Good Booms, Bad Booms[*]

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Abstract

Credit booms are not rare; some end in a crisis (*bad booms*) while others do not (*good booms*). We document that credit booms start with an increase in productivity growth, which subsequently falls faster during bad booms. We develop a model in which a crisis happens when a credit boom transits towards an information regime with careful examination of collateral. As this examination is more valuable when collateral backs projects with low productivity, crises are more likely during booms that display larger productivity declines. We test the main predictions of the model and identify the default probability as the main component of measured productivity that lies behind crises.

1   Introduction

Credit booms, productivity growth, and financial crises are interrelated. We study 34 countries over 50 years and show that credit booms are not rare, and that some end in a financial crisis (*bad booms*) and others do not (*good booms*).[1] Credit booms start with a *positive shock* to productivity growth, but in bad booms productivity growth tends to die off quickly while this is not the case for good booms.[2] Credit booms average eleven years, so these are low frequency interactions. We then develop a simple framework to understand how *positive productivity shocks* can lead to credit booms that sometimes end with a financial crash and sometimes do not. Finally, we test some implications of the model.

The model begins with the arrival of a new technology. Firms finance projects that use the technology with short-term collateralized debt, e.g. repo.[3] Lenders can learn the quality of the collateral at a cost, but it is not always optimal to produce this information, in particular when the loan is financing projects that are productive and not very likely to default. If collateral is not examined, there is a depreciation of information in credit markets over time such that more and more assets can successfully be used as collateral. This induces a credit boom in which more and more firms obtain financing and gradually adopt new projects. We assume decreasing returns such that the quality of the marginal project that is financed declines with the overall level of economic activity. So there is also a feedback link between the credit boom and productivity growth in the economy.

As a credit boom evolves, the average productivity in the economy endogenously declines, in which case lenders increasingly have incentives to acquire information about the collateral backing a loan. If at some point the average productivity of the economy decays enough, in a bad boom, there is a change of the information regime in credit markets that leads to the examination of the collateral that is used to obtain credit. As a result, some firms that used to obtain loans cannot obtain loans anymore and output goes down – *a crisis*. Immediately after the crash fewer firms operate, average productivity improves and the process restarts - *a sequence of bad booms*. To highlight the main

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[1]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 highlighted by Dell'Ariccia et al. (2012) and Herrera, Ordonez, and Trebesch (2014).

[2]In the case of the recent U.S. financial crisis, for example, Fernald (2012) documents a steady decline in U.S. productivity growth after 2004, during the credit boom that preceded it.

[3]More generally, the debt can be any short-term debt, e.g., repo or commercial paper, and "collateral" can refer to the backing assets, such as mortgage-backed securities.

channel of interest, we characterize the set of parameters under which the economy experiences this endogenous credit cycle, which is deterministic and not triggered by any contemporaneous fundamental shock. Interestingly, in our model it is the trend of productivity and not its cyclical component which determines the cyclical properties of the economy.

If the new technology keeps exogenously improving over time, as the credit boom evolves, the endogenous decline in average productivity may be compensated for by an exogenous improvement in the quality of projects such that no change of the information regime is ever triggered. If this is the case, the credit boom ends, but not in a crisis – *a good boom*.[4]

In our setting "productivity" has two components: the probability that a project succeeds and the productivity conditional on success. Empirically, productivity is usually measured as a residual, such as total factor productivity (TFP), but our analysis suggests that the two components have different implications for the generation of crises. The component that induces information acquisition about collateral in credit markets is the one that drives the probability that projects succeed, as this determines the probability that firms default and that lenders end up owning the collateral. The second component determines the surplus for the firms conditional on success and does not affect lenders' incentives to acquire information about collateral, consequently it does not affect the likelihood of a crisis.

While most of the macroeconomic literature implicitly assumes that firms always succeed and focuses on the second component, we explicitly differentiate between the two: the first component critically affects debt markets, while the second is more relevant for equity markets. Based on these considerations we construct an index for the *distance to insolvency* (a proxy for the average default probability in the economy - the first component) using the methodology developed by Atkeson, Eisfeldt, and Weill (2013) for the countries in our sample. Using these data we test two implications of the model in terms of the decomposition of productivity. First, we complement our finding that bad booms are more likely when productivity declines over the boom, showing that this effect comes mostly from an increase of the probability of default over the boom – the relevant component of productivity for credit markets. Then, we show that the average default probability is indeed significant in explaining the dynamics of TFP.

Modeling financial crises as a change of the information regime in credit markets is

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[4]There is no normative connotation in calling these two types of booms *good* and *bad*, as in both cases they imply more credit and higher output. The names are related to how booms end.

motivated by 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 (or short-term stores of value) 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, and in our model in credit. In the setting of Dang, Gorton, and Holmström (2013), a financial crisis is a switch from information-insensitive debt to information-sensitive debt when agents produce information about the backing collateral.

We differ from Gorton and Ordonez (2014) in two very important respects. 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. This extension is critical to understand the relation between the evolution of productivity and the generation of crises. Second, in contrast to Gorton and Ordonez (2014) who focus on one-sided information production (only lenders could produce information about collateral), 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 exogenous "shocks" to the value of collateral, as in their case, but as a response to the endogenous productivity growth of the projects financed using collateral.

We find that credit booms are on average eleven years long and that these booms begin with a positive productivity shock. In our model the positive productivity shock is akin to Schumpeter's (1930) argument that new products and technologies, give rise to "gales of creative destruction", which would have an impact for a long time. Similarly, Mokyr (1990) argues that technological progress is discontinuous and that occasional seminal inventions are the key sources of economic growth. Examples include the steam engine, telegraph, and electricity. Field (2010), studying the period 1890-2004 in the U.S., argues that TFP growth rates are "consistent with a view that the arrival of economically important innovations may be quite discontinuous and cluster in particular epochs" (p. 329).[5] Here we claim that these technological breakthroughs also play

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[5]The impact of these technologies has been studied by economic historians and growth economists. See, e.g., Kendrick (1961), Abramovitz (1956), Gordon (2010) and Shackleton (2013). These high impact technologies have been formalized as General Purpose Technologies (GPTs), technologies whose introduction affects the entire economy. There is now a large literature on GPTs. See, e.g., Helpman (1998), David (1990) and Breshnahan and Trajtenberg (1995). The eleven year average length of credit booms is

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a critical role in shaping the cyclical properties of aggregate economic activity and the recurrence of financial crises.

Our finding that credit booms average eleven years is related to studies of "medium-term business cycles" as well. Cao and L'Huiller (2014) also link technological change to crises. They analyze three important crises: the U.S. in 2007-2008, the Japanese stagnation of the 1990s and the Great Depression. They show that each of these was preceded by a technological revolution and find a ten year lag between the technological revolution and the start of the crisis. 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).[6] 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. Their main finding is the existence of a medium-term component in credit fluctuations. Similar conclusions are reached by Claessens, Motto, and Terrones (2011)). We show that there is a difference in productivity growth over credit booms that end in a financial crisis and booms that do not end in a crisis, which is relevant for understanding the conditions under which these technological changes are related to subsequent financial crashes.

Aguiar and Gopinath (2007) show that shocks to the trend are perhaps more relevant sources of fluctuations in emerging markets than transitory shocks around a stable trend. Our results also highlight the difficulty of interpreting business cycles purely as transitory shocks around a stable trend, as changes in the trend affects the properties of business cycles. In our model, different trends induce different reactions of economic variables to the same transitory shocks. Then, our model complements theirs. Behind business cycles we have not only shocks to trends but also different business cycles reactions to those different trends.

A recent paper that revives the discussion of purely endogenous cycles, as in our setting, is Beaudry, Galizia, and Portier (2018). 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 information constraints bind, our model displays deterministic cycles that are not smooth – long booms that suddenly and dramatically end in crises.

roughly consistent with the diffusion of GPTs.

[6]The U.S. S&L crisis never threatened the solvency of the entire financial system; it was costly to clean up, but not *systemic*.

The sharp reversals after lending booms have been documented by Gopinath (2004) and Ordonez (2013) among others, but in our case it is generated by the evolution of information acquisition incentives and not from search frictions or learning inertia.

In the next section we describe the data and analyze productivity growth, both factor productivity and labor productivity, over both good and bad credit booms. In Section 3 we describe and solve the model, focusing on the information properties of collateralized debt. In Section 4 we study the aggregate and informational dynamic implications of the model, focusing on endogenous cycles. We test the main predictions of the model and decompose the two components of productivity 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 shocks and trends, both for total factor productivity (TFP) and labor productivity (LP), during booms. Below we first define and identify "credit booms" in the data and then we analyze the aggregate-level relations between credit, TFP and LP growth and the occurrence of financial crises.

2.1   Data

To empirically focus on financial crises requires facing a trade-off between breadth of countries and length of series, as developed countries have better data and longer time series, but fewer events of financial distress. We study a cross section that includes emerging countries at the cost of time series length, as do Gourinchas, Valdes, and Landerretche (2001), Mendoza and Terrones (2008) and Herrera, Ordonez, and Trebesch (2014). More specifically, 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 these countries is in the Appendix Table A.1.

For credit we use domestic credit to the private sector over GDP, from the World Bank Macro Dataset.[7] This variable is defined as the financial resources provided to the pri-

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[7]Later, we also use the Bank for International Settlements (BIS) "Total Credit Statistics". The BIS provides data on credit to households and credit to corporations. As we discuss later, however, this panel data is not as complete as the World Bank series on credit.

vate sector, such as loans, purchases of non-equity securities, trade credit and other account receivables, that establish a claim for repayment. 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 – it includes not only bank credit but also corporate bonds and trade credit. Details about the definition of the variables and about the data sources are provided in the Appendix Table A.2.

For total factor productivity, we obtain measured aggregate TFP constructed by Mendoza and Terrones (2008) 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. For labor productivity we use the hours-adjusted output-labor ratio from the Total Economy Database (TED).

