

Crises and Productivity in Good Booms and in Bad Booms*

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Abstract

Credit booms usually precede financial crises. However, some credit booms end in a crisis (bad booms) and other booms do not (good booms). We document that, while all booms start with an increase in the growth of Total Factor Productivity (TFP), 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 quality of investment opportunities also grow, the credit boom may not end in a crisis because there is a gradual adoption of low quality projects, but those projects are also of better quality, not inducing information about collateral.

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1 Introduction

The recent financial crisis poses challenges for macroeconomists. Models which display financial crises are needed and, these models must be consistent with the credit booms that typically precede crises. Then, there is the question of whether crises and credit booms are related to changes in Total Factor Productivity (TFP). This last issue is important for determining whether one integrated framework can encompass recessions, financial crises and growth, or whether financial crises are so special that a completely different model is needed. In this paper we take up this challenge, at least in a preliminary way, linking credit booms to TFP growth which may then end in a financial crisis.

Changes in TFP, “technology shocks,” have played a central and controversial role in macroeconomics and growth.¹ With respect to business cycles, Prescott (1986) argues that technology shocks (measured by TFP) are highly procyclical and “account for more than half the fluctuations in the postwar period.” Also, the historical time series of TFP has been linked to long periods of growth due to technological innovation, such as the steam locomotive, telegraph, electricity or IT.² But, there is substantial variation in growth rates in different historical epochs.

A large literature documents that a financial crisis is usually preceded by a credit boom.³ But not all credit booms end in a crisis; some do (bad booms) and some do not (good booms). Why are some booms good and others bad? We first study a panel

¹We do not review the vast literature on this; some survey-like papers include Aiyagari (1994), Cochrane (1994), and Rebelo (2005).

²See, for example, Kendrick (1961), Abramovitz (1956), Field (2009), Gordon (2010) and Shackleton (2013).

³For example, Jorda, Schularick, and Taylor (2011) study fourteen developed countries over 140 years (1870-2008) and conclude: “Our overall result is that credit growth emerges as the best single predictor of financial instability (p. 1). 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). Mendoza and Terrones (2008) find that on average credit booms are not strong crisis predictors.

of 34 countries over 50 years to empirically document that credit booms are related to productivity growth. We propose a definition of a “credit boom” that is very agnostic. It does not rely on future data or on detrending. We show that all booms start with a positive shock to TFP, but TFP growth falls much faster subsequently for bad booms. Empirically, the dynamics of TFP are sometimes prolonged, looking like growth, while other times they are short, at a business cycle frequency.

We then develop a simple framework to explain this. Firms are financed with short-term collateralized debt. If agents do not produce information about the quality of collateral, a credit boom develops. As credit booms more firms obtain financing and gradually adopt lower quality projects such that the incentive for lenders to acquire information increases, eventually triggering information production about collateral and a crisis. When the quality of projects is also growing, there can be a credit boom which does not end in a crisis. Even though firms gradually adopt lower quality projects as credit booms, those projects are also of better quality, avoiding the trigger of information acquisition about collateral and a crisis.

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. 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 “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, the 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 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 Ordóñez (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 growth with a very short lag, then, on average, they could tell whether a boom is good or bad and take action.

The dynamics of the model, although linked to changes in TFP, are different than those of real business cycle (RBC) models. RBC models require a negative and contemporaneous TFP shock that then leads to subsequent dynamics. But, these dynamics do not include credit booms and crises. 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 has arrived. It is an improvement in technology, but may have the feature that the quality of the projects becomes low as the boom proceeds. As in Gorton (1985), Dang, Gorton, and Holmström (2013) and Gorton and Ordóñez (2014) the crisis is an information event.

In the next section we introduce the dataset and analyze TFP 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 and policy implications under that possibility. In Section 5, we conclude.

2 Good Booms, Bad Booms: Empirical Evidence

Not all credit booms end in a financial crisis.⁴ Why do some booms end in a crisis while others do not? To address this question empirically we investigate productivity (total factor productivity) trends during booms. Clearly, not all growth of credit stems from movements in TFP. A positive TFP shock, improving the median firm's ability to combine inputs to create output, likely means that it may seek more credit. Even though TFP growth is not the only source of credit growth it seems to be a primary driver of credit growth, and we empirically investigate this. In this section

⁴This is also noted by Dell'Ariccia et al. (2012).

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 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

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 non-equity 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 from the dataset used 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. In some of our analysis 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 growth over booms, we use the presence of financial crises at the end of the boom to assess the ex-post efficiency of the boom. For this we rely on the classification in Laeven and Valencia (2012), who, by using an extensive cross-country dataset, identify financial crises worldwide since 1960.⁵ Their definition of a crisis is given below.

⁵Laeven and Valencia (2012) start in 1970, while our data starts in 1960. Under our definition of a

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 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, $c_{i,\hat{t}}$, 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, \hat{t} , such that credit growth is high when compared to the time series standard deviation:

$$c_{i,\hat{t}} \geq \phi\sigma(c_i).$$

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

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

for $i = \{s, e\}$ where $t^s < \hat{t} < t^e$. 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.

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 approach we take is different. We do not detrend the series for each country, but define as a boom 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. Examples are given below. 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 we observe at least three years of subsequent positive credit growth with annual growth above a threshold x^s . The boom ends whenever we observe at least two years of credit growth below a threshold 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.⁶ Their database covers the period 1970 to 2011. They define a systemic banking

⁶In 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).

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.

Of the 88 credit booms under our definition, 33 end in a financial crisis. See Table A.1 in the Appendix for a detailed list of booms and crises. The definition of a credit boom is very inclusive. There are very long booms; the longest is in Australia from the 1980s to 2010 (28 years). The definition also results in booms being relative frequent. Of the 1,700 years in the sample, 1,001 are spent in a boom by our definition. So, booms are not rare. On average, over 50 years, on average a country spent 20.4 years in a boom, 9.4 of which were spent in a boom that ended in a crisis.

Table 1 provides an overview of the booms. In the table LP refers to labor productivity. The last column shows the t-statistics 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. At a 95% confidence interval all the variables are significantly different between crisis and no crisis episodes.⁷ The table shows that credit growth over a boom is higher on average for booms that end in crisis. The booms that end in a crisis are also significantly longer. Table A.2 in the Appendix also shows more information about these booms – number of booms, number of bad booms, the frequency of boom periods and the average time between booms for each country.

A concern might be that credit booms and, in particular, those that end in a crisis are more likely to occur in emerging economies rather than advanced economies.⁸ The

⁷The subsamples for crisis and non-crisis booms are small, as shown in Table 1, so there may be 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.

⁸The classification of countries into advanced or emerging comes from the World Bank. Advanced include the U.S., U.K., Austria, Belgium, Denmark, France, the Netherlands, Japan, Finland, Greece, Ireland, Portugal, Spain, Australia, and NZ. Emerging are: Turkey, Argentina, Brazil, Chile, Colombia, Costa Rica, Ecuador, Mexico, Peru, Uruguay, Israel, Korea, Malaysia, Pakistan, the Philippines and

second panel of Table 1 shows the descriptive statistics when the data are divided into advanced and emerging economies. The years spent in booms are similar, 541 for advanced economies and 440 in emerging economies. The average emerging market economy spends 22 years in a boom, of which 11 are spent in a boom that ends badly. These numbers for advanced economies are 19.9 and 9, so again the two types seem similar.

