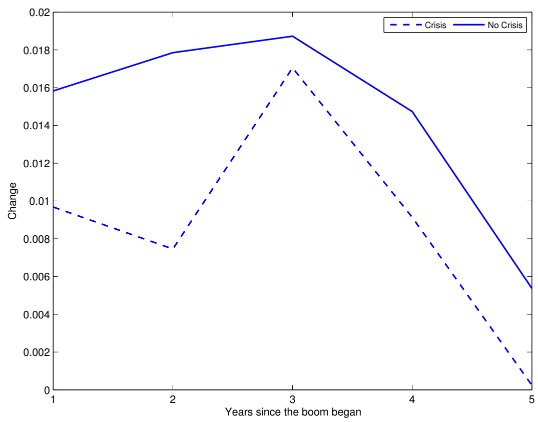
	# Crises
Total number of crises in the sample	89
Number of crises occurring at the end of a boom	32
Number of crises occurring not at the end of a boom	41
Number of crises not associated with booms	16

2.3 Booms, Crises and Productivity

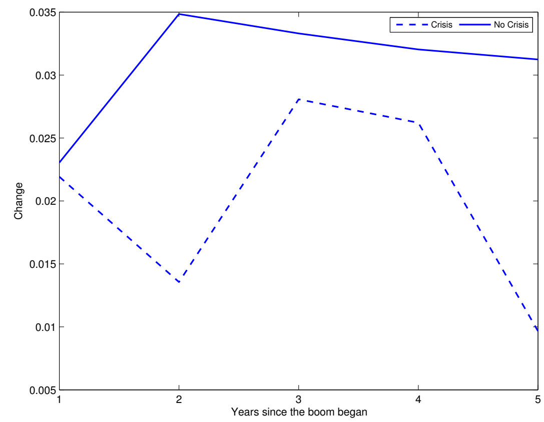
The second point we want to make is shown in Figure 1, which shows plots of the average growth rates for TFP growth, LP growth, real GDP growth, and the growth rate of capital formation, both for good booms and bad booms. Figure A.1 in the Appendix shows the median growth rates for the same variables.

Note first that the plots in Figure 1 show that a credit boom starts with a positive shock to productivity, but then the paths of growth rates differ for good booms and bad booms. In bad booms, the productivity growth rates die off as do the growth rates for real GDP and capital formation. Our preferred measure of productivity is labor productivity (it is measured with less error). Panel (b) makes the point dramatically. In good booms LP growth is high and flat, while in bad booms it nose dives by the fourth year the booms starts.

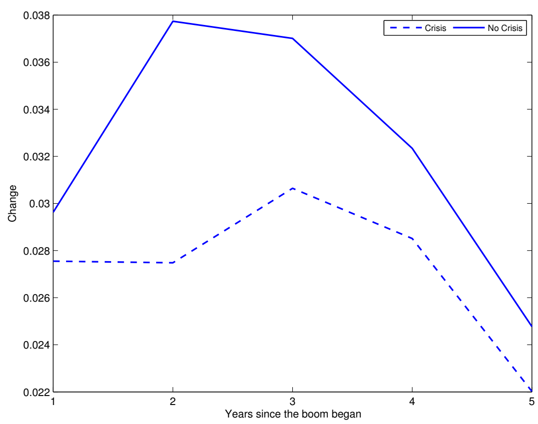
Figure 1: Average Productivity over Good and Bad Booms



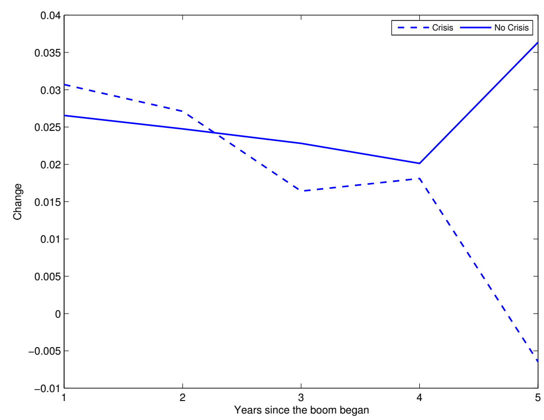
(a) Total Factor Productivity



(b) Labor Productivity



(c) Real GDP



(d) Capital Formation (Investment)

We now turn to more formally examining the effects of TFP and LP growth on the likelihood of a financial crisis. If the paths are different, then the likelihood of a crisis should be lower to the extent that TFP and LP growth rates are higher. We study this in the context of predicting financial crises with a Logit model. The literature has converged on the growth in credit as the key predicting variable. For example, Jorda, Schularick, and Taylor (2011) summarize the state of the literature as follows: "Our overall result is that credit growth merges as the best single predictor of financial instability" (p.1). We first verify that this is true in our sample.

We examine how lagged measures of credit growth predict financial crises with a Logit model:

$$Logit\left(Crisis_{t,j}\left|\Delta Cred_{t-1,j}\right.\right) = \Phi\left(\alpha + \beta \Delta Cred_{t-1,j}\right)$$

$Crisis_{t,j}$ is the odds ratio of a crisis, defined by $ln[Pr(Crisis_{t,j})/(1 - Pr(Crisis_{t,j}))]$, where $Pr(Crisis_{t,j})$ is the probability of a crisis at period t in country j.

We follow the literature and examine two measures of lagged credit growth, the change in credit over the previous five years (5Ychange) and the lagged five-year moving average of credit growth (5YchangeMA). The results, with and without country fixed effects, are shown in Table 9 . Since introducing fixed effects into a logit model has well-known problems, such as the incidental parameter problem (see Arellano and Hahn (2007) and Greene (2004)), we also run a linear probability model (LPM) to assess the relevance of country fixed effects.

$$\mathbb{1}\left(Crisis_{t,j}\left|\Delta Cred_{t-1,j}\right.\right) = \Phi\left(\alpha + \beta \Delta Cred_{t-1,j}\right)$$

where $\mathbb{1}\left(Crisis_{t,j}\right)$ is an indicator function that assigns 1 when country j experiences a crisis in period t, and zero otherwise.

The table shows that both measures of credit growth are significant predictors of the likelihood of a financial crisis, and that country fixed effects are not a critical determinant in this relation.

The marginal effect in the table shows the change in the probability of a crisis given a change of one standard deviation in the credit. The first column, for example, shows that an increase of one standard deviation in the volume of lagged credit increases the probability of a crisis by 1%.

Table 9: Credit as Crisis Predictor

	5Ychange			5YchangeMA		
	LOGIT	LPM		LOGIT	LPM	
α	-2.93	0.05		-2.82	0.06	
t-Statistic	-23.73	7.54		-22.36	7.52	
β	0.52	0.04	0.05	0.59	0.05	0.07
t-Statistic	3.22	3.36	4.16	2.68	2.74	3.77
Marginal	0.01	0.02	0.02	0.01	0.02	0.03
R^2		0.01	0.06		0.02	0.07
N	1525	1525	1525	1389	1389	1389
FE	No	No	Yes	No	No	Yes

We now turn to asking whether changes in TFP and LP during the boom, measured by the lagged five-year change and the lagged five-year moving average, reduce the likelihood of the boom ending in a financial crisis, as suggested by Figure 1.

$$Logit\left(Crisis_{t,j}\left|\Delta Cred_{t-1,j}, \Delta TFP_{t-1,j}\right.\right) = \Phi\left(\alpha + \beta\Delta Cred_{t-1,j} + \gamma\Delta TFP_{t-1,j}\right)$$

The results are shown in Table 10. By both measures, the higher the growth in TFP, the less likely that the boom ends in a financial crisis. Table 11 shows the results when the change in LP is used as a predictor. Like the change in TFP, it significantly reduces the likelihood of the boom ending in a financial crisis.

Table 10: Credit and TFP Growth as Crises Predictors

	5Ychange			5YchangeMA		
	LOGIT	LPM		LOGIT	LPM	
α	-2.86	0.05		-2.75	0.06	
t-Statistic	-23.07	7.91		-21.85	8.04	
β	0.55	0.04	0.05	0.65	0.05	0.07
t-Statistic	3.41	3.57	4.27	3.00	3.08	3.92
Marginal	0.01	0.02	0.03	0.01	0.02	0.03
γ	-2.45	-0.14	-0.10	-3.65	-0.22	-0.15
t-Statistic	-2.25	-2.35	-1.74	-2.78	-2.88	-1.87
Marginal	-0.01	-0.01	-0.01	-0.02	-0.02	-0.01
R^2		0.01	0.07		0.02	0.08
N	1525	1525	1525	1389	1389	1389
FE	No	No	Yes	No	No	Yes

This pattern does not arise with HP-filters. In the Appendix, Figures A.2 and A.3 are the counterparts to Figures 1 and A.1 except that they are based on the credit booms determined by HP-filtering. Here we use the Mendoza and Terrones (2008)

Table 11: Credit and LP Growth as Crises Predictors

	5Ychange			5YchangeMA		
	LOGIT	LPM		LOGIT	LPM	
α	-2.77	0.06		-2.70	0.06	
t-Statistic	-14.38	6.10		-13.08	5.72	
β	0.47	0.03	0.04	0.60	0.04	0.06
t-Statistic	2.55	2.67	2.97	2.45	2.57	3.18
Marginal	0.01	0.02	0.02	0.01	0.02	0.02
γ	-2.56	-0.12	-0.02	-2.49	-0.13	0.02
t-Statistic	-2.24	-2.36	-0.40	-1.99	-2.14	0.22
Marginal	-0.01	-0.01	-0.00	-0.01	-0.01	0.00
R^2		0.33	0.36		0.34	0.38
N	1217	1217	1217	1097	1097	1097
FE	No	No	Yes	No	No	Yes

definition of a credit boom, where a boom occurs when credit to the private sector grows by more than a typical business cycle expansion, as described in equation (1) with $\phi = 1.75$. These figures do not display any clear difference between booms that end in a crisis and those that do not. Similarly, there is no predictive power of the growth in productivity on the likelihood of a crisis conditional on credit growth. Tables A.4 and A.5 in the Appendix are the counterparts to the above Tables 10 and 11, except that the booms were determined by HP-filtering.

2.4 Summary

We take the following points from this empirical study:

1. Credit booms are not rare and occur in both advanced and emerging economies.
2. Booms start with a positive shock to TFP and LP growth.
3. The subsequent dynamics of productivity growth differ between booms that end in a crisis and those that do not. Growth rates quickly decline in booms that end in a crisis.
4. Crises are less likely with larger TFP and LP growth during the preceding boom.
5. These findings are not found when applying HP filtering.

Point 1 emerges once we adopt the agnostic boom definition, which does not take out a trend. This leaves us with significantly more booms which are significantly longer. Point 2 is the connection with the economic history literature which looks at average TFP growth over longer periods, often ten years which is the average duration of a boom in our data. Point 2 also suggests a link between growth and aggregate cyclical behavior, in particular financial crises. Point 3 notes that the paths of the productivity growth rates differ over booms which end in a crisis and those that do not. Point 4 emphasizes the role of productivity growth being associated with a boom being less likely to end in a crisis. Although LP growth also shows the same pattern when HP filtered booms are examined, in general HP filtering misses these findings.

We now turn to a model that captures these empirical findings.

3 The Model

The model is an extension of Gorton and Ordonez (2014), as mentioned above. In this section we review this model and explain our two extensions.

3.1 Setting

The economy is characterized by two overlapping generations – young and old – each a continuum of agents with mass 1, and three types of goods – *numeraire*, *managerial skills* and *"land"*. Each generation is risk neutral and derives utility from consuming numeraire at the end of each period. Numeraire is non-storable, productive and reproducible – it can be used as *"capital"* to produce more numeraire, hence we denote it by K. Land is storable, but non-productive and non-reproducible. Managerial skills are non-transferrable, their use cannot be imposed and does not generate disutility.