For financial crises, we follow the definitions of Laeven and Valencia (2012). Their database covers the period 1970 to 2011.[8] 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 put in place; (5) there are significant asset purchases (at least five percent of GDP); (6) there are deposit freezes and/or bank holidays.

2.2 Definition and Classification of Credit Booms

There is now a rich body of evidence showing that credit *growth* predicts crises where credit growth is typically defined as the previous three years or five years of cumulative growth.[9] But, with regard to credit *booms* there is no consensus in the literature as to

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[8]There is a censoring problem at the end of our sample because in some cases the credit boom continues in spite of the recent 2007 financial crisis in the U.S. and the wave of 2008 financial crises in Europe. The results are robust to eliminating these crises from the sample.

[9]For example, Jorda, Schularick, and Taylor (2011) study fourteen developed countries over 140 years (1870-2008) and conclude that "...credit growth emerges as the single best predictor of financial instability." Laeven and Valencia (2012) study 42 systemic crises in 37 countries over the period 1970 to 2007 and conclude "Banking crises are . . . often preceded by credit booms, with pre-crisis rapid credit growth

what constitutes a "credit boom."

What is a credit boom? There are only a few of papers that venture to put forth a definition to capture it empirically. These are Gourinchas, Valdes, and Landerretche (2001), Dell'Ariccia et al. (2016), Mendoza and Terrones (2008) and Richter, Schularick, and Wachtel (2017).All of these authors are interested in the relationship between credit booms and crises. Gourinchas, Valdes, and Landerretche (2001) "define a lending boom episode as a deviation of the ratio between nominal private credit and nominal GDP from a rolling, backward-looking, country-specific stochastic trend" (p. 52). They require that the deviation be larger than a given threshold. Dell'Ariccia et al. (2016) use a definition close to that of Gourinchas, Valdes, and Landerretche (2001) but using a backward-looking country-specific cubic trend. Mendoza and Terrones (2008) use real credit per capita and detrend with the Hodrick-Prescott filter. Richter, Schularick, and Wachtel (2017) also use a version of the Hodrick-Prescott filter that is based on Hamilton (2016). Does the definition matter? It depends on the question. Does it matter to identify booms? Dell'Ariccia et al. (2016) show that pairwise correlations across boom definitions are all above 50%, which implies that they all capture well events of large increases in credit. Does it matter to learn about a boom dynamics? By construction different detrending procedures capture different phases of credit booms and then impose preconceptions on the evolution of related macro variables.[10] Distinguishing the role of different definitions on capturing different phases of credit booms is clearly an area for future research.

For our study we want to impose as few preconceptions as possible so we propose a definition of a "credit boom" that is very simple with regard to trends. We only detrend implicitly using the ratio of credit to the private sector divided by GDP. This means that credit has to grow faster than GDP to possibly be part of a credit boom. Such "detrending" is country-specific but we do not further detrend this ratio. We then define a credit boom as starting whenever a country experiences three consecutive years of positive credit growth (as a fraction of GDP) that average more than x^s. The boom ends whenever a country experiences at least two years of credit growth (also as

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in about 30 percent of crises." Desmirguc-Kunt and Detragiache (1998) obtain the same result using a multivariate logit model in a panel of 45-65 countries (depending on the specification) over the period 1980-1994. Other examples include Gourinchas and Obstfeld (2012), Claessens, Kose, and Terrones (2011), Schularick and Taylor (2012), Reinhart and Rogoff (2009), Borio and Drehmann (2009), Gourinchas, Valdes, and Landerretche (2001), Kaminsky and Reinhart (1999), Hardy and Pazarbasioglu (1991) and Goldfajn and Valdez (1997).

[10]As the HP filter is forward looking, for example, it does not consider the initial and the final phases of a credit expansion as part of a boom, potentially missing related changes in other macro variables during those phases.

a fraction of GDP) 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. We find 87 booms based on this definition, which are listed in the Appendix Table A.3.

There are several reasons for our approach. First, we do not want to implicitly set an upper bound on the length of the boom by further detrending the ratio of credit to GDP. Using deviations from a trend implies that a boom has predetermined maximum length, as a protracted boom would be included in the trend component. We want to avoid this so the data inform us as to whether crises are associated with longer or shorter booms. Second, as also Aguiar and Gopinath (2007) argue, shocks to the trend may be the source of cyclical behavior rather than transitory shock around a trend. To allow for this possibility we do not want to detrend twice. Third, 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 relevant for studying "credit booms."

Once we have identified the credit booms, we can classify them into bad or good depending on whether they are accompanied by a financial crisis in a neighborhood of three years of the end of the boom, or not, respectively.[11] In our sample there are 47 crises identified by Laeven and Valencia (2012). Table 1 shows that 34 of those crises happened at the end of one of the 87 booms we have identified (hence we have 34 bad booms in the sample). There were eight crises that did not occur at the end of a boom (but occurred during a boom), and there were five crises that were not associated with any boom. So, there are good booms and bad booms, but also crises unrelated to the end of booms, or with no booms at all.

Table 1: Financial Crises in the Sample

Number of crises occurring at the end of a boom	34
Number of crises occurring not at the end of a boom	8
Number of crises not associated with booms	5
Total number of crises in the sample	47

Figure A.1 in the Appendix shows good booms (light blue bars), bad booms (dark red bars) and crises (black dots) for each country in our sample. There is enormous heterogeneity, which we exploit next when comparing these different booms.

[11]As dating the start is typically based on observing government actions it is difficult to precisely date crises, so we use a three year window. See Boyd, De Nicolo, and Loukoianova (2011). Our results are not significantly altered, however, if for example we look for crises within two years of the end of the boom.

2.3 Properties of Good Booms and Bad Booms

In Table 2 we present summary statistics of a number of variables over different periods, which include total credit as a fraction of GDP, credit to households and to the corporate sector, TFP, patents, real GDP, investment, and labor productivity. Consistent with the technological change discussed in the Introduction the average length of a boom is about eleven years. The table also provides an overview of booms periods compared to non-boom periods and it compares booms that end with a crisis with booms that did not end in crises.[12] The variable "Credit" is our main measure of credit (granted to the private sector as a fraction of GDP) from the World Bank Macro Dataset; 'Total Cr'd" is the growth in total credit (the numerator on "Credit"). "H'd Cr'd" refers to credit to the household sector from the BIS data; "C't Cr'd" is credit granted to the corporate sector, also from BIS.[13]

Comparing boom periods to non-boom periods what stands out is that all measures of credit (the first four rows) are significantly larger during booms. Notice, however, that this result is not embedded in our construction of a credit boom, but still consistent with the general view that during booms credit is higher in average. The average change in capital expenditures (the variable "INV growth') is significantly higher during booms compared to non-booms, consistent with investment booms coinciding with credit booms. Real GDP growth (rGDP) is also higher during booms as is credit both to the corporate sector and to households. Turning now to comparing good booms and bad booms, we see that the average growth in TFP and LP are significantly higher in good booms as compared to bad booms. Real GDP growth is also higher in good booms, but not investment nor credit.

Figure 1 shows the evolution of the average growth rates for TFP, LP, real GDP, and capital formation, around the initial stages of both good booms and bad booms.[14] The figure shows that both types of credit booms start with a positive shock to productivity but then the paths of growth rates subsequently differ for good booms and bad booms. At the onset of credit booms (date 0 in the figure) TFP grows at 1.5% compared to an average of 1% in the previous three years for good booms and 1% versus an average of 0.2% for bad booms. For LP these differences are 3% versus an average of 2.05%

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[12]The subsamples for crisis and non-crisis booms are small, as shown in Table 2, 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.

[13]The variable "Pt Gn't" refers to patents granted from the World Intellectual Property Organization (http://www.wipo.int/en/statistics/patents/).

[14]Figure A.2 in the Appendix shows the median growth rates for the same variables.

	Whole Sample	Non Booms	Booms	t-Statistic for Means	Booms with a Crisis	Booms without a Crisis	t-Statistic for Means
Avg. Credit growth (%)	3.83	-2.41	8.96	15.02	9.84	8.30	1.27
Avg. Total Cr'd growth (%)	8.09	1.59	13.43	14.34	13.95	13.03	0.70
Avg. H'd Cr'd growth (%)	6.07	3.93	7.55	1.07	6.71	8.47	-1.64
Avg. C't Cr'd growth (%)	1.76	-0.83	3.58	6.39	3.57	3.59	-0.04
Avg. TFP growth (%)	0.83	0.78	0.87	0.62	0.47	1.17	-3.57
Avg. Pt Gnt'd growth (%)	3.87	3.72	3.99	0.10	2.33	5.48	-0.90
Avg. rGDP growth (%)	2.56	2.29	2.78	3.08	2.40	3.07	-3.28
Avg. INV growth (%)	1.48	1.08	1.79	2.19	1.67	1.88	-0.49
Avg. LP growth (%)	2.52	2.45	2.57	0.72	2.06	2.96	-4.29
Avg. Duration (years)			10.68		11.76	9.98	0.93
Avg. Time spent in boom			27.32		11.76	15.56	
Number of Booms			87		34	53	
Sample Size (years)	1695	766	929		400	529	

for good booms and 1.7% versus an average of 1.6% for bad booms. In bad booms, however, the productivity growth rates remain lower and die off faster than in good booms (as do the growth rates for real GDP and capital formation). Panel (b) makes the point dramatically for labor productivity, which is measured with less error. In good booms LP growth is high and flat, while in bad booms it nose dives by the fourth year after the boom starts. These figures are stylized so next we confirm more systematically that the different patterns between good booms and bad booms suggested in panels (a) and (b) of Figure 1 are statistically significant.

We ask whether the changes in TFP and LP predict the type of boom, by running the following regression.

$$Pr(BadBoom_{j,t}|Boom_{j,t}) = F_L\left(\alpha + \beta \Delta X_{j,t}\right). \tag{1}$$

where F_L is the cumulative logistic function, $F_L(z) = \frac{1}{1+e^{-z}}$, $BadBoom_{j,t}$ represents a boom in country j at period t that has been identified as bad and $\Delta X = \{\Delta TFP, \Delta LP\}$ is the change in the respective measure of productivity in country j between periods $t-1$ and period t.