Table 1: Descriptive Statistics

	Whole sample	Booms	Booms w/ crisis	Booms w/o crisis	t-stat for means
Avg. Credit growth (%)	3.75	9.25	10.80	8.10	1.75
Avg. TFP growth (%)	0.75	0.60	0.21	0.85	-1.5
Avg. LP growth (%)	2.44	2.36	1.77	2.75	-1.9
Avg. duration (years)		8.5	9.8	7.6	1.8
Number of booms		88	33	55	
Sample size (years)	1,700	923	297	626	

	Advanced Economies			Emerging Economies		
	All	Booms w/ crisis	Booms w/o crisis	All	Booms w/ crisis	Booms w/o crisis
Avg. Credit growth (%)	7.60	8.40	7.20	12.50	14	11
Avg. TFP growth (%)	0.54	0.27	0.67	0.71	0.14	1.30
Avg. LP growth (%)	2.20	2.30	2.30	2.70	1.40	4.10
Avg. duration (years)	8.9	11	8	7.4	8.2	6.6
Number of Booms	31	7	24	57	26	31
Sample size (years)	541	97	444	440	234	224

A difference between the two types of economy is the number of booms, with 31 for advanced economies and 57 for emerging economies. Emerging economies have about half of the booms ending in a crisis while in advanced economies 23 percent of the booms end in a crisis. There are some other differences as well. Average credit growth during booms is higher in emerging economies than in advanced economies and this holds for booms ending in a crisis and those not ending in a crisis.⁹ TFP growth and labor productivity growth are notably higher in booms that do not end in a crisis, for both advanced and emerging economies. This foreshadows the analysis below.

Thailand.

⁹The sample sizes are really too small to test for statistically significant differences.

Our results differ from both Gourinchas, Valdes, and Landerretche (2001) and Mendoza and Terrones (2008) who find an asymmetry between boom episodes in emerging and advanced countries. Gourinchas et al. find that emerging markets are more prone to credit booms. Mendoza and Terrones 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. Both studies use credit boom definitions that are biased towards identifying short booms (since they detrend the data).

Another important difference concerns the large cross-country variation in the time series of credit and productivity. To illustrate this, Figure 1 show the time series for credit and labor productivity for Germany, the U.S., and Argentina. The y-axis is in real dollars. Credit is the amount of credit outstanding in real dollars per dollar of GDP. Labor productivity is the amount of GDP in real dollars produced per unit of labor.

The main point of the three cases in Figure 1 is that they are very different. Germany displays a pattern of financial deepening which tracks labor productivity growth. The United States shows a structural break in 1985. Prior to 1985 credit and labor productivity grew in tandem, but after 1985 credit shows an upward trend relative to labor productivity. Argentina shows wild fluctuations in credit unrelated to labor productivity. So, one pattern is a smooth and slow deviation from productivity, the U.S. In Argentina there are large fluctuations unrelated to productivity. Our definition of a boom admits both of these types. The U.S. and Argentina both had crises, many more in Argentina.

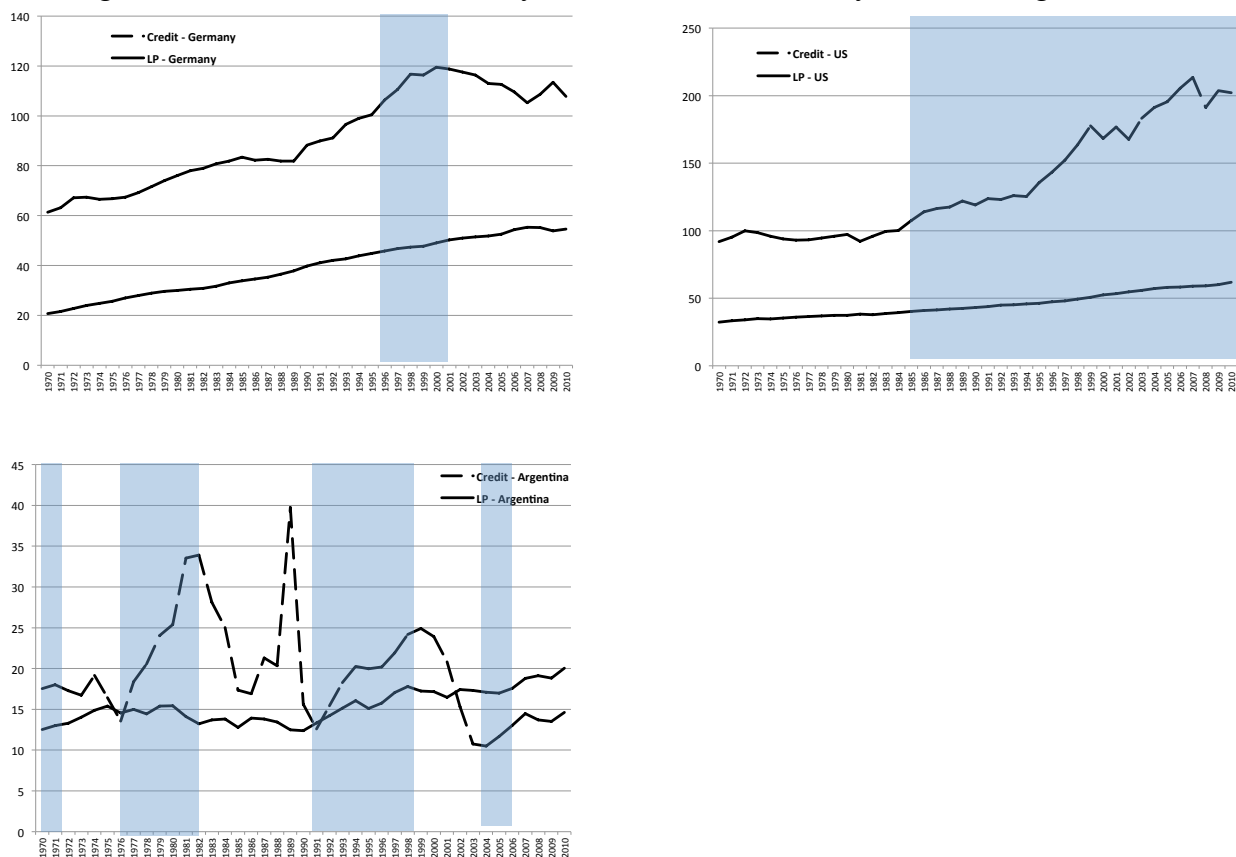
Figure 2 shows a histogram of average credit growth over booms. Most booms display average growth between five and ten percent, with another peak around fifteen percent. The fat tail is due to experiences in Chile and Venezuela in the early 2000s.

2.3 Booms and Crises. The Role of TFP growth.

We begin by examining the relationship between average credit growth and average TFP growth over a credit boom. The unit of analysis in this subsection is not the years in the boom but the boom itself. So, the sample size is 88 observations.