We interpret the young generation as *"households"* and the old generation as *"firms"*. Only firms have access to an inelastic fixed supply of managerial skills, which we denote by L^*. These skills can be combined with numeraire in a stochastic Leontief technology to produce more numeraire, K'.

$$K' = \begin{cases} A\min\{K, L^*\} & \texttt{with prob. } q \\ 0 & \texttt{with prob. } (1-q). \end{cases}$$

The first extension of Gorton and Ordonez (2014) is as follows. The quality of technology is given by q, subject to exogenous shocks but also driven endogenously by the size of the credit boom. The technology is determined by a limited supply of projects in the economy, also with mass 1. There are two types of projects that are available: A fraction ψ has *high* probability of success, q_H, and the rest have a *low* probability of success, q_L. We assume all projects are efficient, i.e., $q_H A > q_L A > 1$, which implies that the optimal scale of numeraire in production is $K^* = L^*$ for all projects, independent of their success probability $q \in \{q_L, q_H\}$. We characterize an "opportunity set" by the average quality of projects ψ. For now we assume there is a single opportunity set, but later we allow for shocks to opportunity sets that come from shocks to the average quality of projects, ψ.

Households and firms not only differ in their managerial skills, but also in their initial endowments. Only households born with an endowment of numeraire $\overline{K} > K^*$, which is enough to sustain optimal production.

Even though non-productive, land potentially has an intrinsic value. If land is *"good"*, it can delivers C units of numeraire, but only once. If land is *"bad"*, it does not deliver anything. We assume a fraction $\widehat{p}$ of land is good. At the beginning of the period, different units of land i can potentially be viewed differently, with respect to their quality. We denote these priors of being good p_i and assume they are commonly known by all agents in the economy.[12]

Privately observing the quality of land costs γ_l units of numeraire to land non-holders (lenders) and γ_b units of managerial skills to land holders (borrowers). Lenders only have numeraire at the beginning of the period and using γ_l for monitoring diverts its use for consumption. Similarly, borrowers only have managerial skills at the beginning of the period and using γ_b for monitoring diverts their use for production.

To fix ideas it is useful to think of an example. Assume gold is the intrinsic value of land. Land is good if it has gold underground, with a market value C in terms of numeraire. Land is bad if it does not have any gold underground. Gold is non-observable at first sight, but there is a common perception about the probability each unit of land has gold underground, which is possible to confirm by mining the land at a cost γ_b for those holding land, or γ_l for those not holding land.

[12]When no confusion is created we will dispense with the use of i and refer to p as the probability a generic unit of land is good.

In this simple setting, resources are in the wrong hands. Households only have numeraire while firms have managerial skills but no numeraire that is essential to produce. Since production is efficient, if output was verifiable it would be possible for households to lend the optimal amount of numeraire K^* to firms using state contingent claims. In contrast, if output is non-verifiable, firms would never repay and households would never be willing to lend.

We will focus on this latter case, in which firms can hide the numeraire. However, we will assume firms cannot hide land, which makes land useful as *collateral*. Firms can credibly promise to transfer a fraction of land to households in the event of not repaying numeraire, which relaxes the financing constraint from output non-verifiability. Hence, since land can be transferred across generations, firms hold land. When young, agents use their endowment of numeraire to buy land, which is then useful as collateral to borrow and to produce when old.

The perception about the quality of collateral then becomes critical in facilitating loans. To be precise, we further assume that $C > K^*$. This implies that land that is known to be good can sustain the optimal loan, K^*. Contrarily, land that is known to be bad is not able to sustain any loan. We refer to firms that have land with a positive probability of being good ($p > 0$) as *active firms*. In contrast to firms that are known to hold bad land, these firms can actively participate in the loan market to raise funds to start their projects.[13]

Returning to the technology, we assume that active firms are randomly assigned to a queue to choose their project. Naturally, when it is a firm's opportunity to choose according to its position in the queue, an active firm picks the project with the highest q among those remaining in the pool. We assume that lenders know (or can infer in equilibrium) the mass of active firms in the economy, which we denote by η, but not each firm's position in the queue. This implies that only firms know their individual project quality, q, but lenders just know the average productivity of projects in the economy. Then, lenders' beliefs of the probability of success for any single firm are

$$\widehat{q}(\eta) = \begin{cases} q_H & \texttt{if } \eta < \psi \\ \frac{\psi}{\eta} q_H + \left(1 - \frac{\psi}{\eta}\right) q_L & \texttt{if } \eta \geq \psi. \end{cases}$$

[13]The assumption that active firms are those for whom $p > 0$ is just imposed for simplicity, and is clearly not restrictive. If we add a fixed cost of operation, then it would be necessary a minimum amount of funding to operate, and firms having collateral with small but strictly positive beliefs p would not be active either.

This implies that the average productivity of projects in the economy (also the lender's beliefs about the probability of success of a any given firm), $\widehat{q}(\eta)$, weakly declines with the mass of active firms, η, and reaches the minimum when all firms are active (i.e, when $\eta = 1$).

3.2 Optimal loan for a single firm

To start we study the optimal short-term collateralized debt for a single firm, with a project that has a probability of success q and when there is a total mass of active firms η. Both borrowers and lenders may want to produce information about its collateral, which is good with probability p.[14] Loans that trigger information production (information-sensitive debt) are costly – either borrowers acquire information at a cost γ_b or have to to compensate lenders for their information cost γ_l. However, loans that do not trigger information production (information-insensitive debt) may be infeasible because they introduce the fear of asymmetric information – they introduce incentives for either the borrower or the lender to deviate and acquire private information to take advantage of its counterparty. The magnitude of this fear determines the information-sensitivity of the debt and, ultimately the volume and dynamics of information in the economy.

3.2.1 Information-Sensitive Debt

Lenders can learn the true value of the borrower's land by using γ_l of numeraire. Borrowers can learn the value of their own land by using γ_b of managerial skills, and then can just assign $L^* - \gamma_b$ of managerial skills for production. Following the assumed Leontief technology this implies that, in case the firm acquires information about the land's quality, the project generates $A \min\{K, L^* - \gamma_b\}$ in case of success (with probability q), and 0 otherwise.

If lenders are the ones acquiring information, assuming lenders are risk neutral and

[14]It may seem odd that the borrower has to produce information about his own collateral. But, in the context of corporations owning land, for example, they would not know the value of their land holdings all the time. Similarly, if the collateral being offered by the firm is an asset-backed security, as its value is not known because these securities are complicated and do not trade frequently or on centralized exchanges where the price is observable and coveys information.

competitive, then:[15]

$$p[\widehat{q}(\eta)R^l_{IS} + (1-\widehat{q}(\eta))x^l_{IS}C] = pK + \gamma_l,$$

where K is the size of the loan, R^l_{IS} is the face value of the debt and x^l_{IS} is the fraction of land posted by the firm as collateral. The subscript IS denotes an *"information-sensitive"* loan, while the superscript l denotes that lenders acquire information.

In this setting debt is risk-free, that is firms will pay the same in the case of success or failure. If $R^l_{IS} > x^l_{IS}C$, firms always default, handing in the collateral rather than repaying the debt. Contrarily, if $R^l_{IS} < x^l_{IS}C$ firms always sell the collateral directly at a price C and repay lenders R^l_{IS}. This condition pins down the fraction of collateral posted by a firm, which is a function of p and independent of q:

$$R^l_{IS} = x^l_{IS}C \qquad \Rightarrow \qquad x^l_{IS} = \frac{pK + \gamma_l}{pC} \leq 1.$$

Note that, since interest rates and the fraction of land posted as collateral do not depend on q because debt is risk-free, firms cannot signal their q by offering to pay different interest rates. Intuitively, since collateral prevents default completely, the loan cannot be used to signal the probability of default.

Expected total consumption for firms is $pC + p(qAK - x^l_{IS}C)$. Then, plugging x^l_{IS} in equilibrium, *expected net profits* (net of the land value pC from the first term) from information-sensitive debt, conditional on lenders acquiring information, are

$$E(\pi|p, q, IS, l) = \max\{pK^*(qA-1) - \gamma_l, 0\}.$$

Intuitively, with probability p collateral is good and sustains $K^*(qA-1)$ numeraire in expectation and with probability $(1-p)$ collateral is bad and does not sustain any borrowing. The firm always has to compensate lenders for not consuming γ_l.

Similarly, we can compute these expected net profits in the case borrowers acquire information directly, at a cost γ_b in terms of managerial skills. Regardless of what the borrower finds, the firm will only have $L^* - \gamma_b$ managerial skills remaining for using in the project. If the borrower finds out that the land is good, with probability p, he

[15]Risk neutrality is without loss of generality because we will show that debt is risk-free. Perfect competition can be simply rationalized by assuming that only a fraction of firms have skills L^*, then existing more lenders offering loans than borrowers requiring loans.

will then just borrow $K^* - \gamma_b$ to operate at the, new lower, optimal scale.

In this case lenders also break even after borrowers demonstrate the land is good.

$$\widehat{q}(\eta)R^b_{IS} + (1 - \widehat{q}(\eta))x^b_{IS}C - K = 0.$$

Since debt is risk-free, $R^b_{IS} = x^b_{IS}C$ and $x^b_{IS} = \frac{K}{C}$. Ex-ante expected total consumption for the borrower is $pC + p(qAK - x^b_{IS}C)$. Then, plugging x^b_{IS} in equilibrium, *expected net profits* (again net of the land value pC) are

$$E(\pi|p, q, IS, b) = \max\{p(K^* - \gamma_b)(qA - 1), 0\}.$$

Then, expected profits from information-sensitive debt effectively are,[16]

$$E(\pi|p, q, IS) = \max\{pK^*(qA - 1) - \gamma, 0\} \tag{2}$$

where

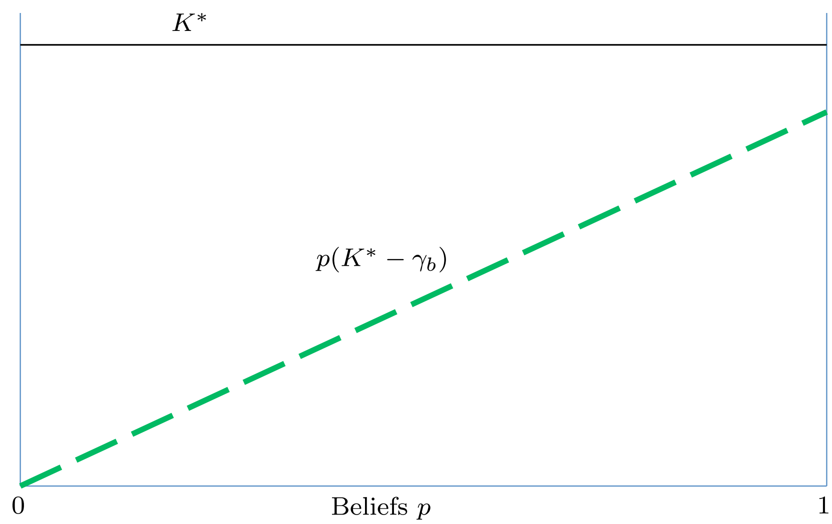
$$\gamma \equiv \min\{\gamma_l, \gamma_b p(qA - 1)\}$$

In case of using an information-sensitive loan, firms choose to produce information themselves if $\gamma_b p(qA - 1) < \gamma_l$, and prefer lenders to produce information otherwise. When lenders produce information, borrowers should compensate them for not consuming γ_l. When borrowers produce information, they face the cost of diverting resources away from the project only in case they found out the land is good (with probability p), as in such case they cannot exploit γ_b managerial skills for production.