If the change in TFP, for example, is on average declining over the boom, then the coefficient on the prediction of bad booms should be negative, i.e., a positive change in TFP is making the boom less likely to be a bad boom.[15] We see exactly this pattern in Table 3, for both our measures of productivity change.[16]

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[15]As we run the regressions conditional on being in a boom, positive changes in productivity should predict good booms, and the coefficient should be the same but with the opposite sign.

[16]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.

Figure 1: Average Productivity Growth over Good and Bad Booms

(a) Total Factor Productivity

(b) Labor Productivity

(c) Real GDP

(d) Capital Formation (Investment)
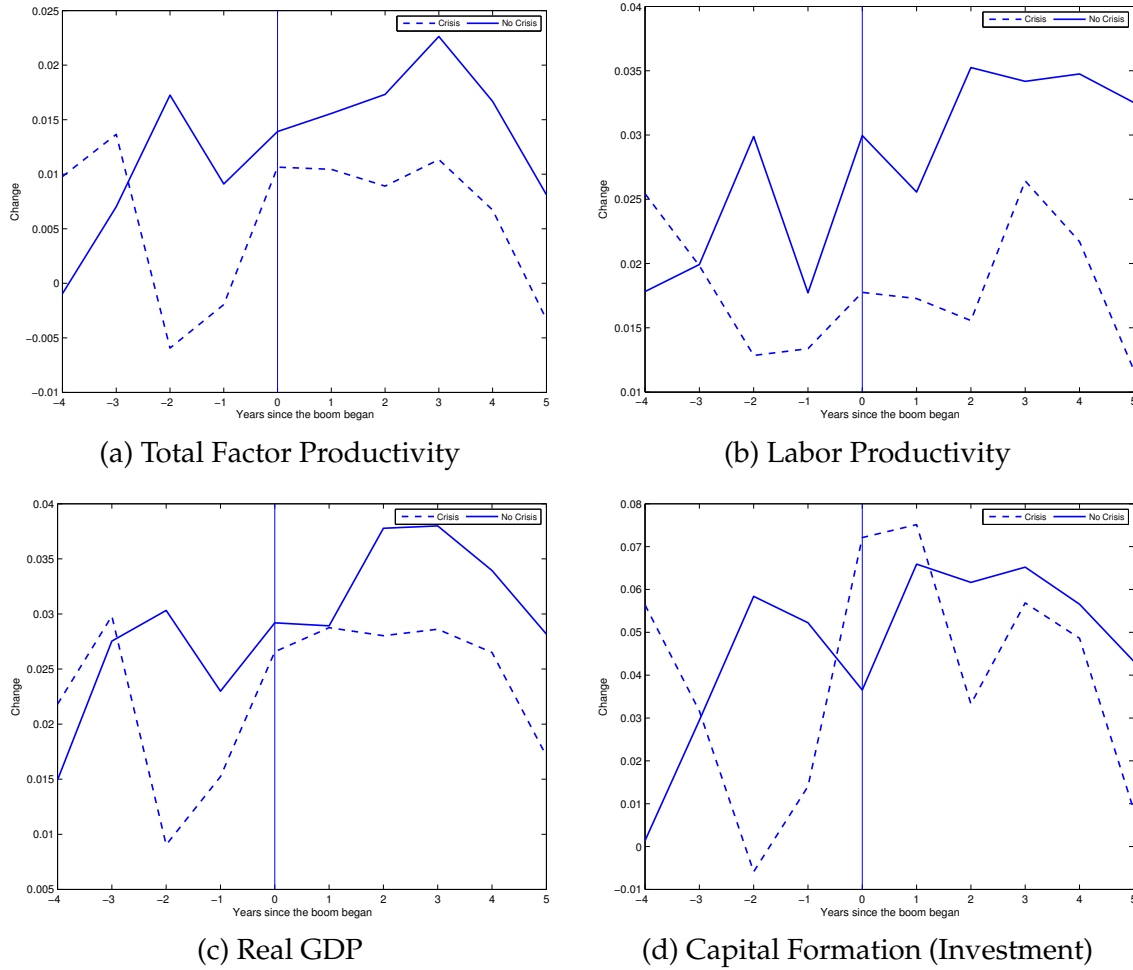
The marginal effect in the table shows the change in the probability of being in a bad boom given a change of one standard deviation in the relevant productivity growth variable. The first column of Table 3, for example, shows that, conditional on being in a boom, an increase of one standard deviation in TFP reduces the probability of being in a bad boom (a boom that will end in a crisis) by 6%.[17]

How do credit booms start? This is a question so far unaddressed by the literature. The data suggest that there is a positive technology shock that triggers the start of a credit boom. Panels (a) and (b) in Figure 1 are also suggestive as they show the change in TFP and LP for the five years prior to the start of the boom are positive. We investigate this further by asking whether changes in TFP and LP predict the start of a boom, by

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[17]The marginal effects are the average change in the conditional expectation function implied by the model. See the discussion in Angrist and Pischke (2009).

Table 3: Productivity Growth as an Indicator of Bad Booms

	TFP			Labor Productivity		
	LOGIT	LPM		LOGIT	LPM	
α	-0.23	0.44		-0.02	0.49	
t-Statistic	-3.39	26.91		-0.15	21.19	
β	-7.09	-1.70	-1.41	-9.86	-2.31	-3.02
t-Statistic	-3.72	-3.82	-4.29	-4.05	-4.18	-7.06
Marginal	-0.06	-0.06	-0.05	-0.08	-0.07	-0.10
R^2		0.01	0.48		0.02	0.49
N	929	929	929	761	761	761
FE	No	No	Yes	No	No	Yes

running the following regression.

$$Pr(Boom_{j,t}) = F_L\left(\alpha + \beta \Delta X_{j,t}\right). \tag{2}$$

where F_L is the cumulative logistic function, $F_L(z) = \frac{1}{1+e^{-z}}$, $Boom_{j,t}$ is an indicator variable for the year of the start of a boom in country j at period t and $\Delta X = \{\Delta TFP, \Delta LP\}$ is the change in the respective measure of productivity in country j at period t. Table 4 shows that lagged changes of TFP are significant predictors of the start of a credit boom, on total credit but not on credit to households. This is not the case for labor productivity.[18] In Appendix B we discuss in detail a famous case of a bad boom in the U.S., the Roaring Twenties. This example describes the technological innovation that started at the beginning of that decade and gave rise to a boom, the variety of credit granted during the boom and how the decline or maturing of the technological innovation led up to the subsequent crisis.

Table 4: An Increase in TFP Predicts Credit Booms

	TFP		LP	
	Credit	HHCredit	Credit	HHCredit
α	-2.97	-2.99	-3.00	-2.86
t-Statistic	-25.24	-18.31	-14.90	-12.37
β	5.27	2.50	11.81	-1.51
t-Statistic	1.75	0.67	1.80	-0.22
Marginal	0.01	0.01	0.02	-0.00
N	1695	1367	610	610

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[18]We show here the logit specification, but the same holds for LPM regressions.

2.4 The Effect of Productivity Growth on Crises

Now that we have characterized what happens at the onset and during these two types of booms, we turn to examining directly the effects of TFP and LP growth on the likelihood of a financial crisis. Recent studies, such as Jorda, Schularick, and Taylor (2011), have converged on the growth in credit as the key predictor of financial crises. We first verify that this is also true in our sample by examining how lagged measures of credit growth predict financial crises with a Logit model

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

where $Pr(Crisis_{j,t})$ 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 5. Consistent with previous literature, 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%. This is an economically significant effect as well when considering that the unconditional probability of a crisis in the sample is 2.7% (46 crises in a sample of 34 countries and 50 years).

Table 5: Credit as Crisis Predictor

	5Ychange			5YchangeMA		
	LOGIT	LPM		LOGIT	LPM	
α	-4.05	0.01		-3.93	0.02	
t-Statistic	-20.11	3.59		-19.28	3.78	
β	0.78	0.03	0.04	0.89	0.04	0.04
t-Statistic	4.04	4.48	4.63	3.25	3.42	3.59
Marginal	0.01	0.02	0.02	0.01	0.01	0.02
R^2		0.01	0.02		0.01	0.02
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.

$$Pr(Crisis_{j,t}) = F_L\left(\alpha + \beta\Delta Cred_{j,t-1} + \gamma\Delta X_{j,t-1}\right),$$

where $\Delta X = \{\Delta TFP, \Delta LP\}$.

Table 6: Credit and Productivity Growth as Crises Predictors

	TFP			Labor Productivity		
	LOGIT	LPM		LOGIT	LPM	
α	-3.93	0.02		-3.68	0.03	
t-Statistic	-21.51	5.58		-17.80	5.29	
β	1.11	0.05	0.05	1.02	0.05	0.05
t-Statistic	2.19	2.43	2.49	1.93	2.18	2.23
Marginal	0.00	0.01	0.01	0.00	0.01	0.01
γ	-9.27	-0.22	-0.23	-11.74	-0.29	-0.34
t-Statistic	-2.42	-2.43	-2.51	-2.46	-2.48	-2.71
Marginal	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
R^2		0.01	0.02		0.01	0.02
N	1661	1661	1661	1337	1337	1337
FE	No	No	Yes	No	No	Yes

The results are shown in Table 6. Growth in TFP and LP both mitigate the likelihood of a crisis, while credit growth remains statistically. To put this result in context, even though an increase of one standard deviation in credit over GDP increases the probability of a crisis by roughly 1%, if this increase is accompanied by a contemporaneous increase of one standard deviation in productivity the probability of a crisis also declines by roughly 1%, making the increase in credit relatively innocuous.