First, we are interested in knowing whether an increase in credit growth is associated with an increase in TFP. This association would be consistent with the notion that

Figure 1: Credit and Productivity over Booms - Germany, US and Argentina



credit growth is financing the TFP growth. We expect the link to be weaker during booms that end in a crisis. We run the following regression:

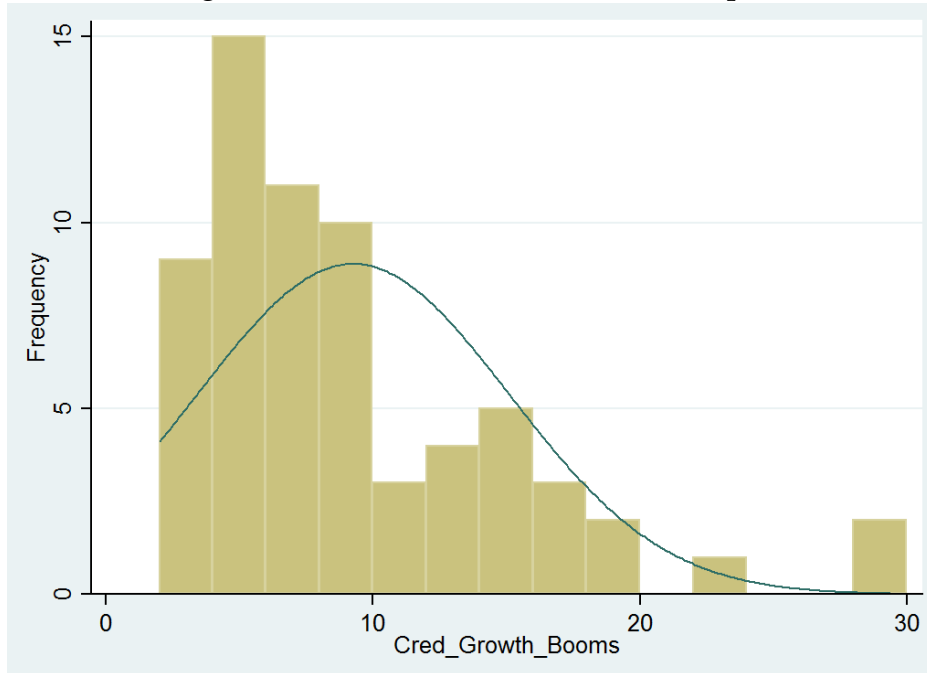
$$\Delta CRED_j = \alpha + \beta \Delta TFP_j + \gamma \mathbb{I}_j + \epsilon_j$$

where j indexes credit booms and where \mathbb{I}_j is set to 1 if the boom ends in a crisis. Table 2 shows that TFP growth is associated with growth in credit, and more so for booms that end in a crisis.

Table 2: TFP and Credit over Booms

	α	β	γ
Coefficient	6.1	2.7	2.6
t-stat	19.1	2.6	4.7

Figure 2: Credit over Booms in the Sample



Credit growth has been shown to be a significant predictor of crises.¹⁰ Conditional on credit growth, does TFP growth predict crises? We examine this question with a Probit regression. The model is as follows.

$$Pr(\mathbb{I}_j = 1 | \Delta TFP_j, \Delta CRED_j) = \Phi(\alpha + \beta \Delta CRED_j + \gamma \Delta TFP_j) \quad (1)$$

where Φ indicated the normal cdf. Table 3 reports the estimation using maximum likelihood.

Table 3: TFP and Credit as Crisis Predictors

	α	β	γ
Coefficient	-0.6	-0.16	0.04
t-stat	-2.1	-1.85	1.70
Marginal		-0.06	0.015

The table uses the average growth over the boom, so $N = 88$. The main result is that even controlling for credit, TFP growth is negatively related to the probability of a crisis. To interpret these results the last row shows the marginal effect, which is

¹⁰See, for example, Desmirguc-Kunt and Detragiache (1998) and Kaminsky and Reinhart (1999).

equivalent to the change in the probability of observing a crisis following a change in the corresponding covariate.

2.4 Productivity over the Boom

In this subsection we show three important stylized facts: (1) TFP over a credit boom falls much faster for booms that are followed by a crisis; (2) booms start with a high positive TFP realization; and (3) the initial TFP shock is higher for booms that end in a crisis. To establish these findings we ask whether TFP behaves differently during booms that end in a crisis and those that do not.

We start by testing for whether booms that end in a crisis show a different relationship between credit growth and TFP growth. We run the following regression:

$$\Delta Credit_{n,t} = \alpha + \beta \Delta TFP_{n,t} + \gamma \mathbb{I}_n(crisis) + \delta \mathbb{I}_{n,t}(crisis * \Delta TFP) + \epsilon_{n,t} \quad (2)$$

where $\Delta Credit_{n,t}$ and $\Delta TFP_{n,t}$ are Credit and TFP growth respectively over boom n in year t and \mathbb{I} is an indicator function ($\mathbb{I}_n(crisis) = 1$ and $\mathbb{I}_{n,t}(crisis * \Delta TFP) = \Delta TFP_{n,t}$ if the boom n ended in a crisis). We run this regression using the panel of boom-years (n, t) and also just the panel of booms (n) .

Table 4: Crisis and the TFP growth - Credit growth relationship

	boom-years (N=1,001)			
	α	β	γ	δ
Coefficient	7.80	0.35	3.16	-0.69
t-stat	10.49	1.53	2.45	-2.13
	booms (N=88)			
	α	β	γ	δ
Coefficient	8.20	0.42	3.90	-2.27
t-stat	8.27	0.80	2.70	-2.90

Table 4 shows that booms that end in a crisis have a different relationship between credit growth and TFP growth. By either measure of a boom, the presence of a crisis reverses the positive relationship between credit and TFP, i.e., β is positive while δ is negative.

Next we turn to investigating how TFP growth and Credit growth vary over time. We run the following regression over the boom years, starting the year after the boom begins:

$$\Delta TFP_{n,t} = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + \mathbb{I}_n(\beta_0 + \beta_1 t + \beta_2 t^2) + \epsilon_{n,t} \quad (3)$$

where $\Delta TFP_{n,t}$ is TFP growth over boom n in year t after the boom has started. \mathbb{I}_n is an indicator that takes the value of 1 if boom n is followed by a financial crisis. If the pattern of TFP over booms is unrelated to crises, then all the betas should be insignificantly different from zero. If β_0 (or β_1 , or β_2) is significantly different from zero, then it would show that the level (or slope, or curvature) of TFP growth over crisis booms are different from TFP growth over non-crisis booms.

The regression results are shown below.¹¹

Table 5: Trend of TFP growth over booms (without outliers)

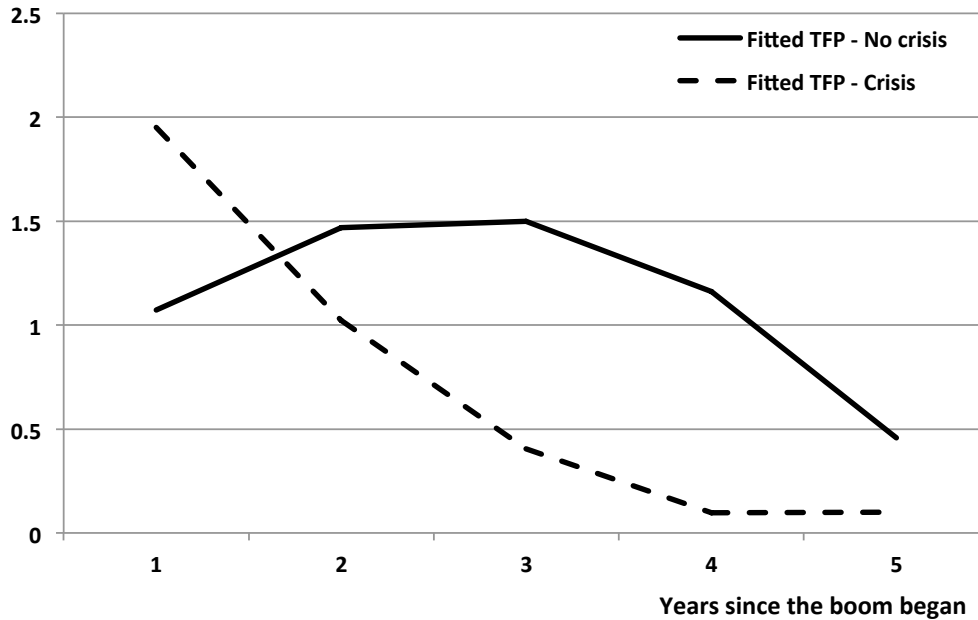
	α_0	α_1	α_2	β_0	β_1	β_2
Coefficient	0.3	0.94	-0.18	2.8	-2.3	0.33
t-stat	0.45	1.8	-2.1	2.5	-2.6	2.3

All the coefficients are significant at least at the 10 percent level, except for α_0 . The reason α_0 is insignificant seems to be that TFP peaks after credit peaks, consistent with forward-looking rational expectations. Booms that end in crisis show the two series moving in tandem. To summarize, TFP growth is higher at the start and decays faster for booms that end in a crisis.