In Figure 2 we show the expected information-sensitive loan for the case in which $\gamma_b p(qA - 1) < \gamma_l$ for all p. As can be seen the loan is declining in p as the project is less likely to be financed when the collateral is less likely to be good, and it is always below the optimal loan, K^*, as managerial skills are inefficiently wasted in monitoring the quality of land.

[16]In case borrowers, as lenders, cannot use γ_b for consumption either, the cost of observing the land's quality is $\gamma_b(1 - p)(qA - 1) + \gamma_b = \gamma_b(p + (1 - p)qA)$.

Figure 2: Expected Loan Size with Information-Sensitivity Debt



3.2.2 Information-Insensitive Debt

Another possibility for firms is to borrow without triggering information acquisition. Information acquisition is private, however, and there may be incentives to deviate. We assume information is private immediately after being obtained and becomes public at the end of the period. Still, the agent can credibly disclose his private information immediately if it is beneficial to do so. This introduces incentives both for lenders and borrowers to obtain information before the loan is negotiated and to take advantage of such private information before it becomes common knowledge.

Still it should be the case that lenders break even in equilibrium

$$\widehat{q}(\eta)R_{II} + (1 - \widehat{q}(\eta))px_{II}C = K,$$

subject to debt being risk-free, $R_{II} = x_{II}pC$. Then

$$x_{II} = \frac{K}{pC} \leq 1.$$

For this contract to be information-insensitive, we have to guarantee that neither lenders nor borrowers have incentives to deviate and check the value of collateral privately. Lenders want to deviate because they can lend at beneficial contract provisions if the collateral is good, and not lend at all if the collateral is bad. Borrowers want to deviate because they can borrow at beneficial contract provisions if the collateral is bad and renegotiate even better conditions if the collateral is good.

Lenders want to deviate if the expected gains from acquiring information, evaluated at x_{II} and R_{II}, are greater than the private losses, γ_l, from acquiring information,

$$p[\widehat{q}(\eta)R_{II} + (1-\widehat{q}(\eta))x_{II}C - K] > \gamma_l \qquad \Rightarrow \qquad (1-p)(1-\widehat{q}(\eta))K > \gamma_l.$$

More specifically, the benefits of acquiring information comes from not lending when the collateral is bad and making profits in expectation from lending when the collateral is good, which happens with probability p. In this last case, if there is default, which occurs with probability $(1-\widehat{q}(\eta))$, the lender can sell collateral that was obtained at $px_{II}C = K$ at a price $x_{II}C$, making a net gain of $(1-p)x_{II}C = (1-p)\frac{K}{p}$. The condition that guarantees that lenders do not want to produce information when facing information-insensitive debt can then be expressed in terms of the loan size,

$$K < \frac{\gamma_l}{(1-p)(1-\widehat{q}(\eta))}. \tag{3}$$

Note that this condition for no information acquisition by lenders depends on the lenders' *expected* probability of success, $\widehat{q}(\eta)$. This is central to the dynamics we will discuss subsequently.

Loans would never be larger than K^* (as the optimal size of the project is L^*) and the lender would never lend more than pC, which is the expected value of the whole unit of land. Given these two "technological" restrictions and the informational restriction from equation (3), information insensitive loans are such that

$$K < K^l(p|\widehat{q}(\eta), II) \equiv \min\left\{K^*, \frac{\gamma_l}{(1-p)(1-\widehat{q}(\eta))}, pC\right\} \tag{4}$$

As depicted in Figure 3, the region of information insensitive debt that does not induce lenders to privately deviate and acquire information is the one under the blue solid curve.

Similarly, borrowers want to deviate if the expected gains from acquiring information, evaluated at x_{II} and R_{II}, are greater than the losses γ_b from acquiring information. Specifically, if borrowers acquire information, their expected benefits are $p(K^* - \gamma_b)(qA-1) + (1-p)\min\{K, K^* - \gamma_b\}(qA-1)$. With probability p land is good and the firm borrows $K^* - \gamma_b$ as there are only $L^* - \gamma_b$ managerial skills remaining. With probability $1-p$ land is bad and the firm borrows the minimum between the original contract K or the optimum conditional on having already spent managerial skills privately, $K^* - \gamma_b$. If borrowers do not acquire information, their benefits are $K(qA-1)$. Hence borrowers do not acquire information if

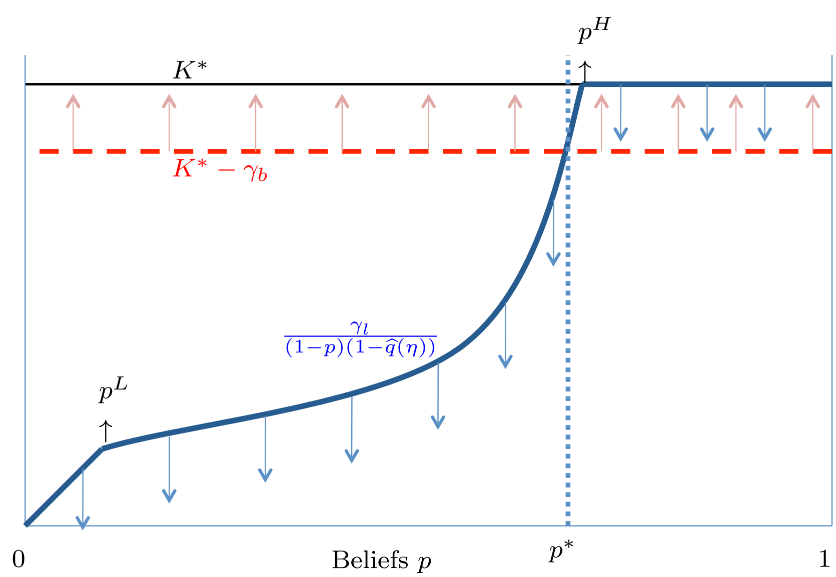
$$p(K^* - \gamma_b)(qA-1) + (1-p)\min\{K, K^* - \gamma_b\}(qA-1) < K(qA-1).$$

The condition that guarantees that borrowers do not want to produce information under information-insensitive debt can also be expressed in terms of the loan size,

$$K > K^b(p|\widehat{q}(\eta), II) \equiv K^* - \gamma_b \tag{5}$$

As depicted in Figure 3, the region of information insensitive debt that does not induce borrowers to privately deviate and acquire information is the one above the red dotted line.

Figure 3: Expected Loan Size with Information-Insensitive Debt



Combining the two conditions (4) and (5), information-insensitive debt is feasible only when the loan is both above the red dotted line in Figure 3 (to avoid information acquisition by borrowers) and below the blue solid line (to avoid information acquisition by lenders). In other words, information-insensitive debt is feasible only when $p > p^*$, where the threshold p^* is given by the point in which $K^l(p^*) = K^b(p^*)$ from equations (4) and (5). Then

$$p^* = \max\left\{1 - \frac{\gamma_l}{(K^* - \gamma_b)(1 - \widehat{q}(\eta))}, \frac{K^* - \gamma_b}{C}\right\}. \tag{6}$$

It is clear from this condition that the region of information-insensitive debt is larger when either γ_b or γ_l is large. It is also clear that this information-insensitive debt is always feasible at relatively high beliefs p whenever $\gamma_b > 0$ or $\gamma_l > 0$.

Finally, it is also relevant to highlight that the optimal loan K^* is feasible with information-insensitive debt when $p > p^H$, where the threshold p^H is given by the point in which $\frac{\gamma_l}{(1-p^H)(1-\widehat{q}(\eta))} = K^*$ from equation (4). Then

$$p^H = 1 - \frac{\gamma_l}{K^*(1 - \widehat{q}(\eta))}. \tag{7}$$

Finally, and just for completeness as this kink will not be relevant for the coming results, the threshold p_L is given by the point in which $\frac{\gamma_l}{(1-p^L)(1-\widehat{q}(\eta))} = p^L C$ from equation (4). Then [17]

$$p^L = \frac{1}{2} - \sqrt{\frac{1}{4} - \frac{\gamma_l}{C(1 - \widehat{q}(\eta))}}. \tag{8}$$

3.2.3 Loans With or Without Information?

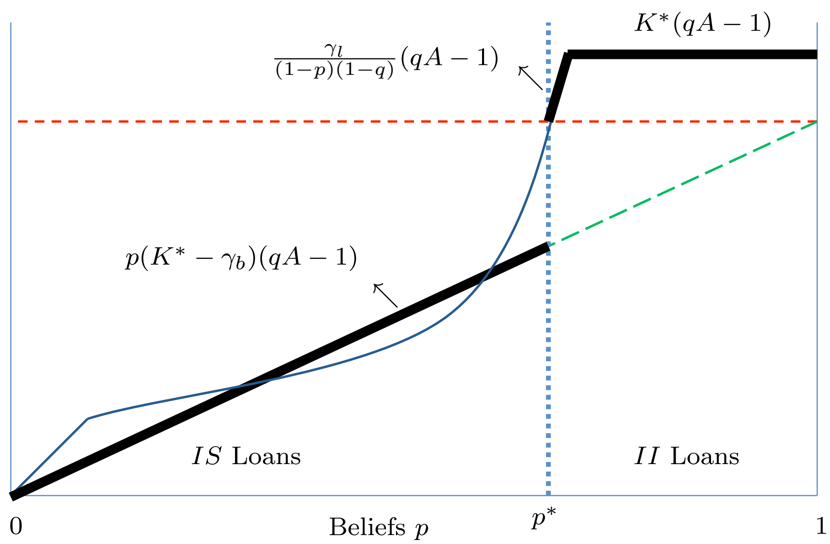
Figure 4 shows the ex-ante expected profits in both regimes (information-sensitive and information-insensitive debt) for a firm with private information about its own probability of success q, net of the expected value of land, for each possible p, assuming $\gamma_b(qA - 1) \leq \gamma_l$ for $q \in [q_L, q_H]$. This is naturally a sufficient condition such that, from equation (2), if there is information acquisition, borrowers are the ones spending on information.[18]

We can summarize the expected loan sizes for different beliefs p, graphically repre-

[17] The positive root for the solution of $pC = \gamma/(1-p)(1-q)$ is irrelevant since it is greater than p^H, and then it is not binding given all firms with a collateral that is good with probability $p > p^H$ can borrow the optimal level of capital K^* without triggering information acquisition.

[18] The case for which $\gamma_l < \gamma_b(qA - 1)$ is extensively studied in Gorton and Ordonez (2014), where we assume $\gamma_b = \infty$.

Figure 4: Expected Profits in Equilibrium



sented with a wide black discontinuous function in Figure 4, by

$$K(p|\gamma_l,\gamma_b,\eta)=\begin{cases} K^* & \text{if } p^H<p \\ \frac{\gamma_l}{(1-p)(1-\widehat{q}(\eta))} & \text{if } p^*<p<p^H \\ p(K^*-\gamma_b) & \text{if } \quad p<p^*. \end{cases}$$

It is interesting to highlight at this point that collateral with large γ_b and γ_l allows for more borrowing, since information production is discouraged both by borrowers and lenders, increasing both the optimality and feasibility of information insensitive debt.

It is also simple to see that $K(p)$ increases with $\widehat{q}(\eta)$ in the second range and is independent of $\widehat{q}(\eta)$ in the other ranges. Furthermore, the range in which information-insensitive loans are optimal (the first range) increases with $\widehat{q}(\eta)$ (from equation (7), as p^H decreases with $\widehat{q}(\eta)$). Similarly, the range in which only information-sensitive loans are feasible (the third range) decreases with $\widehat{q}(\eta)$ (from equation (6), as p^* weakly decreases with $\widehat{q}(\eta)$).