2.5 Types of Credit Granted During a Boom

What type of credit is being granted during a boom? Some have argued that housing credit, in particular mortgages, is the important component of credit booms that end in crises. See, e.g., Leamer (2007), Jorda, Schularick, and Taylor (2014 and 2015), Mian and Sufi (2014), and Mian, Sufi, and Verner (2016). We saw above in Table 2 that investment booms (capital formation) tend to accompany credit booms so it seems that more is going on than just mortgage lending. Gourinchas, Valdes, and Landerretche (2001), for example, also point out that lending booms are associated with domestic investment booms. In this subsection we explore this further.

The Bank for International Settlements (BIS) "Total Credit Statistics" provides data on credit to households and credit to corporations. This panel data is not as complete

as our series "credit to the private sector" from the World Bank. In fact, it is quite sparse. Of our 34 countries only 23 have observations in this data set. Only one of the countries has data starting in 1960, only four have data that starts prior to 1970; and only eight countries have data starting prior to 1980. Table A.4 in the Appendix shows the coverage of the data sets.

Table 7 shows the correlations of the levels and changes. In the table "Credit" refers to credit to the private sector divided by GDP. Credit to the household sector (HHCredit) has a significant correlation of 0.83 with Credit and credit to corporations (CorpCredit) has a correlation of 0.71 with Credit (no surprisingly then the credit to households and corporations are also positively and significantly correlated). In other words, countries with a large fraction of credit of GDP have this credit flowing to both households and corporations. The table also shows these correlations for changes in credit. Even though all correlations are positive, the only statistically significant case is the correlation between Credit and CorpCredit, suggesting that it is the credit to corporations that commove more strongly with total credit.

Table 7: Correlation of Credit with its Components (Levels and Changes)

	$CorpCredit$	$HHCredit$	$Credit$
$CorpCredit$	1.000		
$HHCredit$	0.596***	1.000	
$Credit$	0.712***	0.830***	1.000

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	$\Delta CorpCredit$	$\Delta HHCredit$	$\Delta Credit$
$\Delta CorpCredit$	1.000		
$\Delta HHCredit$	0.018	1.000	
$\Delta Credit$	0.203***	0.063	1.000

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Looking just at the two BIS series, Table 8 shows the mean difference between the amount of credit granted to households and credit granted (as a percent of GDP) to corporations during good and bad booms and also the differences in changes in credit over the two types of booms. While credit to corporations is always greater in levels than credit to households, in both types of booms, the increase in credit to households is larger than the increase in credit to corporations in both types of booms. This is consistent with investment booms occurring during both types of boom, as households have more access to credit to consume and corporations have more access to credit to invest and produce to cover the larger demand.

To get at this further, and to focus on credit to households, we repeat the analysis of the previous section using only HHCredit, in which case we get 32 booms, 17 of which

Table 8: Credit to Households and Corporations

	Household	Corporate	t-Statistic for Means
Credit - Good Booms	38.780	64.760	-9.44
Credit Change - Good Booms	0.085	0.036	4.38
Credit - Bad Booms	60.803	88.980	-8.99
Credit Change - Bad Booms	0.067	0.036	4.48

ended in a crisis, compared to 87 booms in the full data set using total credit, of which 34 ended in a crisis. Of the 32 booms based on credit to households, 28 start within two years of the start of the booms defined previously.

Table 9 shows that over the booms defined with HHCredit, there is a significantly larger average TFP and LP growth in good booms relative to bad booms. However, unlike the large literature on growth in credit predicting crises, HHCredit growth does not predict crises (in a logit context as above, omitted here to save space).

Table 9: Descriptive Statistics using Credit to Households

	Whole Sample	Non Booms	Booms	t-Statistic for Means	Booms with a Crisis	Booms without a Crisis	t-Statistic for Means
Avg. H'd Cr'd growth (%)	6.07	3.13	7.99	1.40	6.99	9.62	-2.30
Avg. TFP growth (%)	0.53	0.29	0.69	1.82	0.41	1.15	-2.65
Avg. Pt Gnt'd growth (%)	-0.81	-2.14	-0.00	0.72	2.76	-4.84	1.72
Avg. rGDP growth (%)	2.28	1.83	2.58	3.16	2.23	3.16	-2.91
Avg. INV growth (%)	1.87	1.60	2.04	0.89	1.92	2.24	-0.47
Avg. LP growth (%)	2.13	2.07	2.17	0.47	1.95	2.54	-2.09
Avg. Duration (years)			11.53		13.41	9.40	1.61
Avg. Time spent in boom			18.45		11.40	7.05	
Number of Booms			32		17	15	
Sample Size (years)	610	241	369		228	141	

During a credit boom, credit to households is highly correlated with other types of credit. Household credit does not seem to be divorced from the positive technology shock that starts the credit boom. Instead, household credit seems to be a part of the overall phenomenon, which responds to the technology shock and results in an investment boom. For our purposes it is not necessary, however, to take a strong stand on the possible separate role of household credit. Even though we will present a model based on credit to firms, in the online Appendix C we develop a model of credit to households and show that the forces and dynamics are the same.

2.6 Summary

We find interesting interactions between technology, credit booms, and financial crises at lower frequencies than are usually analyzed. Booms tend to start with a positive

shock to productivity growth. Credit booms are eleven years long on average. Our finding that positive productivity shocks occur at the start of the boom has been already noted by economic historians and growth economists.[19] Here we show that these technological revolutions and their posterior evolution can also play a critical role in shaping the cyclical properties and the recurrence of financial crises. Our novel finding concerns the productivity growth patterns over good booms and bad booms. Financial crises are prone to occur when technological change slows down subsequent to the technology shock, ending in a bad boom. So, the seeds of a financial crisis are planted many years before the actual event. We now turn to a model of booms and crises that captures and rationalizes these empirical findings.

3 The Model

In this section we first present the model (in subsection 3.1), describe the timing and define the equilibrium (subsection 3.2). In subsection 3.3 we characterize the optimal type of loan for a single firm. Loans may be information-sensitive (IS), in which case information is produced about collateral quality, or information insensitive (II), simply based on beliefs about collateral quality, without information production. Finally, in subsection 3.4 we construct the model's counterparts to the macroeconomic variables analyzed in the empirical section above, in particular productivity and credit.

3.1 Setting

Time is discrete and denoted by $t \in \{0, 1, ...\}$. The economy is characterized by two overlapping generations – young and old – each with a mass 1 continuum of agents, and three types of goods – *numeraire*, *land* and *labor*. 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 to produce more numeraire, hence we denote it by K. Land is storable, but non-productive and non-reproducible. Labor, which we denote by L, is non-transferable and its use does not generate disutility.

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[19]Indeed, in the long-term, technology such as the steam locomotive, telegraph, electricity or IT has played a central role in understanding growth (see Kendrick (1961), Abramovitz (1956), Gordon (2010) and Shackleton (2013)). Field (2010), studying the period 1890 - 2004 in the U.S., argues that TFP growth rates are "consistent with a view that the arrival of economically important innovations may be quite discontinuous and cluster in particular epochs" (p. 329).

We interpret the young generation as *households* and the old generation as *firms*. Households have an inelastic fixed supply $\overline{L}$ of labor that they use to produce numeraire linearly and deterministically, $\overline{K} = \overline{L}$, at the beginning of the period. Firms have an inelastic fixed supply L^* of labor that can be combined with numeraire in a stochastic production function that generates $A \min\{K, L\}$ with probability q and nothing otherwise at the end of the period.

We assume that there is a limited supply of projects in the economy per period, 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 it is optimal that households use all their labor in the project, $L = L^*$ and that use $K^* = L^*$ as the optimal scale of numeraire for all projects, independent of their *quality* $q \in \{q_L, q_H\}$.

We say a firm is *active* if it can obtain a loan in the credit market. We denote by η the *mass of active firms*, which we will show later is endogenous to available credit in the economy. We assume that active firms are randomly assigned to a queue to choose their project. When a firm has its turn to choose its project according to its position in the queue, an active firm naturally picks the project with the highest q among those remaining in the pool. This protocol induces an average productivity of projects among active firms, which we denote by $\widehat{q}(\eta)$, that is given by

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

The average quality of projects in the economy depends on two factors – an exogenous fraction of good projects in the economy, ψ and the endogenous fraction of operating projects, η.[20]

We assume land is non-productive (does not participate in the project) but may have an intrinsic value. If land is *"good"*, it can deliver 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 in every period.[21] At the beginning of the period, different units of land i can potentially be viewed differently, with respect to their type. We denote these beliefs that land is

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[20]The specific assumptions of a Leontief production function and the average productivity $\widehat{q}(\eta)$ are useful to the analytical exposition of the model. The results hold as long as the projects have an optimal scale of operation and projects display decreasing marginal returns.

[21]We abstract in this paper from a time varying quality of land, which we have explored in Gorton and Ordonez (2014)

good p_i and assume they are commonly known by all agents in the economy at the beginning of the period.

The land type can be privately observed (and certified) at the beginning of the period, at a cost γ_l in units of numeraire by households (diverting its use from consumption) and/or at a cost γ_b in units of labor by firms (diverting its use from production). We assume information (the certification) is private immediately after being obtained and becomes public at the end of the period. Still, the agent can credibly disclose his private information (the certificate) immediately if it is beneficial to do so.

We can now point out two important differences with Gorton and Ordonez (2014). First, in that paper the quality of the projects, q, is constant and crises are generated by exogenous shocks that reduce the average quality of collateral, $\widehat{p}$. In this paper, we maintain the average quality of collateral fixed while the average quality of projects, $\widehat{q}(\eta|\psi)$ change endogenously with changes in η or exogenously with changes in ψ. Therefore, in contrast to Gorton and Ordonez (2014), the source of the shock that may induce a crisis here is in the production sector and it has an endogenous component that evolves with credit. Second, in that paper $\gamma_b = \infty$. In this paper, when γ_b is sufficiently small there may be discontinuous drops in output during crises, which happen as the economy moves from a regime in which collateral is not investigated to a regime in which it is. These two additions combined allows us to capture a situation in which the fundamentals in the production sector moves continuously and endogenously as credit grows, but once it crosses a threshold those fundamentals may trigger a discontinuous change in credit and output.