Figure 3 displays the estimated time pattern of average TFP over booms that end in a crisis and those that do not for the five years after the initial TFP increase. Booms that end in a crisis start with a higher initial positive TFP shock. For booms that do not end in a crisis, TFP peaks one to two years after the start of the boom. In crisis booms the starting TFP shock is higher and the decay begins immediately.

¹¹This regression excludes outliers. There are a few odd cases where TFP growth, for example, is less than -20 percent or greater than 20 percent, relative to an average TFP growth of 1.8 percent. Notably, Argentina and Brazil experienced rapid capital inflows and then outflows in 1989 and 1992 respectively. In both cases, credit growth was around 120 percent in one year and -90 percent in the next year. We exclude these observations and overall we exclude eight observations in which TFP growth is higher than 5 percent in absolute value; this is about one percent of the sample of booms. The outliers are identified in the Appendix.

Figure 3: TFP over Good and Bad Booms



2.5 Results with Detrended Data

In this subsection we examine the robustness of the above conclusions to the method of defining credit booms. In particular, we will review the results when we use the Mendoza-Terrones method for defining booms relative to an HP filter for country-specific data.¹² As above, we use our panel of countries, label booms according to the Mendoza-Terrones criterion, and label crisis and non-crisis booms following Laeven and Valencia.

With this procedure, TFP growth and credit growth are positively correlated in the cross section of booms, as occurs under our method. The sample correlation is 15 percent and a regression of credit growth on TFP growth has a significant positive coefficient.

We turn now to test our main hypothesis, that credit booms associated with lower TFP growth lead to a higher likelihood of a crisis. We investigate a Probit model for

¹²We use exactly the same method as MT for detrending the data with one exception. The difference is that MT detrend raw credit (so economic growth and financial deepening are eliminated). We detrend credit over GDP (so we also eliminate financial deepening).

the probability of a crisis:

$$Pr(\mathbb{I}_k = 1 | \Delta TFP_k, \Delta CRED_k) = \Phi(\alpha + \beta \Delta CRED_k + \gamma \Delta TFP_k).$$

The unit of observation is a credit boom. The results are shown in Table 6. The coefficient β is significant at the 5% level, consistent with our previous result, that for a given level of credit growth, a negative TFP shock increases the likelihood of a financial crisis in the next four years. Hence, these results are consistent with our previous results.

Table 6: TFP and Credit as Crisis Predictors - Mendoza-Terrones classification

	α	β	γ
Coefficient	1.40	-0.14	-0.61
t-stat	1.14	-1.74	-1.09

To summarize we have the following results:

1. Credit booms are not rare and occur in both advanced and emerging economies.
2. Controlling for credit growth, TFP growth reduces the likelihood of a crisis ending the boom (Table 3; equation (1)).
3. All booms start with a positive TFP shock (on average), TFP behaves differently, decaying faster, for credit booms that end in a crisis (Table 4; equation (2)).
4. TFP dynamics over booms are different depending on whether the boom ends in a crisis or not (Table 5; equation (3)).

We now turn to a model to try to understand these results.

3 The Model

The model is an extension of Gorton and Ordenez (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 two types of goods – *numeraire* 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.

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

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

The first extension of Gorton and Ordonez (2014) is as follows. There is a limited supply of projects in the economy, also with mass 1. There are two types of projects 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, then $q_H A > q_L A > 1$, which implies that the optimal scale of numeraire in production is $\hat{K}^* = L^*$ 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. Firms are born with an endowment of numeraire $\bar{K}_f < \hat{K}^*$, not enough to sustain optimal production in the economy. Similarly, households are born with an endowment of numeraire $\bar{K} > K^* \equiv \hat{K}^* - \bar{K}_f$, such that there is enough endowment in the economy to sustain optimal production.

Even when non-productive, land potentially has an intrinsic value. If land is “*good*”, it can deliver C units of K , but only once. If land is “*bad*”, it does not deliver anything. We assume a fraction \hat{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.¹³ Observing the quality of land costs γ_b units of numeraire to land holders (young borrowers), and γ_l units of numeraire to land non-holders (old lenders).

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.

In this simple setting, resources are in the wrong hands. Households only have numeraire while firms have managerial skills but less numeraire than needed. 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 promise to transfer a fraction of land to households in the event of not repaying numeraire, which relaxes the finance 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 produce when old.

The perception about the quality of collateral then becomes critical in facilitating loans. To be precise, we will 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.¹⁴

¹³When 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.

¹⁴The 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 considered active either.

Returning to the technology, we assume that, before approaching households for a loan, 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 a project with a higher q than those projects remaining in the pool, so the firm privately knows its project quality, q , while lenders only know the mass of active firms in the economy. Since q is non-verifiable, denoting by $\eta \in [0, 1]$ the mass of active firms, lenders' beliefs about the probability of success of any firm are

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

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

3.2 Optimal loan for a single firm

We now turn to the two-sided information acquisition, which is the second extension of Gorton and Ordonez (2014). 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 .¹⁵ Loans that trigger information production (information-sensitive debt) are costly – either borrowers acquire information at a cost γ_b or have 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.

¹⁵It 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, then its value is not known since these securities are complicated and do not trade frequently and not on centralized exchanges where the price would be observable.

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 numeraire. Since borrowers have to divert numeraire from production to discover the quality of the collateral, their opportunity cost is $\gamma_b qA$.

If lenders are the ones acquiring information, assuming lenders are risk neutral and competitive, then:¹⁶

$$p(\widehat{q}(\eta)R_{IS}^l + (1 - \widehat{q}(\eta))x_{IS}^l C - K) = \gamma_l,$$

where K is the size of the loan, R_{IS}^l is the face value of the debt and x_{IS}^l 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 $R_{IS}^l > x_{IS}^l C$, firms always default, handing in the collateral rather than repaying the debt. Contrarily, if $R_{IS}^l < x_{IS}^l C$ firms always sell the collateral directly at a price C and repay lenders R_{IS}^l . This condition pins down the fraction of collateral posted by a firm, as a function of p and independent of q :

$$R_{IS}^l = x_{IS}^l C \quad \Rightarrow \quad x_{IS}^l = \frac{pK + \gamma_l}{pC} \leq 1.$$

Note that, since the interest rates and the fraction of collateral that has to be posted 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 profits are $p(qAK - x_{IS}^l C) + \bar{K}_f(qA - 1) + pC$. Then, plugging x_{IS}^l in equilibrium, *expected net profits* (net of the land value pC and net of production using own numeraire $\bar{K}_f(qA - 1)$) from information-sensitive debt when lenders acquire information are

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

¹⁶Risk neutrality is without loss of generality since we will show next that debt is risk free. The assumption of perfect competition is simple to sustain, for example by assuming that only a fraction of firms have skills L^* , and then there are more lenders than borrowers.