Remark: In this model productivity is qA, hence a combination of the probability of success and the output in case of success. We constructed the model such that only the average component q affects incentives to acquire information about collateral in credit markets. Similarly, it is possible to accommodate a trend in productivity that does not affect incentives to acquire information as long as the trend applies purely to A. We discuss this further in subsection 4.1.

3.3 Aggregation

The expected consumption of a household that lends to a firm with land that is good with probability p, conditional on an expected probability of default $\widehat{q}(\eta)$, is $\overline{K} - K(p|\widehat{q}(\eta)) + E_q\{E(repay|p, q, \eta)\}$. The expected consumption of a firm that borrows using land that is good with probability p and has a privately known probability of success q is $E(K'|p, q, \eta) - E(repay|p, q, \eta)$ (recall this is 0 for inactive firms). Then, the ex-ante (before observing its position in the queue for projects) aggregate consumption of firms is $E_q\{E(K'|p, q, \eta) - E(repay|p, q, \eta)\}$. Expected aggregate consumption is the sum of the consumption of all households and firms. Since $E(K'|p, q, \eta) = qAK(p|\widehat{q}(\eta))$, with $K(p|\widehat{q}(\eta))$ fixed for each p given an average quality of the projects, $\widehat{q}(\eta)$, then $E_q\{E(K'|p, q, \eta)\} = \widehat{q}(\eta)AK(p|\widehat{q}(\eta))$, and

$$W_t = \overline{K} + \int_0^1 K(p|\widehat{q}(\eta))(\widehat{q}(\eta)A - 1)f(p)dp$$

where $f(p)$ is the distribution of beliefs about collateral types and, as shown above, $K(p|\widehat{q}(\eta))$ is monotonically increasing in p and decreasing in η, as a larger η implies a lower $\widehat{q}(\eta)$.

In the unconstrained first best (the case of verifiable output, for example) all firms borrow, are active (i.e., $\eta = 1$), and operate with $K^* = L^*$, regardless of beliefs p about the collateral. This implies the unconstrained first-best aggregate consumption is

$$W^* = \overline{K} + K^*(\widehat{q}(1)A - 1).$$

Since collateral with relatively low p is not able to sustain loans of K^*, the deviation of consumption from the unconstrained first best critically depends on the distribution of beliefs p in the economy. When this distribution is biased towards low perceptions about collateral values, financial constraints hinder the productive capacity of the economy. This distribution also introduces heterogeneity in production, purely given by heterogeneity in collateral and financial constraints, not by heterogeneity in technological possibilities.

In the next section we study how this distribution of p evolves over time, affecting the fraction of operating firms η, that at the time determines the average probability of success in the economy $\widehat{q}$ and the evolution of beliefs. Then, we study the potential for completely endogenous cycles in credit, productivity and production.

4 Dynamics

In this section we follow Gorton and Ordonez (2014) and assume that each unit of land changes quality over time, mean reverting towards the average quality of collateral in the economy, and we study how endogenous information acquisition shapes the distribution of beliefs over time, and then the evolution of credit, productivity and production in the economy.

We impose a specific process of idiosyncratic mean reverting shocks that are useful in characterizing analytically the endogenous dynamic effects of information production on aggregate output and consumption. First, we assume idiosyncratic shocks are observable, but not their realization, unless information is produced. Second, we assume that the probability that land faces an idiosyncratic shock is independent of its type. Finally, we assume the probability that land becomes good, conditional on having an idiosyncratic shock, is also independent of its type. These assumptions are just imposed to simplify the exposition. The main results of the paper are robust to different processes, as long as there is mean reversion of collateral in the economy.

We assume that initially (at period 0) there is perfect information about which collateral is good and which is bad, a situation that we denote by *"symmetric information"*. In every period, with probability λ the true quality of each unit of land remains unchanged and with probability $(1-\lambda)$ there is an idiosyncratic shock that changes its type. In this last case, land becomes good with a probability $\widehat{p}$, independent of its current type. Even when the shock is observable, the realization of the new quality is not, unless managerial skills are used to learn about it.[19]

In this simple stochastic process for idiosyncratic shocks, the belief distribution has a three-point support: 0, $\widehat{p}$ and 1. Since firms with beliefs 0 do not get any loans, and

[19]To guarantee that all land is traded, buyers of good collateral should be willing to pay C for good land even when facing the probability that land may become bad next period, with probability $(1-\lambda)$. The sufficient condition is given by enough persistence of collateral such that $\lambda K^*(\widehat{q}(1)A-1) > (1-\lambda)C$. Furthermore they should have enough resources to buy good collateral, then $\overline{K} > C$.

hence do not operate, the mass η of active firms is the fraction of firms with beliefs $\widehat{p}$ and 1. Then $\eta = f(\widehat{p}) + f(1)$.

The next proposition shows the parametric conditions under which the economy remains in a *symmetric information* regime, with information being constantly renewed and production constant at a level below the unconstrained production W^*.

Define $\chi \equiv \lambda\widehat{p}+(1-\lambda)$. This is the fraction of active firms after idiosyncratic shocks in a single period. A fraction $(1-\lambda)$ of all collateral suffers the shock and their perceived quality, absent information acquisition, is $\widehat{p}$ while a fraction λ of collateral known to be good (a fraction $\widehat{p}$ of all collateral) remain with such a perception.

Proposition 1 *Constant Symmetric Information - Constant Consumption.*

If $\widehat{q}(\chi)$ is such that $\widehat{p} < p^*(\widehat{q}(\chi))$, from equation (6), then there is information acquisition for collateral suffering idiosyncratic shocks and consumption is constant every period,

$$\overline{W}(\widehat{p}) = \overline{K} + \widehat{p}(K^* - \gamma_b(1-\lambda))(\widehat{q}(\widehat{p})A - 1). \tag{9}$$

Proof In this case, $\eta = \chi$ after the first round of idiosyncratic shocks. Information about the fraction $(1-\lambda)$ of collateral that gets an idiosyncratic shock is reacquired every period t, since $\widehat{p}$ is in the region where information-insensitive debt is not feasible. Then $f(1) = \lambda\widehat{p}$, $f(\widehat{p}) = (1-\lambda)$ and $f(0) = \lambda(1-\widehat{p})$. Hence

$$W_t^{IS} = \overline{W}(\widehat{p}) = \overline{K} + [\lambda\widehat{p}K(1) + (1-\lambda)K(\widehat{p})]\,(\widehat{q}(\widehat{p})A - 1).$$

Since $K(0) = 0$, $K(1) = K^*$ and $K(\widehat{p}) = \widehat{p}(K^* - \gamma_b)$. Then consumption is constant at the level at which information is reacquired every period (equation (9)). Q.E.D.

If, in contrast to the assumption that characterizes the previous proposition, $\widehat{p}$ is relatively high, the incentives to acquire information depend on the evolution of the relevant threshold for information acquisition, given by p^* in Figure 4. As is clear from equation (6), this threshold depends on $\widehat{q}(\eta)$ as discussed in the next Lemma.

Lemma 1 *The cutoff p^* is monotonically increasing in η.*

Proof The proof is straightforward from inspecting equation (6), where it is clear that p^* weakly decreases with $\widehat{q}(\eta)$, which we assume decreasing in η. This implies that increases in η shrinks the range of information-insensitive debt. Q.E.D.

We say there are "*Information Cycles*" if the economy fluctuates between booms with no information acquisition and crashes with information acquisition. The next Proposition shows the conditions under which the economy fluctuates endogenously in this way, with periods of booms followed by sudden collapses.

Proposition 2 *Information Cycles.*

If $\widehat{q}(\chi)$ is such that $\widehat{p} > p^*(\widehat{q}(\chi))$ and $\widehat{q}(1)$ is such that $\widehat{p} < p^*(\widehat{q}(1))$, from equation (6), then there are information cycles. There is a length of the boom t^* at which consumption crashes to the symmetric information consumption, restarting the cycle.

Proof Starting from a situation of perfect information, in the first period $\eta_1 = \chi$, and if $\widehat{q}(\chi)$ is such that $\widehat{p} > p^*(\widehat{q}(\chi))$ there are no incentives to acquire information about the collateral with beliefs $\widehat{p}$. This implies there is no information acquisition in the first period. In the second period, $f(1) = \lambda^2\widehat{p}$ and $f(\widehat{p}) = (1-\lambda^2)$, implying that $\eta_2 > \eta_1$, which implies that $\widehat{q}(\eta_2) \leq \widehat{q}(\eta_1)$ and $p^*(\widehat{q}(\eta_2)) \geq p^*(\widehat{q}(\eta_1))$.

Repeating this reasoning over time, information-insensitive loans become infeasible when η_{t^*} is such that $\widehat{p} = p^*(\widehat{q}(\eta_{t^*}))$. We know there is such a point since by assumption $\widehat{p} < p^*(\widehat{q}(1))$. If $W^{II}_{t^*} > W^{II}_0$, the change in regime implies a crash. This crash is larger, the longer and larger the preceding boom. Q.E.D.

The intuition for information cycles is the following. In a situation of symmetric information, in which only a fraction $\widehat{p}$ of firms get financing, the quality of projects in the economy, in terms of their probability of success, is relatively high. If $\widehat{p}$ is high enough, such that information decays over time, more firms are financed and the average quality of projects decline.

When borrowers' information costs are sufficiently smaller than lenders' information costs, the reduction in projects' quality increases both the probability of default in the economy and the incentives for lenders to acquire information. At some point, when the credit boom is large enough, default rates are also large and may induce information acquisition through a change in regime from symmetric ignorance to symmetric information. New information restarts the process at a point in which only a fraction $\widehat{p}$ of firms can operate.

Note that there are no "shocks" needed to generate information cycles. Cycles are generated by changing beliefs relative to the available project quality as time goes on.

The cycles in Proposition 2 require that the same set of projects is available at the start of each cycle. However, if sometimes the set of projects is better, the boom would not end in a crash, while next time a boom with a worse set of projects would end in a crash. If the set of technology opportunities is good enough, then credit booms would end, but not in a crash. If after all firms are active there still no incentives to acquire information (this is, $\widehat{p} > p^*(\widehat{q}(1))$) then the boom would stop because there are no further firms entering into the credit market, but not with a crisis. While innovation determining the set of projects is presumably endogenous, it has the effect of generating the variety of booms that we saw in the data: long booms and short booms, booms that end in crashes and those that do not.

4.1 Productivity Shocks

In this section we explore the evolution of credit and production in the presence of shocks to average productivity, $\widehat{q}A$. We have constructed the model such that shocks to the two different components of measured productivity, the probability of success, $\widehat{q}$, and productivity conditional on success, A, affect credit booms and busts very differently, since only $\widehat{q}$ matters for credit markets. This result arises from the assumption that borrowers use managerial skills to privately learn about the quality of the collateral. Changing this assumption implies that both the individual q and A affect the incentives for firms to acquire information, leading to similar conclusions with a more cumbersome analysis.

In this section we discuss how a credit boom fueled by an initial increase in the average probability of success $\widehat{q}$ for all firms can be sustained by an increase in credit because information-insensitive loans are more likely to be sustained. However, if size of the shock on $\widehat{q}$ is smaller or the growth of $\widehat{q}$ slows down over time, financial crises and credit collapses become more likely.