In this simple setting, resources are in the wrong hands. At the beginning of the period households can produce numeraire while firms just have labor but not the numeraire essential to produce. We assume that $\overline{K} > K^*$ and 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 what follows, however, we assume limited liability and a extreme financial friction – the information about the output of the project is private to the borrower and non-verifiable by the lender. In this case, firms would never repay and households would never be willing to lend against a promise based on numeraire that can be absconded.

Even though we will assume that firms can hide the numeraire, we will also assume that firms cannot hide land, which makes land useful as *collateral* and relax the financial friction. 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, when young agents use the numeraire they have produced to buy land, which is then useful as collateral to borrow and to produce when they become old. For this transfer of land to be feasible we further assume $\overline{K} > C$.

The perception about the quality of collateral then becomes critical in facilitating loans. We further assume that $C > K^*$ so 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*, our parameter η, since in contrast to firms that are known to hold bad land, they can actively raise funds to start their projects.[22]

Remark on the interpretation of collateral: 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 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. Here we have called to collateral "land", but realistically we have in mind a mortgage-backed security or asset-backed security, securities are hard to value. This type of security 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, use land holdings as the basis for borrowing.[23]

3.2 Timing and Equilibrium

We have discussed the environment, preferences, technologies and information structures. Here we discuss the timing in a single period and define the equilibrium

Beginning of the period: Market for loans: At the beginning of the period, households produce $\overline{K}$. Then there is random matching between one household (lender) and one firm (borrower). Both the lender and borrower know the probability p that the land owned by the borrower is good. The borrower knows the quality of its project q, but the lender only knows $\widehat{q}(\eta|\psi)$. The borrower makes a take-it-or-leave-it offer for a loan that

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[22]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.

[23]Firms use their land as pledgeable assets 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. Also, see Gan (2007) and Chaney, Sraer, and Thesmar (2012).

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specifies the size of the loan K, the face value R and the fraction of collateral that should be transferred to the household in case of default x. The borrower also specifies whether the lender (l) or borrower (b) should acquire information (an information-sensitive loan, denoted IS) or not (an information-insensitive loan, denoted II). The lender either accepts or reject the offer.

End of the period: Market for land: At the end of a period, firms produce and fulfill the loan contracts. All information generated about the land (even that privately generated) gets revealed. The household (buyer) makes a take-it-or-leave-it offer for the land that specifies the price that the household is willing to pay to the firm (seller) in terms of numeraire good. The seller either accepts or reject the offer.

Between periods: There are idiosyncratic mean reverting shocks to the type of land. First, we assume these shocks are observable but their realization is not, unless information is produced. Second, we assume that the probability that land faces an idiosyncratic shock is $(1 - \lambda)$, independent of the land type. Finally, we assume the probability that a unit of land becomes good, conditional on having an idiosyncratic shock is $\widehat{p}$, also independent of the land type. These three 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 the collateral type.

Equilibrium: The markets for loans and land operate separately and periods are just linked by the evolution of land beliefs across periods. Borrowers choose the loan contract type ($i \in \{IS^l, IS^b, II\}$ and K_i, R_i and x_i) to maximize expected profits conditional on the lender accepting the offer (participation constraint), the borrower repays when the project succeeds and defaults when the project fails (truth-telling constraint) and there are no private incentives to acquire information in the information-insensitive contract (incentive-compatibility constraint). The buyer also has to choose the offer to buy land conditional on the seller accepting the offer.

We have set up the market for land so that the price is pC, the lowest price the buyer can offer to satisfy the seller's participation constraint. As both agree about p at the end of the period, this price just represents the fundamental expected value of land.[24] As the buyer makes the take-it-or-leave offer, it does not compensate the seller for the expected value that the unit of land has as collateral for the buyer in the next period. In the next section we focus on the market for loans and its information generation.

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[24]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, this is $\overline{K} > C$.

3.3 Optimal loan for a single firm

We first study the optimal short-term collateralized debt for a single firm with a project that has a probability of success q, with a unit of land that is good with probability p, and when there is a total mass of active firms η. 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. Loans that do not trigger information production (information-insensitive debt), however, may not be feasible as they introduce a fear for asymmetric information – they introduce incentives for either the borrower or the lender to deviate and acquire information privately to take advantage of its counterparty. The magnitude of this fear determines the level of debt that can be information-insensitive and, ultimately, the volume and dynamics of information in the economy.

3.3.1 Information-Sensitive Debt (IS)

Lenders can learn the true value of the borrower's land by using γ_l of numeraire. Borrowers can learn the true value of their own land by using γ_b of labor, leaving only $L^* - \gamma_b$ to be used in the project, which would generate $A \min\{K, L^* - \gamma_b\}$ in case of success (with probability q), and 0 otherwise.

If the contract specifies that the lender acquires information, as they are risk neutral, their zero profit condition is[25]

$$p[\widehat{q}(\eta)R_{IS^l} + (1 - \widehat{q}(\eta))x_{IS^l}C] = pK_{IS^l} + \gamma_l.$$

Conditional on the collateral being bad it is not feasible to sustain a loan and conditional on the collateral being good the loan is of optimal size, $K_{IS^l} = K^*$. The truth-telling constraint is $R_{IS^l} = x_{IS^l}C$. Otherwise, if $R_{IS^l} > x_{IS^l}C$, firms always default, handing over 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 pins down the fraction of collateral posted by a firm, which is a function of p and independent of q:

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

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

Note that, since the fraction of land posted as collateral does not depend on q, firms cannot signal their q by posting a different fraction of land as collateral (or similarly, by offering to pay a different rate). Intuitively, since collateral completely prevents default, the loan cannot be used to signal the probability of default.

Expected total consumption for firms is $pC + p(qAK^* - x_{IS^l}C)$. Substituting x_{IS^l} 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 simply

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

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 labor. Lenders participation constraint binds when,

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

Regardless of what the borrower finds, the firm will only have $L^* - \gamma_b$ labor remaining for use in the project. If the borrower finds out that the land is good he will then just borrow $K_{IS^b} = K^* - \gamma_b$ to operate at the, now lower, optimal scale.

The truth-telling constraint is $R_{IS^b} = x_{IS^b}C$ and $x_{IS^b} = \frac{K^* - \gamma_b}{C}$. Ex-ante expected total consumption for the borrower is $pC + p(qA(K^* - \gamma_b) - x_{IS^b}C)$. Substituting x_{IS^b} in equilibrium, *expected net profits* (again net of the land value pC) are

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

Putting these two possibilities together, expected profits from information-sensitive debt effectively are

$$E(\pi|p, q, IS) = \max\{pK^*(qA - 1) - \gamma, 0\} \tag{3}$$

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

In the case of using an information-sensitive loan, firms choose to produce information if $\gamma_b p(qA - 1) < \gamma_l$, and prefer that lenders produce information otherwise. When

lenders produce information, borrowers compensate them for not consuming γ_l. When borrowers produce information, they divert resources away from the project, which is costly, only if they find out the land is good (with probability p) and cannot use 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 expected loan is increasing 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 size, K^*, as labor is inefficiently wasted in monitoring the quality of land.[26]

Figure 2: Expected Loan Size with Information-Sensitive Debt
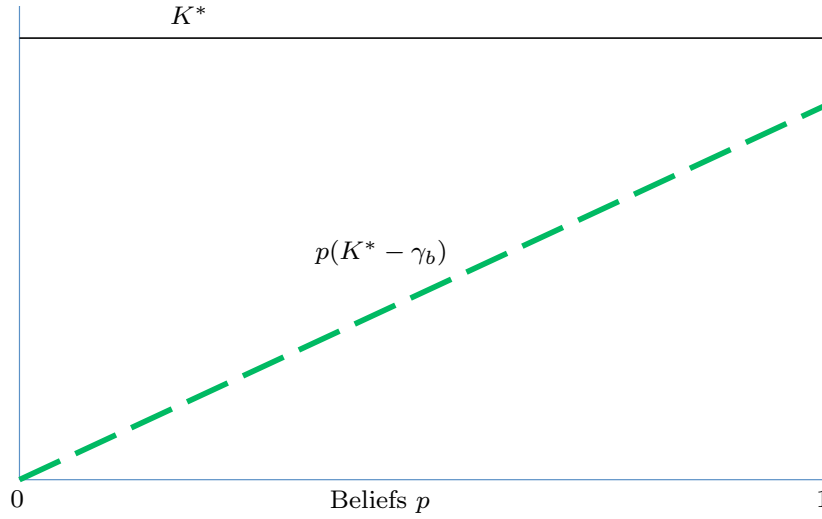
3.3.2 Information-Insensitive Debt (II)

Another possibility for firms is to borrow such that there is no information acquisition. In this case, lenders' participation constraint binds when

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

and subject to the truth-telling constraint, $R_{II} = x_{II}pC$ we obtain,

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

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[26]If $\gamma_b p(qA - 1) > \gamma_l$ the figure is identical but the dotted line intercepts the horizontal axis at $p > 0$. See Gorton and Ordonez (2014).