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 information costs γ_l .

Similarly, we can compute these expected net profits in the case borrowers acquire information directly, at a cost γ_b , and borrow the optimal K^* in the case of finding out that their own land is good, which is the only case where the firm can credibly show such information to lenders. In this case lenders also break even after borrowers demonstrate the land is good.

$$\widehat{q}(\eta)R_{IS}^b + (1 - \widehat{q}(\eta))x_{IS}^bC - K = 0.$$

Since debt is risk-free, $R_{IS}^b = x_{IS}^bC$ and $x_{IS}^b = \frac{K}{C}$. Ex-ante expected total profits are $p(qAK - x_{IS}^bC) + (\bar{K}_f - \gamma_b)(qA - 1) + pC$. Then, plugging x_{IS}^b in equilibrium, *expected net profits* (net of the land value pC and net of production using own funds $\bar{K}_f(qA - 1)$) are

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

It is then obvious that, in case of using information-sensitive debt, firms choose to produce information themselves if $\gamma_b < \gamma_l$ and prefer lenders to produce information otherwise. Then, expected profits from information-sensitive debt effectively are,

$$E(\pi|p, q, IS) = \max\{pK^*(qA - 1) - \min\{\gamma_b(qA - 1), \gamma_l\}, 0\}. \quad (4)$$

3.2.2 Information-Insensitive Debt

Another possibility for firms is to borrow without triggering information acquisition. However, 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 losses γ_l from acquiring information,

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

More specifically, by acquiring information the lender only lends if the collateral is good, which happens with probability p . If there is default, which occurs with probability $(1 - \widehat{q}(\eta))$, the lender can sell at $x_{II}C$ collateral that was obtained at $px_{II}C = K$, 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,

$$K < \frac{\gamma_l}{(1 - p)(1 - \widehat{q}(\eta))}. \quad (5)$$

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.

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, net of the costs of information, are $pK^*(qA - 1) + (1 - p)K(qA - 1) - \gamma_b(qA - 1)$ (with probability p they find the land is good, disclose it and obtain a loan for K^* and with probability $1 - p$ they find the land is bad, do not disclose it and obtain a loan at the original contract K). If borrowers do not acquire information, their benefits are $K(qA - 1)$.

Hence borrowers do not acquire information if

$$p(K^* - K)(qA - 1) < \gamma_b(qA - 1).$$

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,

$$K > K^* - \frac{\gamma_b}{p}. \quad (6)$$

Combining these two conditions for no information production information-insensitive debt is feasible only when

$$\frac{\gamma_l}{(1-p)(1-\hat{q}(\eta))} > K^* - \frac{\gamma_b}{p}. \quad (7)$$

It is clear from this condition that information-insensitive debt is always feasible when either γ_b or γ_l is large. It is also clear that this information-insensitive debt is always feasible at relatively low and high values of p (subject to $\gamma_b > 0$ and $\gamma_l > 0$).

Hence, the loan size from information-insensitive debt is

$$\begin{aligned} K(p|\hat{q}(\eta), II) &= \min \left\{ K^*, \frac{\gamma_l}{(1-p)(1-\hat{q}(\eta))}, pC \right\} \\ \text{s.t. } \frac{\gamma_l}{(1-p)(1-\hat{q}(\eta))} &> K^* - \frac{\gamma_b}{p} \end{aligned} \quad (8)$$

and, if feasible, expected profits, net of the land value pC are

$$E(\pi|p, q, II) = K(p|\hat{q}(\eta), II)(qA - 1). \quad (9)$$

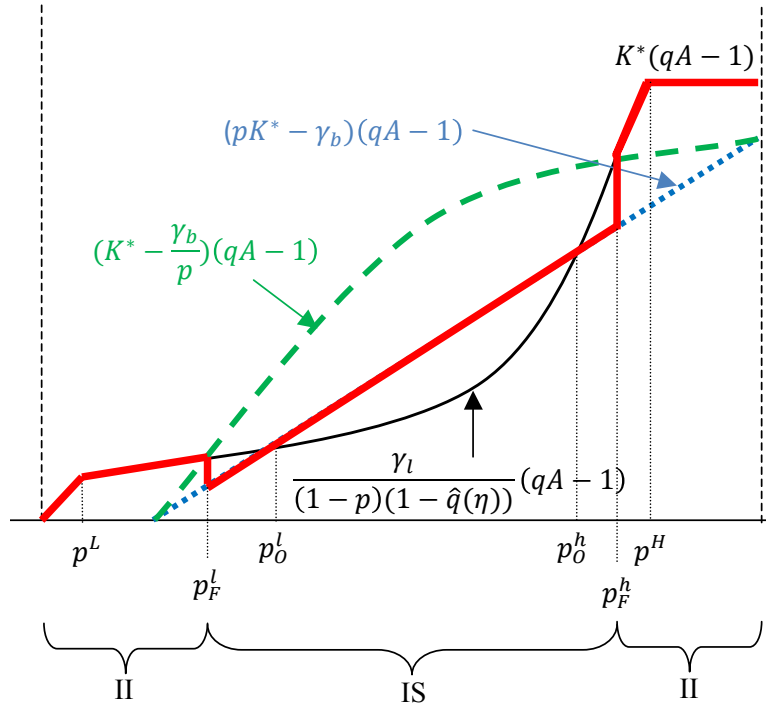
3.2.3 Borrowing Inducing Information or Not?

Figure 4 shows the ex-ante expected profits in both regimes (information sensitive and insensitive) for a firm with private information about its own probability of success q , net of the expected value of land and net of the production that can be funded with own numeraire, for each possible p , assuming $\gamma_b(qA - 1) \leq \gamma_l$ for $q \in [q_L, q_H]$.¹⁷

¹⁷The case for which $\gamma_l < \gamma_b(qA - 1)$ is extensively studied in Gorton and Ordóñez (2014), where we assume $\gamma_b = \infty$.

The dotted blue line shows the net expected profits in the information-sensitive regime (equation 4), while the solid black function shows the net expected profits in the information-insensitive regime (equation 9). The solid black concave curve shows the left hand side of the constraint in equation (7) while the dashed green convex curve shows the right hand side of the constraint.¹⁸ Since the information insensitive regime is infeasible when the concave curve is smaller than the convex curve, the red solid function, which represent the net expected profits of borrowers subject to constraint (7) is equal to the information-sensitive expected profits in the *IS* range and to the information-insensitive expected profits in the *II* range.

Figure 4: Information-Sensitivity with Two-Sided Acquisition



The cutoffs highlighted in Figure 4 are determined in the following way:

1. The cutoff p^H is the belief under which firms reduce borrowing, under optimal K^* , to prevent information production, from equation (5)

$$p^H = 1 - \frac{\gamma_l}{K^*(1 - \hat{q}(\eta))}. \quad (10)$$

¹⁸The left hand side is concave because the cost of producing information for lenders γ_l is fixed and divides by $1 - p$ and the right hand side is convex because the cost of producing information for borrowers γ_b is also fixed and divides by p .