While Proposition 2 describes the conditions for a deterministic cycle when ψ is fixed, in the next Proposition we consider the situation in which ψ suddenly and permanently increases to $\psi' > \psi$ and we characterize the level $\overline{\psi}$ such that after a shock $\psi' > \overline{\psi}$, the economy does not face cycles anymore, and then the ensuing boom does not end in a credit collapse. An increase in ψ implies that the average quality of projects in the economy gets better, such that the average probability of success for a given η increases.[20]

Proposition 3 *Productivity shocks and likelihood of crises.*

Under the conditions of Proposition 2, there is a $\overline{\psi}$ large enough such that, for all $\psi' > \overline{\psi}$ credit booms do not collapse. In particular, $\overline{\psi}$ is defined by $\widehat{p} = p^*(\widehat{q}(1|\overline{\psi})) \equiv p^*(\overline{\psi}q_H + (1-\overline{\psi})q_L)$.

Proof Assume first $\widehat{p}$ is relatively high (i.e., $\widehat{p} > p^*(\widehat{q}(\chi))$). Under the conditions of Proposition 2, there is a deterministic mass of active firms η_{t^*} at which $\widehat{q}(\eta_{t^*})$ is low enough such that information-insensitive loans are not feasible anymore and there is a collapse in credit and production. This situation is guaranteed because, by assumption $\widehat{p} < p^*(\widehat{q}(1))$. If there is a shock that drives the average quality of projects to $\psi' > \psi$ in some period during the credit boom (this is at some t such that $t < t^*$), lenders' expected probability of success of a project becomes $\widehat{q}(\eta_t|\psi')$ for all subsequent periods. This shock ψ' compensates for the reduction in productivity that more active firms generate. From equation (6) it is clear that the cutoff $p^*(\widehat{q}|\psi)$ always decreases with ψ, as ψ weakly increases $\widehat{q}(\eta)$ for all η. Q.E.D.

Intuitively, an increase in the average probability of project's success reduces the incentives for lenders to acquire information and does not change the incentives of the borrowers to acquire information, increasing the range for which information-insensitive loans are sustainable.

The larger the increase in the expected probability of success, the larger the increase of the information-insensitive region, and the longer a boom can be sustained. In the extreme, when ψ' is large enough (specifically $\psi' > \overline{\psi}$), then the there is no information acquisition even if all firms are active (when $\widehat{p} = p^*(\overline{\psi}q_H + (1-\overline{\psi})q_L)$). This implies that large shocks in the fraction of good projects available are more likely to sustain a credit boom that does not end up in a collapse.

This result is consistent with our empirical findings. As long as productivity grows in an economy there are no crises, conditional on such growth being fueled by a higher average quality of projects. Crises arise when the aggregate productivity shock is followed by a process of decline. In our model, during a credit boom there are more active firms and as a consequence, a decline in aggregate productivity. Exogenous

[20] In the extremes, if $\psi = 1$ the average quality of projects is $\widehat{q} = q_H$ even if $\eta = 1$, while if $\psi = 0$ the average quality of projects is $\widehat{q} = q_L$ regardless of $\eta > 0$.

productivity growth can compensate for this endogenous decline created by more activity in the economy.

In good booms, the better pool of projects and subsequent higher aggregate probability of success compensates the reduction that is generated by more, and also less productive, active firms. These two forces maintain average productivity at a level that sustains information-insensitive loans and credit booms, avoiding credit crises.

In bad booms, the pool of projects do not become better and then the aggregate probability of success does not increase, cannot compensating for the reduction that is generated by more, and also less productive, active firms. This decline in aggregate productivity induces information acquisition, then generating the collapse of credit and financial crises.

If ψ' is large enough (a good boom), then a credit boom can be sustained without ending in a credit collapse. Interestingly, this does not imply that the economy cannot have a reversal to a worse quality of projects in average, with a reduction in success probabilities in the future and return to a cycling situation. This is where the nature of the productivity increase is critical to understand the evolution of credit.

Here we have focused on positive shocks to to the pool of projects ($\psi' > \psi$) since that forces the system towards less information acquisition. We could also discuss the effects of negative shocks (this is $\psi' < \psi$), more in line with the standard real business cycles literature, which would have the opposite effects, forcing the system towards more information acquisition and then inducing an otherwise stable credit situation into a collapse. This effect complements the ones highlighted by the real business cycles literature since real negative shocks in productivity feedbacks into credit markets and causes a magnification of real shocks.

It is an interesting avenue for future empirical research to disentangle the effects of productivity shocks into the real effects highlighted by the standard literature and the effects on real activity through the incentives for information acquisition that affect the functioning of credit markets.

4.2 Numerical Illustration

In this Section we illustrate how small differences in the exogenous process of productivity can lead to large differences in the cyclical behavior of the measured credit, productivity and output. We assume an economy that is originally in an "information-sensitive" regime, with stable output below the first-best potential. We then introduce an exogenous permanent productivity shock that increases the average probability of project success. We show that if this shock is not large enough, the economy may enter in regime with deterministic credit booms followed by crises (bad booms). When the shock is larger the economy may experience a credit boom that drives the economy towards the first-best, where the credit boom gets exhausted without experiencing a crisis (good booms). We then discuss how the same result arises from an initial shock of the same size but with a different subsequent growth rate of technology. When the initial shock is not sustained, then the economy is more likely to enter a regime with deterministic cycles.

We assume idiosyncratic shocks happen with probability $(1-\lambda) = 0.1$ per period, in which case the collateral becomes good with probability $\widehat{p} = 0.88$. We also assume $L^* = K^* = 7$, $\bar{K} = 10$ (the endowment is large enough to allow for optimal investment) and $C = 15$ (good collateral is good enough to sustain an optimal loan size). The costs of information are $\gamma_l = 0.35$ for households in terms of numeraire and $\gamma_b = 0.05$ for firms in terms of managerial skills. With respect to the decreasing expected productivity of projects, we assume a fraction $\psi = \widehat{p}$ of projects have a probability of success $q_H = 0.5$ and the rest can only operate with a lower probability of success, $q_L = 0.4$. Finally, we assume an initial productivity of $A = 15$, which grows exogenously at a 0.3% rate per period.

We simulate this economy for 100 periods. During the first 20 periods this set of parameters implies that the economy is in an "information-sensitive" regime, in which every period there is information acquisition about the 10% of collateral that suffers the idiosyncratic shock, and so all collateral is known to be either good or bad.

We assume that in period 20 the economy experiences an exogenous shock that increases the probability of success of "good quality" projects from $q_H = 0.5$ to a permanently higher level, $q'_H > q_H$. We assume this shock is large enough for the economy to initially escape the information-sensitive regime. More formally, we assume two possible shocks. One implies $q'_H = 0.6$ and is represented by blue in Figure 5. The other, slightly larger shock, implies $q'_H = 0.62$ and is represented by red in Figure 5.

After the shock the economy experiences a credit boom, information decays, a larger fraction of firms obtain funds and η grows. As there are more than $\widehat{p}$ obtaining funds during a credit boom, they have to operate with projects with a lower productivity

($q_L = 0.4$ in the example), which decreases the marginal productivity in the economy, $\widehat{q}$. This gradual decline generates a gradual increase in the cutoff $p^*(\widehat{q}(\eta_t))$ over time.

The dynamics of the fraction of active firms, η, and the implied average productivity, $\widehat{q}$, are depicted in Figure 5. When the shock is not sufficiently large the economy enters into a regime with deterministic boom and bust cycles, a bad boom. These are the dynamics in blue. In this example, cycles last 28 periods from trough to peak and during the boom η goes from 0.88 to 0.99 (more than 90% of the firms that did not get credit under symmetric information can obtain loans and operate). However, the boom contains the seeds of the next crisis. As the average probability of success drops from 60% in the troughs to 57% in the peaks, the incentives for information acquisition and the fear of asymmetric information make the boom unsustainable.

In contrast, when the shock is large enough, the gradual increase of $p^*(\widehat{q})$ is never strong enough to induce information-sensitive debt, even when all collateral gets credit. In this situation the credit boom gets exhausted as it converges to the first-best outcome, a good boom. These are the dynamics in red.

Figure 6 shows the evolution of output (and welfare in this economy) under the presence of both types of permanent shocks in period 20. The largest positive shock induces a sustainable boom in the economy, a long-lasting "good boom". The slightly smaller positive shock induces the economy to enter into a regime of boom-bust cycles, a sequence of relatively short-lived "bad booms".

Figure 5: Positive Shocks of Different Size - Activity and Productivity

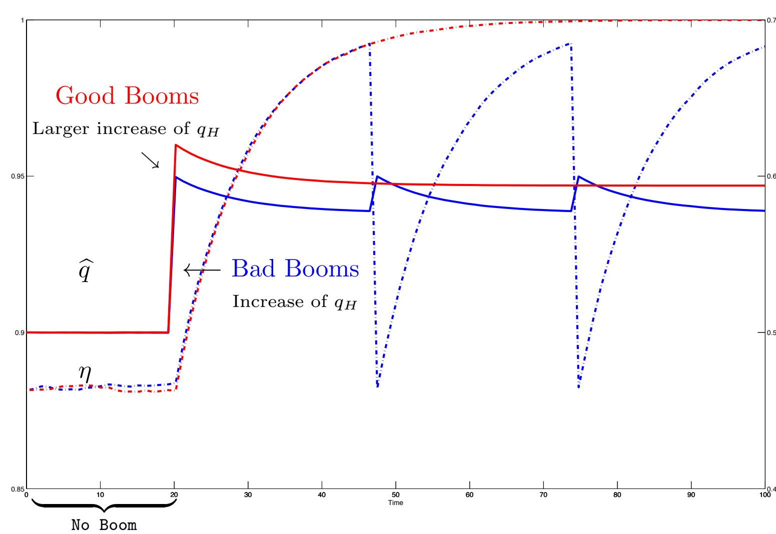
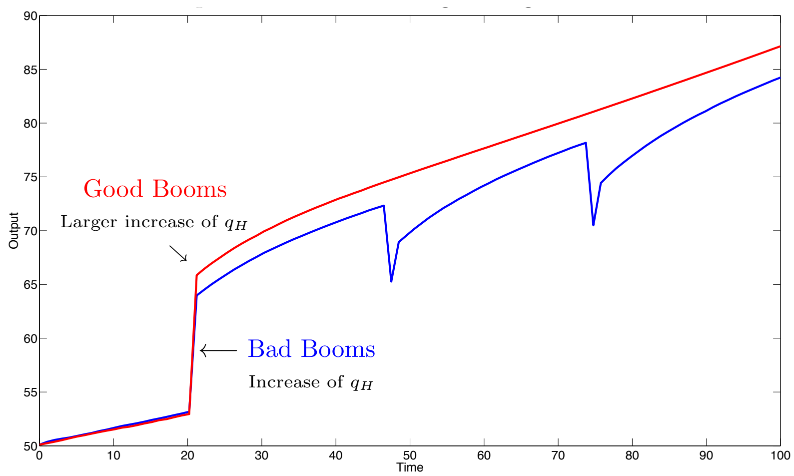
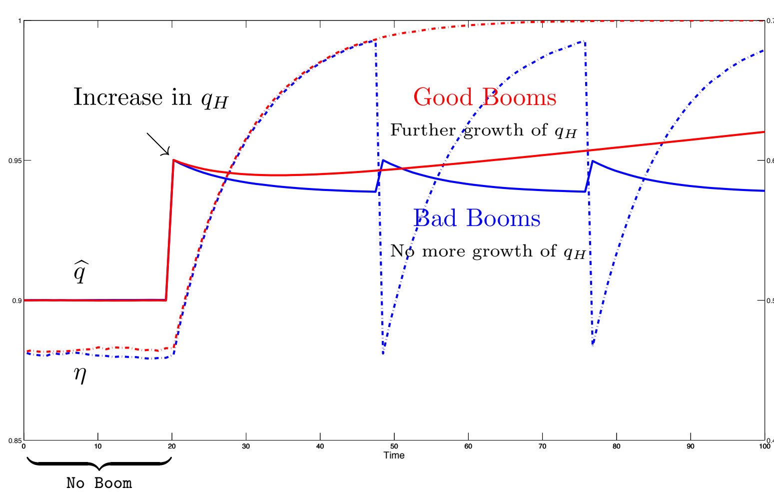