For this contract to be information-insensitive (II), 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, lenders' benefits of acquiring information come from not lending when the collateral is bad and making profits in expectation from lending when the collateral is good. 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,

$$K < \frac{\gamma_l}{(1 - p)(1 - \widehat{q}(\eta))}. \tag{4}$$

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 will never be larger than K^* (as the optimal size of the project is L^*) and the lender will 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 (4), information-insensitive loans are such that

$$K < K^l(p|\widehat{q}(\eta), II) \equiv \min\left\{K^*, \frac{\gamma_l}{(1 - p)(1 - \widehat{q}(\eta))}, pC\right\} \tag{5}$$

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 informa-

Figure 3: Expected Loan Size with Information-Insensitive Debt
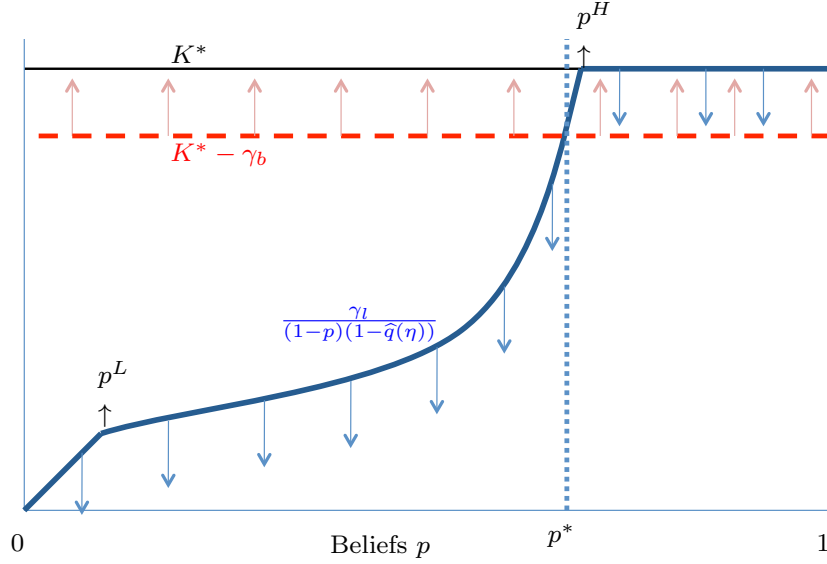
tion. Specifically, if borrowers acquire information, their expected benefits are $p(K^* - \gamma_b)(qA-1)+(1-p)\min\{K, K^*-\gamma_b\}(qA-1)$. With probability p land is good and the firm borrows $K^* - \gamma_b$ as there are only $L^* - \gamma_b$ managerial skills remaining. With probability $1 - p$ land is bad and the firm borrows the minimum between the original contract K or the optimum conditional on having used managerial skills to acquire information, $K^* - \gamma_b$. 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,

$$K > K^b(p|\widehat{q}(\eta), II) \equiv K^* - \gamma_b. \tag{6}$$

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.

Combining the two conditions (5) and (6), 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 for relatively high

beliefs $p > p^*$, where the threshold p^* is given by the point in which $K^l(p^*) = K^b(p^*)$ from equations (5) and (6). Then

$$p^* = \max\left\{1 - \frac{\gamma_l}{(K^* - \gamma_b)(1 - \widehat{q}(\eta))}, \frac{K^* - \gamma_b}{C}\right\}.$$ (7)

It is clear from inspecting equation (7) that the information-insensitive debt region widens with information costs (p^* decreases with γ_b and γ_l) and shrinks with the mass of active firms (p^* increases with η since η reduces $\widehat{q}$). This is summarized in the next Lemma.

Lemma 1 *The cutoff p^* is monotonically decreasing in γ_b and γ_l and increasing in η.*

The optimal loan K^* is feasible under 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 (5). Then

$$p^H = 1 - \frac{\gamma_l}{K^*(1 - \widehat{q}(\eta))}.$$ (8)

Finally, and just for completeness, 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 (5). Then [27]

$$p^L = \frac{1}{2} - \sqrt{\frac{1}{4} - \frac{\gamma_l}{C(1 - \widehat{q}(\eta))}}.$$ (9)

3.3.3 Loans With or Without Information Production?

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 assuming $\gamma_b(q_H A - 1) \leq \gamma_l$ (this is, even firms with $p = 1$ and $q = q_H$ acquire information at a lower cost that lenders).[28]

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[27]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 collateral that is good with probability $p > p^H$ can borrow the optimal level of capital K^* without triggering information acquisition.

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

Figure 4: Expected Profits in Equilibrium
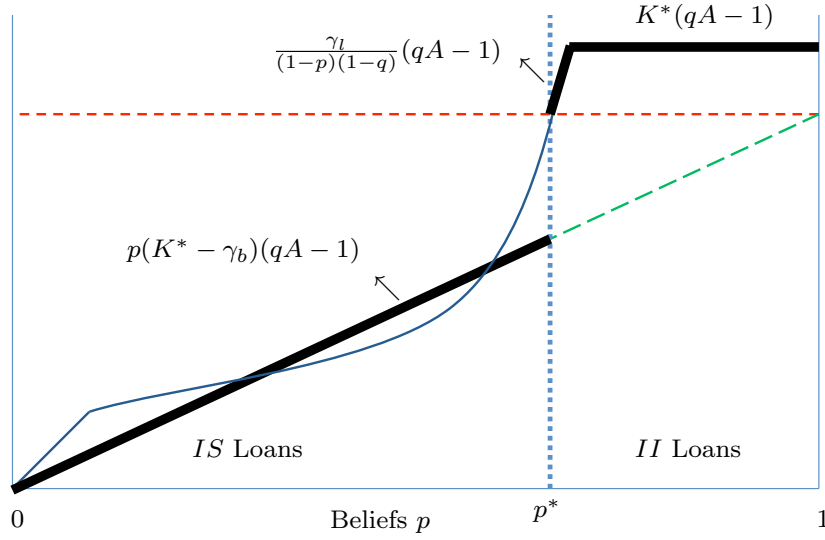
We can summarize the expected loan sizes for different beliefs p, graphically represented with a wide black discontinuous function in Figure 4, by

$$K(p|\widehat{q}(\eta)) = \begin{cases} K^* & \text{if } p^H < p \\ \frac{\gamma_l}{(1-p)(1-\widehat{q}(\eta))} & \text{if } p^* < p < p^H \\ p(K^* - \gamma_b) & \text{if } \quad p < p^*. \end{cases} \tag{10}$$

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, and both the optimality and feasibility of information-insensitive debt increase.[29]

Notice that, as the mass of active firms, η, increases, there is a reduction of the probability of success, $\widehat{q}(\eta)$. This has three effects that induces less credit in the economy. First, the information-insensitive region where firms can obtain the optimal loan size (the first range) shrinks, as p^H decreases with $\widehat{q}(\eta)$. Second, the loan size in the information-insensitive region that is binding by information acquisition (the second range) declines. Finally, the information-sensitive region (the third range) widens, as p^* decreases with $\widehat{q}(\eta)$.

We can now be more precise about the effects of the two main differences with the setting of Gorton and Ordonez (2014). First, in that paper we assume that $\gamma_b = \infty$, which means that the constraint represented by the dotted red line is never binding,

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[29]"Large γ" would correspond, for example, to complex securitization tranches.

and then output does not change discontinuously at p^*. Second, while Gorton and Ordonez (2014) study the effects of moving the average quality of collateral $\widehat{p}$ over the horizontal line, here we focus on changes in the average quality of projects $\widehat{q}$ that move the solid blue curve, then affecting the threshold p^* at which regimes change. In other words, while Gorton and Ordonez (2014) focus on exogenous changes in $\widehat{p}$ around p^*, here we focus on endogenous change sin p^* around $\widehat{p}$.

Remark on adverse selection: In our setting adverse selection never arises in equilibrium. The switch from an information-sensitive contract, with symmetric information, to an information-insensitive contract, with symmetric ignorance, is however triggered by the *threat* of adverse selection. This is an important difference compared with a large body of literature that relies on the preexistence (and sometimes exacerbation) of adverse selection to discuss crises (see Kurlat (2013) and Bigio (2015), for example). In our economy adverse selection appears as an off-equilibrium possibility that puts limits on contracts based on symmetric ignorance, potentially leading to the inferior alternative of symmetric information when adverse selection becomes too big of a threat.

3.4 Aggregation, Productivity and Credit

The previous analysis was based on the markets for loans and land for a single match of a household (young agent) and a firm (old agent) in a given period t. Now we can aggregate the results to construct the model's counterparts of the main macro variables we analyzed in the data.

The total output of households in every period t is $Y_h = \overline{K}$, just generated using a constant amount of labor $L_h = \overline{L}$.

The total net output (after deducting the use of intermediate inputs) of a single firm that has land of quality p, conditional on η_t active firms operating in the economy, is $Y_f = K(p|\widehat{q}(\eta_t))(\widehat{q}(\eta_t)A-1)$, where $K(p|\widehat{q}(\eta_t))$ is the credit obtained by the firm according to equation (10). Thus, aggregating, total credit in the economy is

$$Cr_t(\widehat{q}(\eta_t)) = \int_0^1 K(p|\widehat{q}(\eta_t))f_t(p)dp$$

where $f_t(p)$ is the distribution of beliefs about collateral types in period t. Given the Leontieff production function, the total labor used in firms' production is given by $L_f = Cr_t(\widehat{q}(\eta_t))$.

Summing over the net output of all households and firms, GDP in our model is

$$Y_t = \overline{K} + Cr_t(\widehat{q}(\eta_t))(\widehat{q}(\eta_t)A - 1) \tag{11}$$

Agents are risk-neutral, so welfare is just given by aggregate consumption. The numeraire consumption good is perishable, so there is no intertemporal reallocation and then total welfare is just total output, $W_t = Y_t$. As a benchmark, note that in the unconstrained first best (the case in which output were verifiable, for example) all firms are active (i.e., $\eta = 1$), and operate with $K^* = L^*$, regardless of beliefs p about the collateral. This implies that the unconstrained first-best aggregate consumption (and output) can be defined as

$$W^* = \overline{K} + K^*(\widehat{q}(1)A - 1). \tag{12}$$

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 of 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 data section we focused on studying the relationship between the growth rates of credit over GDP, TFP and labor productivity. To construct the model's counterparts of these growth rates (that we generically denote by g in what follows) we first compute the growth rate of total output,

$$g_Y = \frac{Y_h}{Y}g_{\overline{K}} + \frac{Y_f}{Y}g_{Cr} + \frac{Y_f}{Y}\left[\frac{\widehat{q}ACr}{Y_f}(g_{\widehat{q}} + g_A) + \frac{(\widehat{q}A - 1)\widehat{q}\frac{\partial Cr}{\partial \widehat{q}}}{Y_f}g_{\widehat{q}}\right]$$

Defining $w_f = \frac{Y_f}{Y}$ as the share of firms' output of total output and recalling that $L_h = \overline{K}$ and $L_f = Cr(\widehat{q})$ are the measured labor inputs in the household and firm sectors respectively, we can obtain the Solow residuals as

$$g_{TFP} = g_Y - (1 - w_f)g_{\overline{K}} - w_f g_{Cr}$$

which can be further rewritten as

$$g_{TFP} = w_f \left[\frac{\widehat{q}A}{(\widehat{q}A - 1)} g_A + \left(\frac{\widehat{q}A}{(\widehat{q}A - 1)} + \varepsilon_{Cr,\widehat{q}} \right) \left(\varepsilon_{\widehat{q},\psi} g_\psi + \varepsilon_{\widehat{q},\eta} g_\eta \right) \right] \tag{13}$$

where $\varepsilon_{Cr,\widehat{q}} > 0$ is the elasticity of total credit to the average probability of success in the economy, $\varepsilon_{\widehat{q},\psi} > 0$ is the elasticity of the average probability of success to the exogenous shock ψ and $\varepsilon_{\widehat{q},\eta} < 0$ is the elasticity of the average probability of success to the endogenous mass of active firms η. Notice that there are two sources of exogenous shocks to TFP growth: ψ increases the probability of success of firms' projects and A increases output conditional on success. There is also an endogenous source of TFP decline, η, which evolves with total credit in the economy.