The cutoff p^L is also obtained from equation (5), where the value of collateral is more restrictive than the possibility of information deviation,¹⁹

$$p^L = \frac{1}{2} - \sqrt{\frac{1}{4} - \frac{\gamma_l}{C(1 - \hat{q}(\eta))}}. \quad (11)$$

2. Cutoffs p_O^l and p_O^h show the beliefs at which firms optimally change from one regime to the other, and are obtained from equalizing expected profits of information-sensitive and insensitive loans and solving the quadratic equation

$$pK^* - \gamma_b = \frac{\gamma_l}{(1 - p)(1 - \hat{q}(\eta))}. \quad (12)$$

3. Cutoffs p_F^l and p_F^h show the beliefs at which information-insensitive debt becomes infeasible and are obtained from condition (7)

$$K^* - \frac{\gamma_b}{p} = \frac{\gamma_l}{(1 - p)(1 - \hat{q}(\eta))}. \quad (13)$$

Whenever $\gamma_b(qA - 1) \leq \gamma_l$, as is clear from equations (12) and (13), and shown in the figure, $p_F^l < p_O^l$ and $p_F^h > p_O^h$. This implies that there are regions of beliefs $[p_F^l, p_O^l]$ and $[p_O^h, p_F^h]$ for which the firm would prefer information-insensitive debt, but it is simply infeasible. There is a cost of information γ_b large enough with respect to γ_l such that $p_F^l > p_O^l$ and $p_F^h < p_O^h$. In this case the non-feasibility of information-insensitive debt becomes irrelevant since, even when feasible, firms prefer paying the cost of information production rather than reducing borrowing to discourage information production.

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

¹⁹The 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.

sented in red/bold in Figure 4, by

$$K(p|\gamma_l, \gamma_b, q, \eta) = \begin{cases} K^* & \text{i f } p^H < p \\ \frac{\gamma_l}{(1-p)(1-\hat{q}(\eta))} & \text{i f } p_F^h < p < p^H \\ pK^* - \gamma_b & \text{i f } p_F^l < p < p_F^h \\ \frac{\gamma_l}{(1-p)(1-\hat{q}(\eta))} & \text{i f } p^L < p < p_F^l \\ pC & \text{i f } p < p^L. \end{cases}$$

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 q in the intermediate range, increases with $\hat{q}(\eta)$ in the second and fourth ranges and is independent of q in the first and last ranges. Furthermore, as is clear from equations (10) and (11), the range in which information-insensitive loans are infeasible, $[p_F^l, p_F^h]$ shrinks as $\hat{q}(\eta)$ increases.

Remark: In this model productivity is qA , hence a combination of probability of success and the output in case of success. We constructed the model such that only the 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 $\hat{q}(\eta)$, is $\bar{K} - K(p|\hat{q}(\eta)) + E_q\{E(\text{repay}|p, q, \eta)\}$. The ex-ante (before observing its position in the queue for projects) 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 $E(K'|p, q, \eta) - E(\text{repay}|p, q, \eta)$ (recall this is 0 for inactive firms). The ex-ante aggregate consumption of firms is then $E_q\{E(K'|p, q, \eta) - E(\text{repay}|p, q, \eta)\}$. Expected aggregate consumption is the sum of the consumption of all households and firms.

Since $E_q\{E(K'|p, q, \eta)\} = \hat{q}(\eta)A[\bar{K}_f + K(p|\hat{q}(\eta))]$,

$$W_t = \bar{K} + \int_0^1 [\bar{K}_f + K(p|\hat{q}(\eta))](\hat{q}(\eta)A - 1)f(p)dp$$

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

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

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

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 \hat{q} and the evolution of beliefs. Then, we study the potential for completely endogenous cycles in credit, production and consumption.

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.

Specifically, 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 \hat{p} , independent of its current type. Even when the shock is observable, the realization of the new quality is not, unless some numeraire good $\min\{\gamma_b, \gamma_l\}$ is used to learn about it.²⁰

In this simple stochastic process for idiosyncratic shocks, the belief distribution has a three-point support: 0, \hat{p} and 1. Since firms with beliefs 0 do not get any loans, and hence do not operate, the mass η of active firms is the fraction of firms with beliefs \hat{p} and 1. Then $\eta = f(\hat{p}) + f(1)$.

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

Define $\chi \equiv \lambda\hat{p} + (1 - \lambda)$. 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 \hat{p} while a fraction λ of collateral known to be good (a fraction \hat{p} of all collateral) remain with such a perception.

Proposition 1 *Constant Symmetric Information - Constant Consumption.*

If $\hat{q}(\chi)$ is such that $p_F^l(\hat{q}(\chi)) < \hat{p} < p_F^h(\hat{q}(\chi))$, from equation (13), then there is information acquisition for collateral suffering idiosyncratic shocks and consumption is constant every period,

$$\bar{W}(\hat{p}) = \bar{K} + (\bar{K}_f + \hat{p}K^* - (1 - \lambda)\gamma_b)(q_H A - 1). \quad (14)$$

²⁰To 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 $\lambda K^*(\hat{q}(1)A - 1) > (1 - \lambda)C$. Furthermore they should have enough resources to buy good collateral, then $\bar{K} > C$.

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 \hat{p} is in the region where information-insensitive debt is not feasible. Then $f(1) = \lambda\hat{p}$, $f(\hat{p}) = (1 - \lambda)$ and $f(0) = \lambda(1 - \hat{p})$. Hence

$$W_t^{IS} = \bar{W}(\hat{p}) = \bar{K} + [\bar{K}_f + \lambda\hat{p}K(1) + (1 - \lambda)K(\hat{p})] (q_H A - 1).$$

Since $K(0) = 0$, $K(1) = K^*$ and $K(\hat{p}) = \hat{p}K^* - \gamma_b$. Then consumption is constant (equation (14)) at the level at which information is reacquired every period. Q.E.D.

Maintaining the assumption that \hat{p} is relatively high, the incentives to acquire information depend on the evolution of the relevant threshold for information acquisition, given by p_F^h in Figure 4. As is clear from equation (13), this threshold depends on $\hat{q}(\eta)$. The next Lemma discusses these effects.

Lemma 1 *The cutoff $p_F^h(\hat{q}(\eta))$ is monotonically decreasing in $\hat{q}(\eta)$.*

Proof From equation (13), it is clear that the right hand side increases with $\hat{q}(\eta)$, then decreasing the range of information-insensitive debt, this decreases $p^h(\hat{q}(\eta))$ and increases $p^l(\hat{q}(\eta))$. 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 $\hat{q}(\chi)$ is such that $\hat{p} > p_F^h(\hat{q}(\chi))$ and $\hat{q}(1)$ is such that $\hat{p} < p_F^h(\hat{q}(1))$, from equation (13), then there are information cycles. Under the conditions for consumption growth in the previous proposition, 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 $\hat{q}(\chi)$ is such that $\hat{p} > p_F^h(\hat{q}(\chi))$ there are no incentives to acquire information about the collateral with beliefs \hat{p} . This implies there is no information acquisition in the first

period. In the second period, $f(1) = \lambda^2 \hat{p}$ and $f(\hat{p}) = (1 - \lambda^2)$, implying that $\eta_2 > \eta_1$, which implies that $\hat{q}(\eta_2) \leq \hat{q}(\eta_1)$ and $p_F^h(\hat{q}(\eta_2)) \geq p_F^h(\hat{q}(\eta_1))$.