Figure 6: Positive Shocks of Different Size - Output



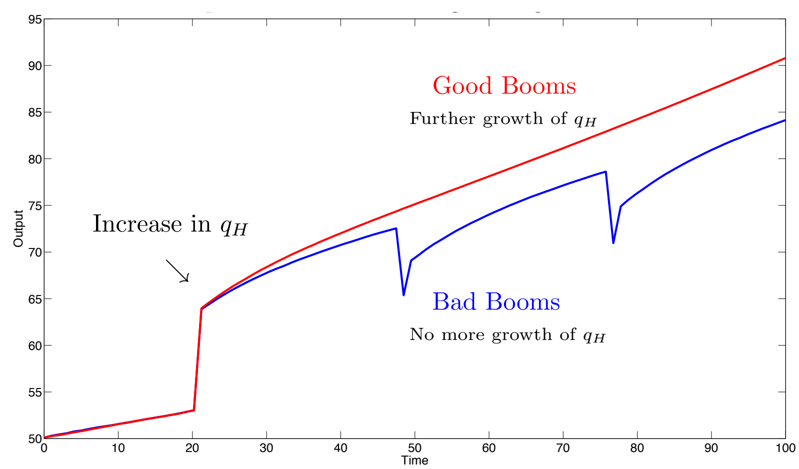
Figures 7-8 conveys the same information as Figures 5-6, but assume the same size of the productivity shock in period 20, but without further growth in one case (the blue line) and with a sustained growth of 0.1% per period (the red line). In this example, when the probability of success keeps growing over time, the credit boom becomes more sustainable and is less likely to end in a crisis because the exogenous growth in q_H compensates for the endogenous decline in $\widehat{q}$ driven by the increase in η, as depicted in red. When the increase in productivity does not compensate the endogenous decline, then it is more likely to enter into a sequence of boom-bust cycles, as depicted in blue.

Figure 7: Positive Shocks with Different Growth Rates - Activity and Productivity



These numerical examples illustrate the rich interactions between productivity and

Figure 8: Positive Shocks with Different Growth Rates- Output



credit in an economy and their implications for its cyclical behavior. An economy may experience credit booms that take the economy from a lower stable output to a higher level of stable output, without financial crises, which we have denoted as "good booms". It can also experience a movement from a stable low output to a sequence of booms and busts that exist even without fundamental changes, which we have denoted as "bad booms".

Remark on Policy Implications: There is a clear externality in our setting. When firms decide to take an information-insensitive loan, it does not internalize the effect in reducing the average productivity in the economy and increasing the incentives to acquire information. In other words, firms do not internalize the effect of their loan on the feasibility of a "symmetric ignorance" regime. A planner can take this effect into consideration, avoiding average productivity to decline too much. More specifically, a planner would never allow credit booms to exceed a fraction η_{t^*} of firms to operate in the economy, for example by restricting credit or leverage, or by producing extra information, but interestingly with the main objective of avoiding too much information from being produced privately.

5 Empirical Tests

In this section we empirically examine some of the implications of the model. The model has the following predictions: (1) Firms should become riskier during credit booms that end in a crisis compared to good booms; literally, more firms should default during bad booms. (2) Booms start when there is a burst of innovation; (3) TFP, being a residual, should be a function of firm fragility.

The first prediction of the model is that, in bad booms, firms are becoming riskier. In the model as the good projects run out, firms are left with the fewer good projects that have a higher probability of getting no output. In other words, there should be more firms defaulting over a bad boom. We do not have bankruptcy data for a panel of countries. However we can use equity data to produce a measure of firm fragility recently introduced and studied by Atkeson, Eisfeldt, and Weill (2013). As a measure of firm fragility, they introduce Distance to Insolvency (DI), based on Merton (1975) and Leland (1994). DI measures the adequacy of a firm's equity cushion relative to its business risk. They show that this can be measured with the inverse of the volatility of a firm's equity returns.

We are interested in the economy as a whole, so we use stock indices for 32 of our 34 countries (essentially the "S&P500 equivalent" in each country, as detailed in Table A.3 in the Appendix); so we examine $\frac{1}{vol_{j,t}}$ for each country, where the daily stock price data is used to calculate $vol_{j,t}$ during boom j at year t. Note that an increase in $\frac{1}{vol_{j,t}}$ corresponds to an economy becoming more fragile. Atkeson, Eisfeldt, and Weill (2013) show that, in the U.S. this measure for the entire economy, is uniquely low for the Great Depression, the recession of 1938-39, and the Crisis of 2007. We examine this, with and without fixed effects, using the framework above:

$$Logit\left(BadBoom_{j,t}\middle|\Delta Cred_{j,t-1},\frac{1}{vol_{j,t-1}}\right)=\Phi\left(\alpha+\beta\Delta Cred_{j,t-1}+\gamma\frac{1}{vol_{j,t-1}}\right).$$

$BadBoom_{j,t}$ is the odds ratio of crisis conditional on being in a boom, defined by $ln[Pr(BadBoom_{j,t})/(1-Pr(BadBoom_{j,t}))]$, where $Pr(BadBoom_{j,t})$ is the probability of a crisis during boom j at period t. Table 12 shows that the coefficient on this variable is negative, the likelihood of a crisis is increasing as the fragility of the firms in the economy increases, but only marginally significant. The results in Table 12 use stock indices rather than, the more ideal, average of individual firm's $1/vol$. In ongoing work we are computing this latter variable for a much larger range of firms than the ones captured in stock indices, typically smaller firms.

The second prediction of the model is that a boom starts when there is a positive productivity shock. In the model this corresponds to the new technology arriving.

Table 12: Default Probability as Crisis Predictor

	5Ychange			5YchangeMA		
	LOGIT	LPM		LOGIT	LPM	
α	-3.21	0.04		-3.19	0.04	
t-Statistic	-16.97	4.30		-14.42	4.67	
β	0.63	0.05	0.06	0.05	0.00	0.02
t-Statistic	3.12	3.41	4.45	0.10	0.10	1.18
Marginal	0.01	0.02	0.03	0.00	0.00	0.01
γ	0.11	0.01	0.00	-0.07	-0.00	-0.01
t-Statistic	0.49	0.58	0.27	-0.13	-0.13	-0.38
Marginal	0.00	0.00	0.00	-0.00	-0.00	-0.00
R^2		0.54	0.58		0.68	0.71
N	844	844	844	702	702	702
FE	No	No	Yes	No	No	Yes

We test this prediction by examining whether there is a burst of patents granted in the years just prior to the start of the boom. In other words, there should predictive power for patents granted prior to the start of the boom. We use patent data from the World Intellectual Property Organization.[21] We estimate the following model, with and without fixed effects:

$$\mathbb{1}(Start\ Boom)_{i,t} = \alpha + \beta\Delta(NewPatents)_{i,t-n} + \gamma\left[\Delta(NewPatents)_{i,t-n} \times \mathbb{1}(Boom)_{i,t-n}\right] + \epsilon_{i,t}$$

where $\mathbb{1}(Start\ Boom)_{i,t}$ is an indicator of whether country i experiences the start of a boom at period t. For the right-hand side variable New Patents Granted we accumulate the number of patents granted over different horizons prior to the start of the boom. Table 13 shows the results. The relevant coefficient, γ, is always significantly positive when country fixed effects are included. So, there is a burst of innovation in the immediate years prior to the start of the boom.

The third prediction of the model is related to the composition of the TFP. Our model includes the term $\widehat{q}A$, where $\widehat{q}$ is average productivity, as discussed above. However, when TFP is estimated, these two components are jointly estimated to be TFP. In our model, as time goes on, bad booms are more likely when firms become increasingly prone to default (this is, $\widehat{q}$ decreases) but not if the productivity conditional on success declines (this is, if A decreases). We examine versions of the following regressions,

[21] http://www.wipo.int/ipstats/en/statistics/patents/

Table 13: Patents Granted as Boom Predictor

	$(n=1)$		$(n=2)$		$(n=3)$		$(n=4)$		$(n=5)$	
α	-1.65		-1.68		-1.71		-1.70		-1.74	
t-Statistic	-29.31		-28.68		-28.23		-28.18		-27.55	
β	-0.19	-0.00	-0.18	-0.00	-0.16	-0.00	-0.16	-0.00	-0.14	-0.00
t-Statistic	-0.99	-0.60	-1.13	-0.60	-1.07	-0.51	-1.12	-0.53	-1.02	-0.31
γ	0.40	0.03	0.35	0.03	0.27	0.01	0.25	0.02	0.22	0.01
t-Statistic	1.78	2.08	1.99	2.81	1.69	1.90	1.70	3.79	1.54	5.17
R^2	0.16	0.17	0.22	0.23	0.27	0.28	0.28	0.29	0.35	0.36
N	1459	1459	1423	1423	1392	1392	1358	1358	1326	1326
FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

with and without fixed effects:

$$\Delta(TFP)_{i,t} = \alpha + \beta\Delta\frac{1}{vol_{i,t-n}} + \epsilon_{i,t}$$

The results are shown in Table 14, confirming that a significant component of estimated TFP is firm fragility, which differs over good booms and bad boom.

Table 14: Default as a Component of TFP

	$(n=0)$		$(n=1)$		$(n=2)$		$(n=3)$		$(n=4)$	
α	0.01		0.01		0.02		0.02		0.03	
t-Statistic	4.67		5.89		7.46		8.79		9.59	
β	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
t-Statistic	2.25	2.24	2.74	2.65	3.27	3.20	2.43	2.22	1.64	1.45
R^2	0.90	0.48	0.88	0.52	0.88	0.56	0.87	0.58	0.87	0.60
N	1016	1016	980	980	945	945	910	910	875	875
FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

6 Conclusions

Financial crises are typically preceded by a credit boom. Moreover, credit booms are not rare. The average country spends over half its time in a boom. And booms average a duration of ten years. The start of a boom is preceded by a burst of innovation. So, credit booms start with a positive productivity shock, which dies off in bad booms. The seeds of a crisis are sewn long before the crisis.

We provided a model to explain these facts. A savings and investment process based on information-insensitive debt has the potential to generate endogenous business cycles as investment opportunity sets change through time. The decay of information about collateral can lead to a credit boom and the build up evolves towards generating new information. Once this pressure is large enough, there is a wave of information production, which destroys credit and generates a crash (recession or depression). After this event, the cycle restarts.

The business cycle is a mirror image of what we call "information cycles" – the transit of the financial system from a "symmetric information" regime to a "symmetric ignorance" regime. The growth of symmetric ignorance endogenously generates a growth in the incentives to generate information and then a decline in the chances that ignorance is sustainable. Effectively the boom plants the seeds for its own destruction.

Tests of three predictions of the model confirm that firms become riskier during bad booms as compared to good booms. This is consistent with the findings of Gorton (1988) where it is shown that banking panics during the National Banking Era, 1863-1914, started with news of an unexpected increase in the liabilities of failed nonfinancial firms. Burns and Mitchell (1946) found this variable to be a leading indicator or recessions. We also found confirmation that booms started with a burst of innovation, as measured by cumulative patent grants prior to the start of the boom. Finally, consistent with the model, estimated TFP is significantly composed of firm fragility during booms, and more so in bad booms.