In our setting labor productivity (LP) growth is identical to TFP growth. The reason is that $g_{LP} = g_Y - g_L$, where $g_L = (1 - w_f)g_{L_h} + w_f g_{L_f}$. Since $L_h = \overline{K}$ and $L_f = Cr$, the result follows.

Finally, the growth rate of credit over GDP is simply defined by $g_{Cr/GDP} = g_{Cr} - g_Y$. Since $g_{\overline{K}} = 0$, then $g_{Cr/GDP} = (1 - w_f)g_{Cr} - g_{TFP}$.

In the model, the state variable that evolves over time is the distribution of beliefs, $f(p)$, which affects the fraction of operating firms η and then the total credit in the economy, $Cr_t(\widehat{q}(\eta_t))$. In the next section we study how an economy that does not replenish information each period experiences a clustering of p values at the mean $\widehat{p}$, which increases η. The increase in η reduces total factor and labor productivity (if not compensated for by exogenous changes in ψ or A), which reduces output for a level of credit, increasing the ratio of credit to GDP. At the same time, the increase in η has a first order effect on increasing credit. Even though more credit also generates more output, the ratio of credit over GDP increases because the output of households does not change with credit. In the next Section we study the intricate dynamics (and potential for completely endogenous cycles) of credit, productivity and production.

4   Model Dynamics

We now assume that each unit of land changes quality over time, mean reverting towards the average quality of land in the economy. We study how endogenous information acquisition shapes the distribution of beliefs over time, characterize the three possible stationary distributions and discuss the evolution of credit, productivity and production during transitions between these stationary distributions.

With the simple stochastic process for idiosyncratic shocks described in the timing of our model, the belief distribution has a three-point support: 0, $\widehat{p}$ and 1. Since firms holding land that is known to be bad ($p = 0$) are inactive, the mass η of active firms is the fraction of firms with beliefs $\widehat{p}$ and 1. Then $\eta = f(\widehat{p}) + f(1)$.

4.1 Stationary Equilibria

Here we study the possible steady states as a function of the fraction of high quality projects, ψ, in the economy. We first define three critical levels of ψ to characterize three possible steady states.

First, we will now introduce definitions that allow to characterize stationary equilibria. Define first $\chi \equiv \lambda \widehat{p} + (1 - \lambda)$ a benchmark parameter that represents the lowest possible fraction of active firms after a single round of idiosyncratic shocks starting from a situation in which all land types are known: a fraction λ of the $\widehat{p}$ of firms that were known to have a good collateral remains so (then having beliefs $p = 1 > 0$)), while a fraction $(1 - \lambda)$ of all collateral suffers the shock and their perceived quality, absent information acquisition, is $\widehat{p} > 0$. These are then active firms.

Fix the average quality of land, $\widehat{p}$. Assuming $\eta = \chi$ average productivity is $\widehat{q}(\chi|\psi) = \frac{\psi}{\chi} q_H + \left(1 - \frac{\psi}{\chi}\right) q_L$ and from equation (7) there is a technology level $\underline{\psi}$ such that $\widehat{p} = p^*(\widehat{q}(\chi|\underline{\psi}))$. Assuming now $\eta = 1$ (all firms are active) average productivity is $\widehat{q}(1|\psi) = \psi q_H + (1 - \psi) q_L$ and from equation (7) there is technology level $\overline{\psi}$ such that $\widehat{p} = p^*(\widehat{q}(1|\overline{\psi}))$. Finally, when $\eta = 1$, from equation (8) there is also a technology level $\overline{\psi}^H$ such that $\widehat{p} = p^H(\widehat{q}(1|\overline{\psi}^H))$.

The next Lemma shows the relation between $\underline{\psi}$, $\overline{\psi}$ and $\overline{\psi}^H$.

Lemma 2 $\underline{\psi} < \overline{\psi} < \overline{\psi}^H$.

Proof By construction $\widehat{p} = p^*(\widehat{q}(\chi|\underline{\psi})) = p^*(\widehat{q}(1|\overline{\psi}))$. Using equation (7), fixing all other parameters, $\widehat{q}(\chi|\underline{\psi}) = \widehat{q}(1|\overline{\psi})$. Then $\underline{\psi} = \chi\overline{\psi}$ and the first inequality follows as $\chi < 1$. The second inequality arises because $p^* < p^H$ for all $\widehat{q}$, p^H is decreasing in $\widehat{q}$ and $\widehat{q}$ is increasing in ψ. Q.E.D.

The next three propositions characterize the stationary equilibrium of the economy in three regions of ψ, *low technology* ($\psi < \underline{\psi}$), *intermediate technology* ($\psi \in [\underline{\psi}, \overline{\psi}]$) and *high technology* ($\psi > \overline{\psi}$).

Proposition 1 *Low Technology: Symmetric Information - Low Steady Consumption.*

If $\psi < \underline{\psi}$, the steady state is characterized by information repeated acquisition about collateral and constant consumption in every period at,

$$\overline{W}(\widehat{p}) = \overline{K} + \widehat{p}(K^* - \gamma_b(1-\lambda))(\widehat{q}(\widehat{p})A - 1) < W^*. \tag{14}$$

Proof In this case, as $\psi < \underline{\psi}$ then $\widehat{p} < p^*(\widehat{q}(\chi|\psi))$. Assuming an $\eta \geq \chi$, then $p^*(\widehat{q}(\eta|\psi)) \geq p^*(\widehat{q}(\chi|\psi))$ and $\widehat{p}$ is always in the region where information-insensitive debt is not feasible. This implies that in the steady state there is always information acquisition and in every period $f(1) = \lambda\widehat{p}$, $f(\widehat{p}) = (1-\lambda)$ and $f(0) = \lambda(1-\widehat{p})$. Since ,

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

as $K(0) = 0$, $K(1) = K^*$ and $K(\widehat{p}) = \widehat{p}(K^* - \gamma_b)$. Then consumption is constant at the level at which information is reacquired every period (equation (14)), which is less than the optimal consumption from equation (12). The economy remains in the symmetric information regime. Q.E.D.

In words, when the technology is poor and the probability of default is large there are high incentives for information acquisition about the collateral, even when there are few active firms. The steady state is characterized by a continuous renewal of information in the economy. In this case, as long as exogenous shocks are absent, the economy does not face any fluctuations and consumption remains below its potential.

We say that there are "*information cycles*" if the economy fluctuates between booms with no information acquisition and crashes with information acquisition. The next Proposition shows this is the case when there is an intermediate technological level, that is $\psi \in [\underline{\psi}, \overline{\psi}]$

Proposition 2 *Intermediate Technology: Information Cycles - Sequence of Bad Booms.*

If $\psi \in [\underline{\psi}, \overline{\psi}]$ there is a deterministic length of the boom $t^*(\psi)$ at the end of which credit and consumption crashes to the symmetric information consumption, restarting the cycle. Furthermore $t^*(\psi)$ is increasing in ψ (the better the technology in this range, the longer the boom before it crashes).

Proof In this case, as $\psi \in [\underline{\psi}, \overline{\psi}]$ then $\widehat{p} \geq p^*(\widehat{q}(\chi|\psi))$ and $\widehat{p} \leq p^*(\widehat{q}(1|\psi))$. Assume $\eta_1 = \chi$, and there are no incentives to acquire information about the collateral with

beliefs $\widehat{p}$. Then 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 because in this region $\widehat{p} \leq p^*(\widehat{q}(1|\psi))$. As $W_{t^*}^{II} > W_0^{II}$, the change in regime implies a crash. This crash is larger, the longer and larger the preceding boom.

Furthermore, as $\widehat{p}$ is given, then $\widehat{q}(\eta_{t^*}) = \frac{\psi}{\eta_{t^*}} q_H + \left(1 - \frac{\psi}{\eta_{t^*}}\right) q_L$ is also given. The larger is ψ the higher is η_{t^*} and the larger $t^*(\psi)$, which is the length of the 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 and there are no incentives to acquire information about collateral, and a credit boom starts. As the boom evolves over time, information decays, more firms are financed and the average quality of projects decline.

The reduction in projects' quality increases both the probability of default in the economy and the incentives for information acquisition. At some point, when the credit boom is large enough, default rates are also large and may induce information acquisition – a change in regime from symmetric ignorance to symmetric information. A crash is characterized by only a fraction $\widehat{p}$ of firms (those with good land) obtaining credit. Then a new boom starts.

The better the technology ψ the longer is the period that a bad boom lasts until it crashes. Note that there are no "shocks" needed to generate information cycles, as the steady state of the economy displays deterministic cycles. Cycles arise from the endogenous evolution of the distribution of collateral beliefs in credit markets.[30]

Finally, the next proposition characterizes the steady state when the technology is high, this is $\psi > \overline{\psi}$.