Repeating this reasoning over time, information-insensitive loans become infeasible when η_{t^*} is such that $\hat{p} = p_F^h(\hat{q}(\eta_{t^*}))$. We know there is such a point since by assumption $\hat{p} < p_F^h(\hat{q}(1))$. If $W_{t^*}^{II} > W_0^{II}$, the change in regime implies a crash. This crash is larger, the longer and larger the preceding boom. The proof when \hat{p} is relatively low (i.e., $p_F^l(q_H) > \hat{p}$) is symmetric. Q.E.D.

The intuition for information cycles is the following. In a situation of symmetric information, in which only a fraction \hat{p} of firms get financing, the quality of projects in the economy, in terms of their probability of success, is relatively high. If \hat{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 \hat{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, $\hat{p} > p_F^h(\hat{q}(1))$) 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 aggregate productivity $\hat{q}A$. Interestingly, shocks to the two different components of measured productivity, the probability of success, \hat{q} , and productivity conditional on success, A , affect credit booms and busts very differently, since only \hat{q} matters for credit markets. We constructed the model such that it has this property and we can disentangle different types of productivity changes.

We show that a credit boom fueled by an increase in the average probability of success \hat{q} for all firms can be sustained by an increase in credit because information-insensitive loans can be sustained. If the growth of \hat{q} stops, then financial crises and credit collapses become more likely.

Assume for simplicity that the average quality of projects ψ changes to ψ' in a given period. An increase in ψ implies that the average quality of projects in the economy gets better. In the extremes, if $\psi = 1$ the average quality of projects is $\hat{q} = q_H$ even if $\eta = 1$, while if $\psi = 0$ the average quality of projects is $\hat{q} = q_L$ regardless of $\eta > 0$. This process implies that the average probability of success for a given η can weakly decline (this is $\psi' < \psi$) or increase (this is $\psi' > \psi$). The analysis of the previous section assumed a fixed ψ , inducing a deterministic cycle under the conditions in Proposition 2, as illustrated in the previous Section.

In the next Proposition we consider, without loss of generality, the situation in which ψ suddenly and permanently increases to $\psi' > \psi$. The next Proposition characterizes the level $\bar{\psi}$ such that after a shock $\psi' > \bar{\psi}$, the economy does not face cycles anymore, and then a boom does not end in a credit collapse.

Proposition 3 *Productivity shocks and likelihood of crises.*

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

Proof Assume first \hat{p} is relatively high (i.e., $p_F^h(q_H) < \hat{p}$). Under the conditions of Proposition 2, there is a deterministic mass of active firms η_{t^*} at which $\hat{q}(\eta_{t^*})$ 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 $\hat{p} < p_F^h(\hat{q}(1))$. 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 (13), the cutoff $p_F^h(\widehat{q})$ always decreases with ψ' since the left hand side does not change, while the right hand side increases with ψ' . 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 $\psi' > \bar{\psi}$), then there is no information acquisition even if all firms are active (when $\hat{p} = p_F^h(\bar{\psi}q_H + (1 - \bar{\psi})q_L)$). 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 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 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 feeds into credit markets and causes a magnification of real shocks.

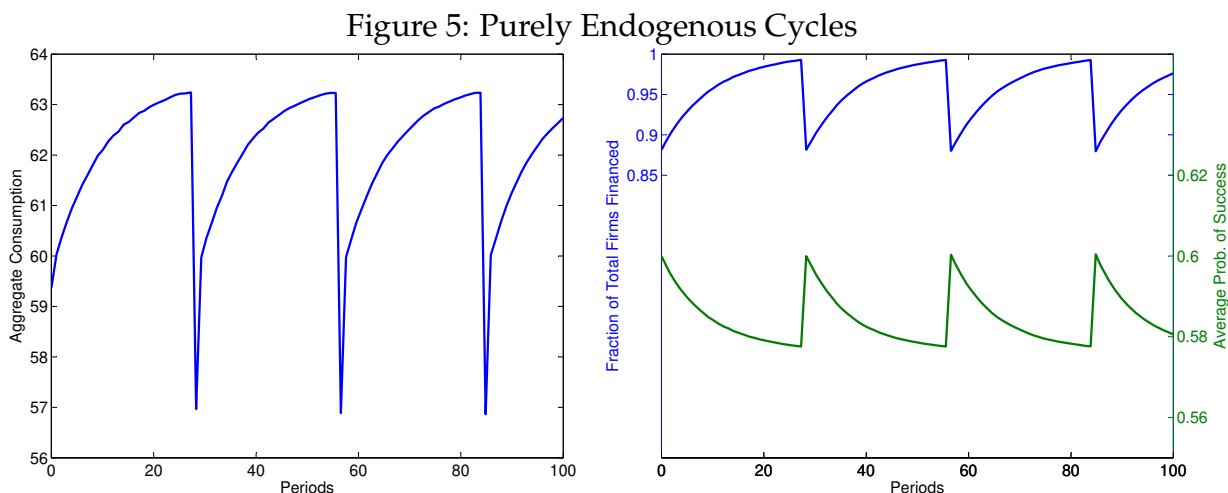
It is an interesting avenue for future empirical research to disentangle the effects of productivity shocks into the real effects highlighted by the standard literature and the effects on real activity through the incentives for information acquisition that affect the functioning of credit markets.

4.2 Numerical Illustration

In this Section we illustrate the possibility of purely endogenous business cycles, the “information cycles” discussed above. We assume idiosyncratic shocks happen with probability $(1 - \lambda) = 0.1$, in which case the collateral becomes good with probability $\hat{p} = 0.88$. Other parameters are $A = 15$, $\bar{K} = 10$, $L^* = K^* = 7$ (the endowment is large enough to allow for optimal investment), $C = 15$, $\gamma_l = 0.35$ and $\gamma_b = 0.05$. This assumption makes p_F^h and p^H very close, implying consumption growth from a boom and large crashes when they do occur. Finally, with respect to decreasing expected productivity of projects, we assume a fraction \hat{p} of projects have a probability of success $q_H = 0.6$ and the rest can only operate with a lower probability of success, $q_L = 0.4$.

We simulate 100 periods, starting from a situation of symmetric information, in which all collateral is known to be either good or bad. In this situation of symmetric information all projects operate with $q_H = 0.6$. Figure 5 shows that over time, as information decays, a larger fraction of firms obtain funds, which implies more projects

in the economy. When the projects that obtain funds exceed \hat{p} , they have to operate with projects of lower productivity, $q_L = 0.4$, which decreases the marginal productivity in the economy. This decline generates a gradual increase in the cutoff $p_F^h(\hat{q}(\eta_t))$ over time. When $p_F^h(\hat{q}(\eta_t)) > \hat{p}$, then information is produced and only good collateral (a fraction \hat{p}) gets credit; there is a collapse in output and consumption and the cycle starts again. Here the dynamics are completely endogenous, generated by an endogenous increase in cutoffs p_F^h and p^H rather than by an exogenous reduction in the expected quality of collateral \hat{p} or in productivity.



In this example $t^* = 28$ (cycles last 28 periods from trough to peak). η goes from 0.88 to 0.99, which implies the boom allows for more than 90% of the firms that did not get credit under symmetric information to obtain loans and operate. However, the boom contains the seeds of the next crisis. Since more firms in the economy decrease the average probability of success from 60% in the troughs to 58% in the peaks, obtaining information about collateral becomes more beneficial, and at some point, when those benefits exceed the cost of information, the fear of asymmetric information makes the continuation of the boom infeasible and information is generated.

4.3 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. Since the incentives to acquire information increase when such av-

verage productivity declines, firms do not internalize the effect on the feasibility of a "symmetric ignorance" regime.