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A Appendix

Our analysis uses data on the countries listed in Table A.1. For each country we use time-series data from 1960 to 2010. Table A.1 shows also the number of booms, number of bad booms, the frequency of boom periods and the average time between booms for each country in our sample. If there was only one boom, then the average time between booms is not available (NA). Otherwise it is computed as the average number of years from a boom end to the subsequent boom start.

Table A.2 shows the classification of the booms identified by our algorithm.

Table A.1: Frequency of Booms

Country	Booms	Bad Booms	Frequency of Boom Periods	Average Time Between Booms
US	1.00	1.00	0.52	NaN
UK	3.00	1.00	0.58	7.00
Austria	1.00	0.00	0.68	NaN
Belgium	3.00	0.00	0.68	9.00
Denmark	2.00	0.00	0.30	14.00
France	2.00	0.00	0.68	13.00
Netherlands	1.00	0.00	1.00	NaN
Sweden	3.00	1.00	0.62	10.00
Japan	3.00	1.00	0.48	8.50
Finland	2.00	1.00	0.40	10.00
Greece	2.00	1.00	0.62	14.00
Ireland	2.00	0.00	0.50	11.00
Portugal	3.00	1.00	0.76	6.00
Spain	3.00	1.00	0.72	8.00
Turkey	4.00	2.00	0.40	10.00
Australia	2.00	0.00	0.76	10.00
New Zealand	3.00	0.00	0.70	3.00
Argentina	4.00	2.00	0.34	8.67
Brazil	3.00	1.00	0.38	13.50
Chile	2.00	1.00	0.52	11.00
Colombia	4.00	2.00	0.38	9.33
Costa Rica	2.00	0.00	0.32	31.00
Ecuador	4.00	2.00	0.58	6.33
Mexico	3.00	1.00	0.36	14.50
Peru	4.00	3.00	0.48	6.00
Uruguay	3.00	2.00	0.42	11.00
Israel	3.00	2.00	0.64	5.50
Egypt	2.00	1.00	0.44	7.00
India	2.00	0.00	0.78	12.00
Korea	4.00	0.00	0.52	7.00
Malaysia	2.00	1.00	0.62	8.00
Pakistan	1.00	1.00	0.18	NaN
Philippines	3.00	2.00	0.60	4.50
Thailand	1.00	1.00	0.62	NaN

Table A.2: Booms in the Sample

	Country	Years	Classification
1	US	1985-2010	crisis
2	UK	1970-1974	no crisis
3	UK	1979-1990	no crisis
4	UK	1999-2010	crisis
5	Austria	1964-1997	no crisis
6	Belgium	1961-1981	no crisis
7	Belgium	1986-1992	no crisis
8	Belgium	2005-2010	no crisis
9	Denmark	1983-1986	no crisis
10	Denmark	2000-2010	no crisis
11	France	1965-1992	no crisis
12	France	2005-2010	no crisis
13	Netherlands	1961-2010	no crisis
14	Sweden	1962-1973	no crisis
15	Sweden	1984-1992	crisis
16	Sweden	2001-2010	no crisis
17	Japan	1961-1966	no crisis
18	Japan	1970-1972	no crisis
19	Japan	1985-1999	crisis
20	Finland	1982-1991	crisis
21	Finland	2001-2010	no crisis
22	Greece	1967-1981	crisis
23	Greece	1995-2010	no crisis
24	Ireland	1976-1983	no crisis
25	Ireland	1994-2010	no crisis
26	Portugal	1963-1975	no crisis
27	Portugal	1979-1983	crisis
28	Portugal	1991-2010	no crisis
29	Spain	1961-1976	crisis
30	Spain	1987-1991	no crisis
31	Spain	1996-2010	no crisis
32	Turkey	1964-1969	no crisis
33	Turkey	1981-1983	crisis
34	Turkey	1995-1997	crisis
35	Turkey	2003-2010	no crisis
36	Australia	1964-1973	no crisis
37	Australia	1983-2010	no crisis
38	New Zealand	1972-1974	no crisis
39	New Zealand	1977-2000	no crisis
40	New Zealand	2003-2010	no crisis
41	Argentina	1968-1971	no crisis
42	Argentina	1977-1982	crisis
43	Argentina	1996-1999	crisis
44	Argentina	2005-2007	no crisis
45	Brazil	1967-1975	no crisis
46	Brazil	1991-1993	crisis
47	Brazil	2004-2010	no crisis
48	Chile	1975-1984	crisis
49	Chile	1995-2010	no crisis
50	Colombia	1967-1970	no crisis
51	Colombia	1980-1984	crisis
52	Colombia	1995-1997	crisis
53	Colombia	2004-2010	no crisis
54	Costa Rica	1963-1965	no crisis
55	Costa Rica	1996-2008	no crisis
56	Ecuador	1966-1968	no crisis
57	Ecuador	1975-1984	crisis
58	Ecuador	1992-2000	crisis
59	Ecuador	2004-2010	no crisis
60	Mexico	1966-1971	no crisis
61	Mexico	1989-1994	crisis
62	Mexico	2005-2010	no crisis
63	Peru	1961-1967	no crisis
64	Peru	1971-1975	crisis
65	Peru	1980-1983	crisis
66	Peru	1992-1999	crisis
67	Uruguay	1962-1964	no crisis
68	Uruguay	1970-1982	crisis
69	Uruguay	1998-2002	crisis
70	Israel	1962-1979	crisis
71	Israel	1982-1984	crisis
72	Israel	1992-2002	no crisis
73	Egypt	1974-1986	crisis
74	Egypt	1993-2001	no crisis
75	India	1961-1986	no crisis
76	India	1998-2010	no crisis
77	Korea	1965-1974	no crisis
78	Korea	1978-1982	no crisis
79	Korea	1996-2002	no crisis
80	Korea	2005-2008	no crisis
81	Malaysia	1961-1986	no crisis
82	Malaysia	1994-1998	crisis
83	Pakistan	1961-1969	crisis
84	Philippines	1961-1967	no crisis
85	Philippines	1972-1983	crisis
86	Philippines	1987-1997	crisis
87	Thailand	1967-1997	crisis

Table A.3: Summary Stock Indices

Country	Stock Index
United States	S&P 500 Composite Price Index (w/GFD extension)
United Kingdom	UK FTSE All-Share Index (w/GFD extension)
Austria	Austria Wiener Boersekammer Share Index (WBKI)
Belgium	Brussels All-Share Price Index (w/GFD extension)
Denmark	OMX Copenhagen All-Share Price Index
France	France CAC All-Tradable Index (w/GFD extension)
Netherlands	Netherlands All-Share Price Index (w/GFD extension)
Sweden	OMX Stockholm All-Share Price Index
Japan	Tokyo SE Price Index (TOPIX) (w/GFD extension)
Finland	OMX Helsinki All-Share Price Index
Greece	Athens SE General Index (w/GFD extension)
Ireland	Ireland ISEQ Overall Price Index (w/GFD extension)
Portugal	Oporto PSI-20 Index
Spain	Madrid SE General Index (w/GFD extension)
Turkey	Istanbul SE IMKB-100 Price Index
Australia	Australia ASX All-Ordinaries (w/GFD extension)
New Zealand	New Zealand SE All-Share Capital Index
Argentina	Buenos Aires SE General Index (IVBNG)
Brazil	Rio de Janeiro IBX-100 Index
Chile	Santiago SE Indice General de Precios de Acciones
Colombia	Colombia IGBC General Index (w/GFD extension)
Costa Rica	Costa Rica Bolsa Nacional de Valores Index
Ecuador	Ecuador Bolsa de Valores de Guayaquil (Dollars)
Mexico	Mexico SE Indice de Precios y Cotizaciones (IPC)
Peru	Lima SE General Index (w/GFD extension)
Uruguay	Bolsa de Valores de Montevideo Index
Israel	Tel Aviv All-Share Index
Egypt	Cairo Capital Market Authority General Index
India	Bombay SE Sensitive Index (w/GFD extension)
Korea	Korea SE Stock Price Index (KOSPI)
Malaysia	Malaysia KLSE Composite
Pakistan	Pakistan Karachi SE-100 Index
Philippines	Manila SE Composite Index
Thailand	Thailand SET General Index

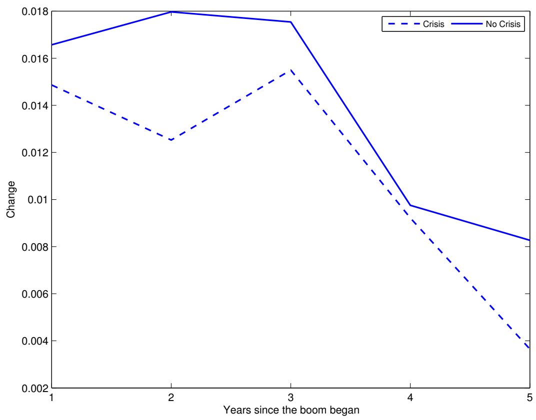
Table A.4: HP-filtered Credit and TFP Growth as Crises Predictors

	5Ychange			5YchangeMA		
	LOGIT	LPM		LOGIT	LPM	
α	-2.88	0.05		-2.81	0.05	
t-Statistic	-23.49	6.92		-21.89	6.72	
β	0.39	0.05	0.05	0.54	0.06	0.08
t-Statistic	3.96	5.45	5.66	3.76	4.85	5.77
Marginal	0.02	0.03	0.04	0.02	0.03	0.04
γ	-2.93	-0.20	-0.17	-4.29	-0.31	-0.25
t-Statistic	-2.58	-3.12	-2.67	-3.13	-3.69	-2.91
Marginal	-0.02	-0.02	-0.02	-0.02	-0.03	-0.02
R^2		0.04	0.09		0.05	0.11
N	1481	1481	1481	1345	1345	1345
FE	No	No	Yes	No	No	Yes

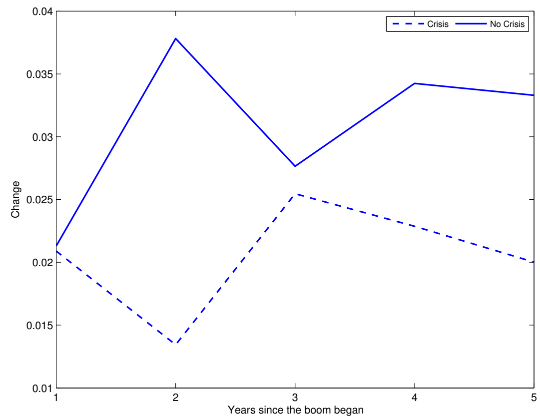
Table A.5: HP-filtered Credit and LP Growth as Crises Predictors

	5Ychange			5YchangeMA		
	LOGIT	LPM		LOGIT	LPM	
α	-2.77	0.06		-2.74	0.06	
t-Statistic	-14.56	5.62		-13.09	5.15	
β	0.38	0.05	0.04	0.55	0.06	0.07
t-Statistic	3.74	5.41	4.75	3.60	5.06	5.14
Marginal	0.01	0.03	0.03	0.01	0.04	0.04
γ	-3.03	-0.18	-0.07	-3.04	-0.20	-0.04
t-Statistic	-2.47	-3.12	-1.00	-2.21	-3.01	-0.46
Marginal	-0.02	-0.02	-0.01	-0.02	-0.02	-0.00
R^2		0.35	0.39		0.38	0.42
N	1168	1168	1168	1048	1048	1048
FE	No	No	Yes	No	No	Yes