A planner can take this effect into consideration, internalizing the danger for the "symmetric ignorance" regime of letting average productivity to decline too much. Hence, a planner would never allow credit booms to exceed a fraction η_{t^*} of firms operating in the economy. If there is more than a fraction η_{t^*} of firms getting loans and producing, the information-insensitive system becomes unsustainable. The planner can implement the optimal policy by producing extra information, but interestingly with the main objective of avoiding too much information from being produced privately.²¹

5 Conclusions

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.

This result has a clear empirical counterpart sustained by evidence from recent business cycles. Average productivity increases on impact after a crisis, recoveries are jobless, as more firms are struggling to obtain funds to operate and financial markets operations seem to be at the heart of these cycles.

Good booms and bad booms differ because of their respective patterns of TFP growth. Both booms start with a positive shock to TFP when there is some innovation, chang-

²¹We do not solve this planning problem as it is very similar to the planners problem solved in Gorton and Ordóñez (2014).

ing the investment opportunity set. But, booms that end in a crisis show quickly decaying TFP growth. In the model, in this latter case, over time more and more firms get loans but there is decreasing marginal productivity of the projects of active firms. This decreasing productivity eventually endogenously triggers information production and a crisis collapse of output and consumption. The cycle then starts over.

Three aspects of the results seem important for future work. First, the information cycles do not rely on exogenous shocks, but instead are linked to technological innovation. The innovation can lead, sometimes years later, to a crisis. Second, the results here link TFP to booms and crises, which is suggestive of a link with existing macro models, where technology shocks are an important driver. And finally, decomposing TFP into its constituent components is perhaps a fruitful approach for future empirical work.

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A Appendix

Our analysis uses data on the following countries: US, UK, Austria, Belgium, Denmark, France, Netherlands, Sweden, Japan, Finland, Greece, Ireland, Portugal, Spain, Turkey, Australia, New Zealand, Argentina, Brazil, Chile, Colombia, Costa Rica, Ecuador, Mexico, Peru, Uruguay, Israel, Egypt, India, Korea, Malaysia, Pakistan, Philippines, Thailand. For reach country we use time-series data from 1960 to 2010. Below we show the classification of the booms identified by our algorithm.

Table A.1: Booms in the Sample

	Country	Year	Classification		Country	Year	Classification
1	US	1985-2010	crisis	45	Argentina	1992-2000	crisis
2	UK	1970-1974	no crisis	46	Argentina	2005-2007	no crisis
3	UK	1979-1990	no crisis	47	Brazil	1967-1976	no crisis
4	UK	2000-2010	crisis	48	Brazil	1986-1994	crisis
5	Austria	1964-1998	no crisis	49	Brazil	2004-2010	no crisis
6	Belgium	1961-1982	no crisis	50	Chile	1975-1985	crisis
7	Belgium	1985-1993	no crisis	51	Chile	1995-2009	no crisis
8	Belgium	2005-2010	no crisis	52	Colombia	1967-1971	no crisis
9	Denmark	1983-1990	no crisis	53	Colombia	1980-1985	crisis
10	Denmark	2000-2010	no crisis	54	Colombia	1995-1998	crisis
11	France	1965-1993	no crisis	55	Colombia	2004-2010	no crisis
12	France	2005-2010	no crisis	56	Costa Rica	1963-1966	no crisis
13	Netherlands	1970-2010	no crisis	57	Costa Rica	1996-2009	no crisis
14	Sweden	1962-1974	no crisis	58	Ecuador	1975-1985	crisis
15	Sweden	1988-1993	crisis	59	Ecuador	1991-1998	crisis
16	Sweden	2001-2010	no crisis	60	Ecuador	2004-2010	no crisis
17	Japan	1961-1967	no crisis	61	Mexico	1966-1972	no crisis
18	Japan	1970-1973	no crisis	62	Mexico	1989-1995	crisis
19	Japan	1985-2001	no crisis	63	Mexico	2005-2010	no crisis
20	Finland	1982-1992	crisis	64	Peru	1961-1968	no crisis
21	Finland	2001-2010	no crisis	65	Peru	1971-1976	crisis
22	Greece	1967-1982	crisis	66	Peru	1980-1984	crisis
23	Greece	1995-2010	no crisis	67	Peru	1992-2000	no crisis
24	Ireland	1976-1984	no crisis	68	Peru	2007-2010	no crisis
25	Ireland	1994-2010	no crisis	69	Uruguay	1962-1965	no crisis
26	Portugal	1963-1976	no crisis	70	Uruguay	1970-1983	crisis
27	Portugal	1979-1984	crisis	71	Uruguay	1998-2003	crisis
28	Portugal	1991-2010	no crisis	72	Israel	1962-1980	crisis
29	Spain	1961-1977	crisis	73	Israel	1982-1985	crisis
30	Spain	1987-1992	no crisis	74	Israel	1992-2003	no crisis
31	Spain	1997-2010	no crisis	75	Egypt	1974-1987	crisis
32	Turkey	1962-1970	no crisis	76	Egypt	1993-2002	no crisis
33	Turkey	1981-1984	crisis	77	India	1961-1987	no crisis
34	Turkey	1986-1988	no crisis	78	India	1998-2010	no crisis
35	Turkey	1995-2001	crisis	79	Korea	1965-1975	no crisis
36	Turkey	2004-2010	no crisis	80	Korea	1978-1983	no crisis
37	Australia	1964-1974	no crisis	81	Korea	1996-2009	no crisis
38	Australia	1983-2010	no crisis	82	Malaysia	1961-1987	no crisis
39	New Zealand	1972-1975	crisis	83	Malaysia	1994-1999	crisis
40	New Zealand	1977-2001	no crisis	84	Pakistan	1961-1970	crisis
41	New Zealand	2003-2010	no crisis	85	Philippines	1961-1968	no crisis
42	Argentina	1966-1971	crisis	86	Philippines	1972-1984	crisis
43	Argentina	1977-1983	crisis	87	Philippines	1987-1998	crisis
44	Argentina	1986-1989	crisis	88	Thailand	1967-1998	crisis

Table A.2 shows 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: Frequency of Booms

Country	Booms	Bad booms	Freq of boom periods	Average time between booms*
Argentina	5	4	0.54	5
Australia	2	0	0.76	10
Austria	1	0	0.68	NA
Belgium	3	0	0.66	10
Brazil	3	1	0.48	11
Chile	2	1	0.48	11
Colombia	4	2	0.56	6
Costa Rica	2	0	0.32	31
Denmark	2	0	0.30	14
Ecuador	3	2	0.48	7
Egypt	2	1	0.46	6
Finland	2	1	0.40	10
France	2	0	0.66	14
Greece	2	1	0.68	14
India	2	0	0.78	12
Ireland	2	0	0.60	10
Israel	3	2	0.64	6
Japan	3	0	0.48	9
Korea	3	0	0.56	9
Malaysia	2	1	0.62	9
Mexico	3	1	0.36	15
Netherlands	1	0	1.00	NA
New Zealand	3	0	0.70	3
Pakistan	1	1	0.20	NA
Peru	5	3	0.56	7
Philippines	3	2	0.60	5
Portugal	3	1	0.76	6
Spain	3	1	0.72	8
Sweden	3	1	0.48	13
Thailand	1	1	0.62	NA
Turkey	5	2	0.50	7
UK	3	1	0.56	7
Uruguay	3	2	0.42	11
US	1	1	0.52	NA