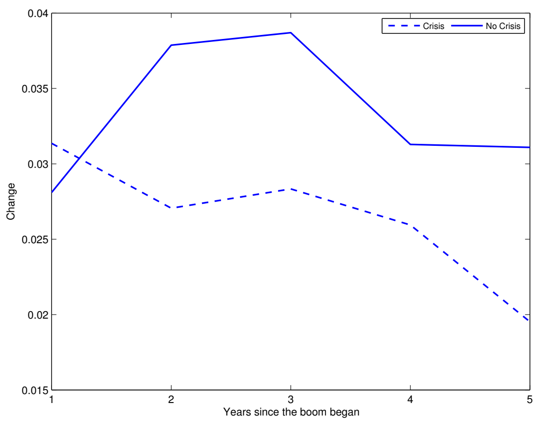
Figure A.1: Median Productivity over Good and Bad Booms



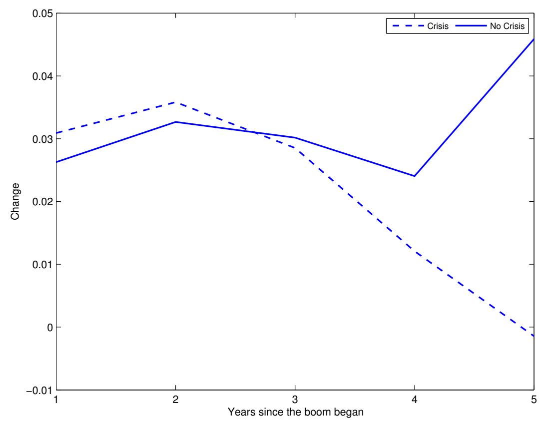
(e) Total Factor Productivity



(f) Labor Productivity

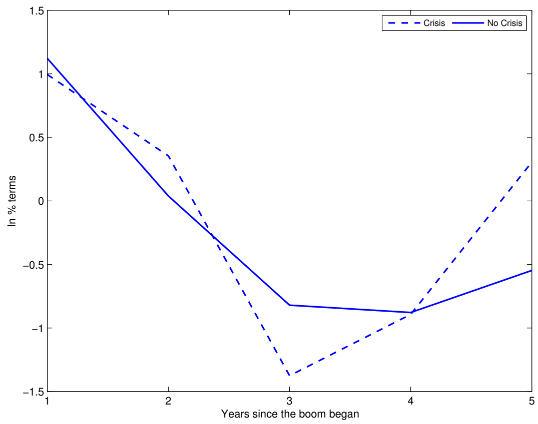


(g) Real GDP

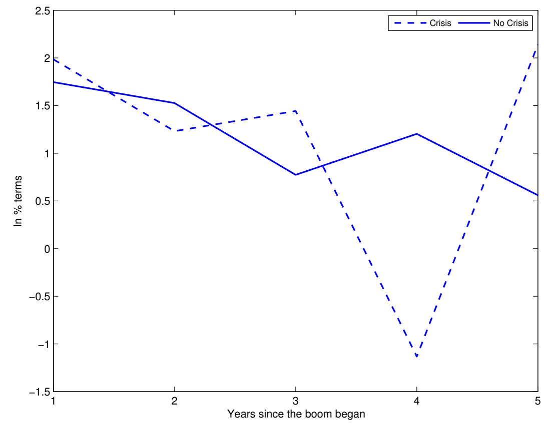


(h) Capital Formation (Investment)

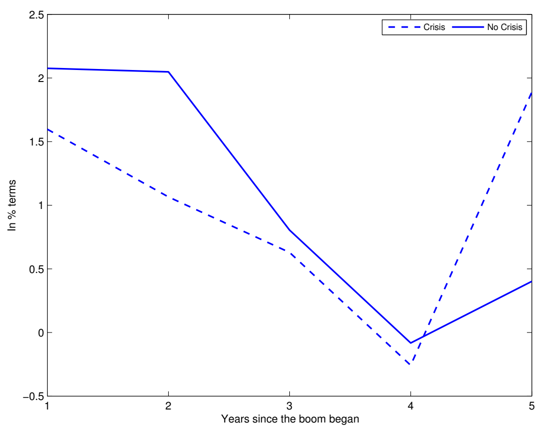
Figure A.2: Average Productivity over Good and Bad Booms (H-P filter)



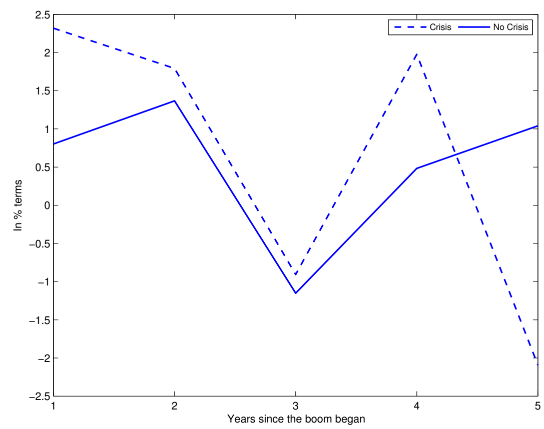
(a) Total Factor Productivity



(b) Labor Productivity

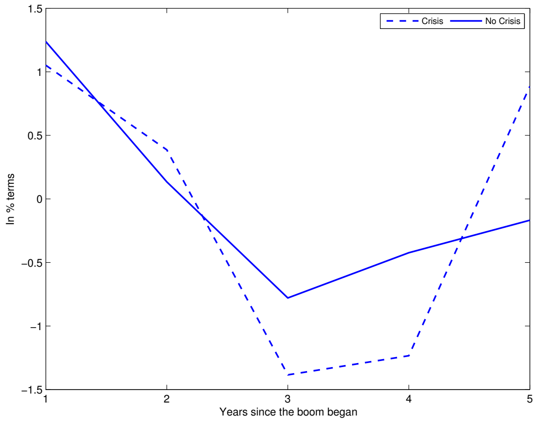


(c) Real GDP

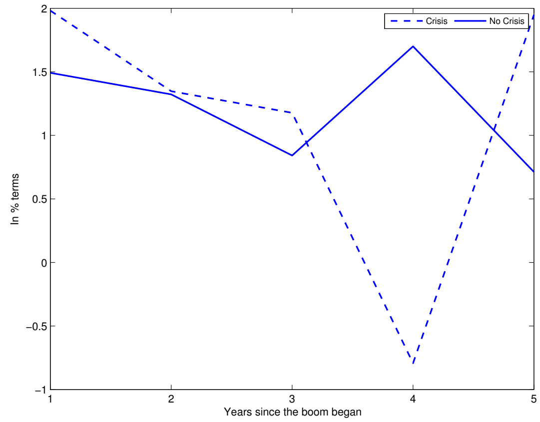


(d) Capital Formation (Investment)

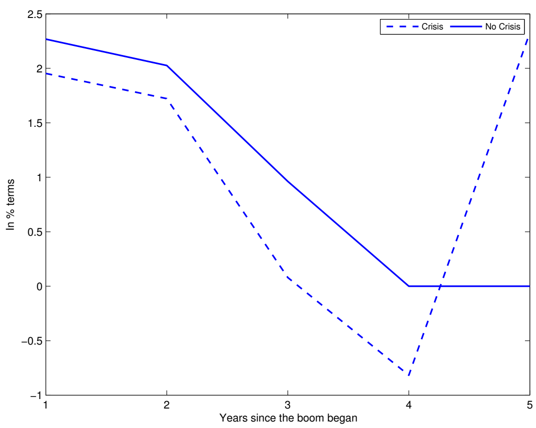
Figure A.3: Median Productivity over Good and Bad Booms (H-P filter)



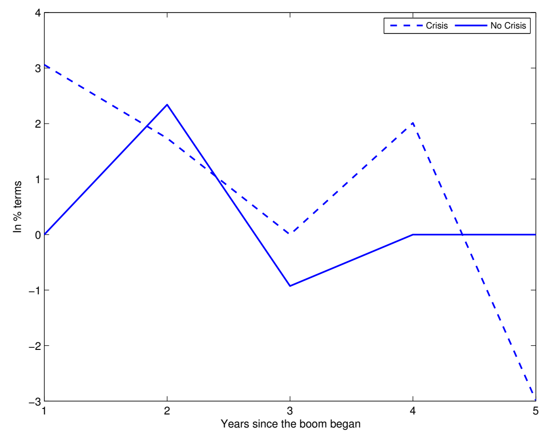
(a) Total Factor Productivity



(b) Labor Productivity

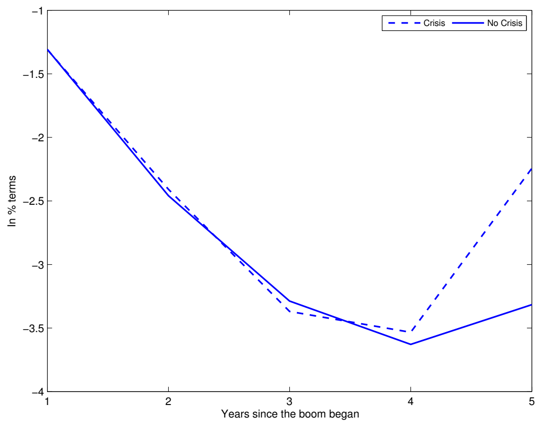


(c) Real GDP

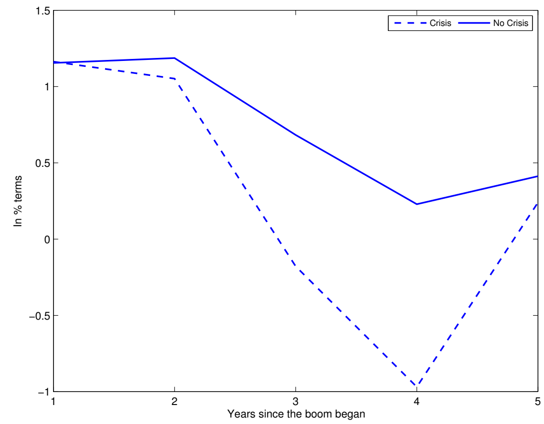


(d) Capital Formation (Investment)

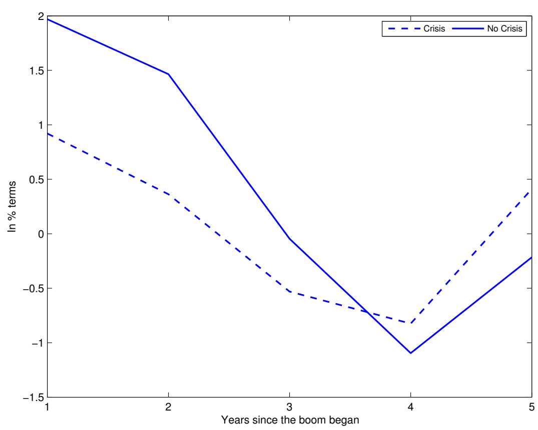
Figure A.4: Fitted Values of Measures of Productivity over Good and Bad Booms (H-P filter)



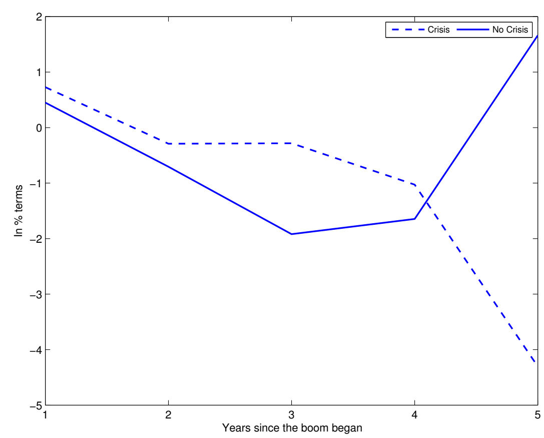
(a) Total Factor Productivity



(b) Labor Productivity



(c) Real GDP



(d) Capital Formation (Investment)