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[30]We have assumed a particular process for idiosyncratic shocks that generates a three-point belief distribution, but endogenous cycles exist as long as there is mean reversion in any such process. As soon as there is mean reversion and information is not acquired, beliefs will tend to concentrate around the average quality of land, $\widehat{p}$, regardless of the specific process of idiosyncratic shocks. As soon as the threshold p^* crosses $\widehat{p}$ a positive measure of land will be affected, creating a crisis-like event. The longer the economy is in a boom without information acquisition the larger will be the affected measure of land.

Proposition 3 *High Technology: Symmetric Ignorance - High Steady Consumption.*

If $\psi > \overline{\psi}$, the steady state is characterized by no information acquisition about collateral and constant consumption in every period. Furthermore, if $\psi > \overline{\psi}^H$ consumption is at the unconstrained optimal level in equation (12).

Proof In this case, as $\psi > \overline{\psi}$ then $\widehat{p} > p^*(\widehat{q}(1|\psi))$. Assume any $\eta \leq 1$, then $p^*(\widehat{q}(\eta|\psi)) \leq p^*(\widehat{q}(1|\psi))$ and there are never incentives to acquire information. Furthermore, if $\psi > \overline{\psi}^H$ all firms obtain a loan K^* in steady state and consumption is at the unconstrained optimum level given by equation (12).   Q.E.D.

In this last region, when technology is high, there are no incentives to acquire information about collateral. Over time all collateral looks alike, and the economy converges to a situation in which all firms obtain a loan and produce without spending resources on information acquisition. If the technology is high enough, output is at the unconstrained first best. This is because financial frictions are not operational given the low expected default probabilities. This is naturally the optimal situation as the economy is stable and with the maximum level of consumption. This suggests that there are also reasons from a credit market perspective for which high productivity and success probabilities are beneficial for the economy, both in terms of level and stability of activity.

Remark on Balanced Growth Paths: Notice first that absent any exogenous shock in the economy the symmetric information and ignorance regions are *deterministic steady states*, as η is fixed, and then $g_{Cr} = 0$ and $g_T FP = 0$ while the asymmetric information region is a *stochastic steady state* as η is fluctuating deterministically over time, the probabilities of the various states will be repeated and remain constant. Second, notice that in case A grows at a constant rate, then the three regions will be in a balanced growth path, with TFP and consumption growing at the same rate, but without changing the characterization of information acquisition in credit markets or the availability of credit in each one of them.

4.2   Transitions

In the previous section we described the three possible stationary equilibria of the economy when technology ψ is fixed. In this section we discuss how the economy reacts to shocks to ψ such that the economy has to transit from one steady state to another. As steady states are ranked in terms of the productivity level, ψ, these shocks can be positive or negative. On the one hand, positive shocks boost credit to a new steady state,

but how the credit boom ends depends on the size of the positive shock. On the other hand, negative shocks have the potential to generate crises in which credit suddenly collapses, more in line with standard views of crises driven by exogenous contemporaneous negative shocks.

If the economy experiences a technological improvement, the dynamics of the economy depends both on the size of the improvement and on the initial technological condition. If the technology is low and increases dramatically (say to high) then the economy transitions from a calm and inefficient symmetric information regime to a calm and more efficient symmetric ignorance regime – a good boom. If the technological improvement is not as dramatic (say from low to intermediate) the economy moves from a stable environment with low consumption to a cyclical environment with higher output but more volatility, characterized by a sequence of booms and busts. If the initial condition of technology is intermediate and improves (say to high) the economy moves from a unstable cyclical situation to a stable economy with higher output.

On the other hand, if the technology is already high (say, for example that the the economy had experienced a good boom in the past), it does not imply that the economy cannot suffer a negative technological shock that induces a crisis and moves it to a worse (either less efficient or more volatile) steady state. In this situation the model also generates interesting insights. A reduction in ψ can always induce a crisis, which is more likely if the shock is larger or if the economy has been in a long boom. In other words, a negative shock can induce a crisis even in the absence of a preceding boom. This story is more in line with the standard view of crises as generated by negative contemporaneous shocks. Also in our setting a negative contemporaneous shock in productivity induces an otherwise stable credit situation to collapse and then transforms what would have been just a recession into a sudden crisis. This effect complements the ones highlighted by papers such as Kiyotaki and Moore (1997), Bernanke and Gertler (1989) or Carlstrom and Fuerst (1997) since real negative shocks in productivity feeds back into credit markets and causes a magnification of real shocks.

In the next section we illustrate numerically the difference between good and bad booms by showing the reaction of the economy to positive shocks to ψ. Negative shocks to ψ just push the economy to a trivial, but potentially permanent, destruction of credit. Even though our informational mechanism is different than most of other stories in the literature, we will dispense to illustrate those cases of negative shocks to ψ as the transitions are sudden and relatively trivial.

Remark on Policy Implications: There is a clear externality in our setting. When firms decide to take an information-insensitive loan, they do not internalize its effect on 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 would take this effect into consideration, keeping average productivity from declining too much. More specifically, a planner would never allow credit booms in which the fraction of firms operating exceeds η_{t^*} to occur, 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. In contrast to the dynamic intervention explored in Gorton and Ordonez (2014), in which the planner would like to subsidize information production to prevent a boom from growing too much and then reducing the expected costs of a crisis generated by a negative exogenous shock, in this paper the planner could prevent a crisis altogether by restricting credit once the average productivity of projects has reached a critical level.

4.3   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 measured credit, productivity and output. For the illustration we assume idiosyncratic shocks happen with probability $(1 - \lambda) = 0.1$ per period, in which case the collateral becomes good with probability $\widehat{p} = 0.88$. Firms' labor is $L^* = K^* = 7$, household's labor is $\bar{L} = \bar{K} = 20$ (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 labor. Finally, a fraction ψ of projects (which we will vary) has a probability of success $q_H = 0.7$ and the rest a lower one, $q_L = 0.4$. Conditional on success the firm produces $A = 15$ units of numeraire.

First, we show how three different levels of technology (captured by ψ) generate three very different steady states as described in Propositions 1, 2 and 3 in Section 4.1. Given the previous parameters, when the technology level is low ($\psi = 0.52$) the economy displays a low credit and low output steady state with continuous information replenishment, as characterized in Proposition 1. This situation is depicted by dashed blue in Figure 5.

When there are more good projects ($\psi = 0.62$) the technology is high and the steady state is characterized by Proposition 3. Credit and output are also stable but higher than in the previous case. This result arises from high levels of credit (as all firms obtain credit and operate) and high levels of GDP (both because there is more activity and TFP is higher). This situation is depicted by dotted black in Figure 5.

Finally, for an intermediate level of technology ($\psi = 0.57$), the steady state is in a cyclical situation, with a sequence of bad booms as characterized in Proposition 2. In this situation both credit and GDP fluctuates periodically, with periods above the level of an economy with worse technology (when credit is growing) but also with periods below it (when there are crises). This situation is depicted by solid red in Figure 5.

Figure 5: Credit and Output - The three possible steady states

(a) Credit
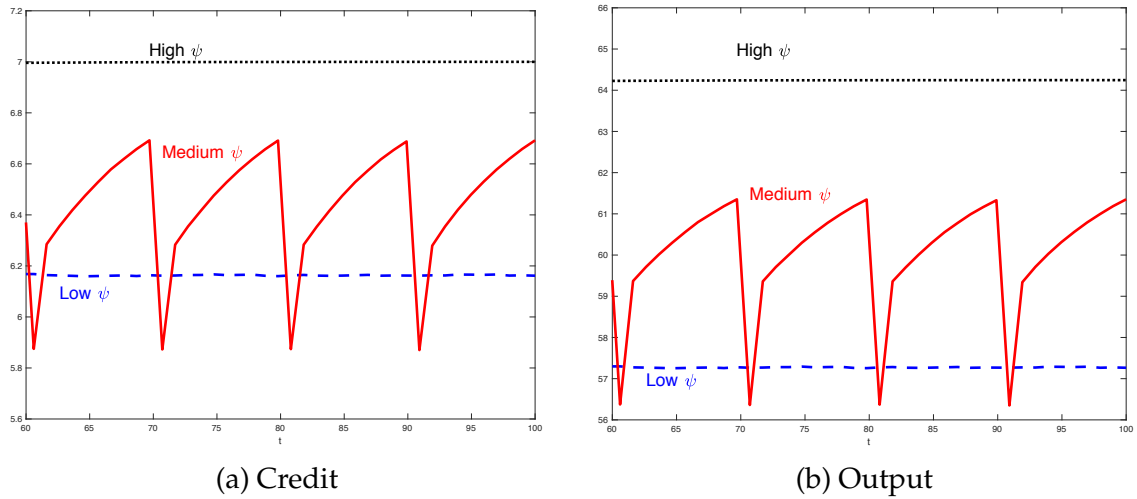
(b) Output

Now, based on Section 4.2, we illustrate transitions. We focus on how an economy that is originally in an information-sensitive regime, with a low and stable output responds to an exogenous positive and permanent productivity shock that increases the average probability of projects succeeding. We show that if this change is not large enough, the economy will transition to a regime with deterministic credit booms followed by crises – a sequence of bad booms. When the shock is followed by a series of other small positive shocks that make further technological improvements, 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 – a good boom.

More precisely, as above we assume that ψ changes from 0.52 to 0.59. In itself this change will make the economy transition to a cyclical steady state. We plot the evolution of the two main variables we measured in the data, credit over GDP (solid red) and

TFP (dashed red) in Figure 6. To compare to a good boom, we assume another situation in which, after the shock, ψ keeps increasing at a rate of 1% for 10 periods, reaching a level of 0.60. This higher level of technology that is achieved during the boom makes the economy transition onto a different, information insensitive steady state – a good boom. This second possibility is depicted in black in the figure.

Figure 6: Transitions - Good and Bad Booms
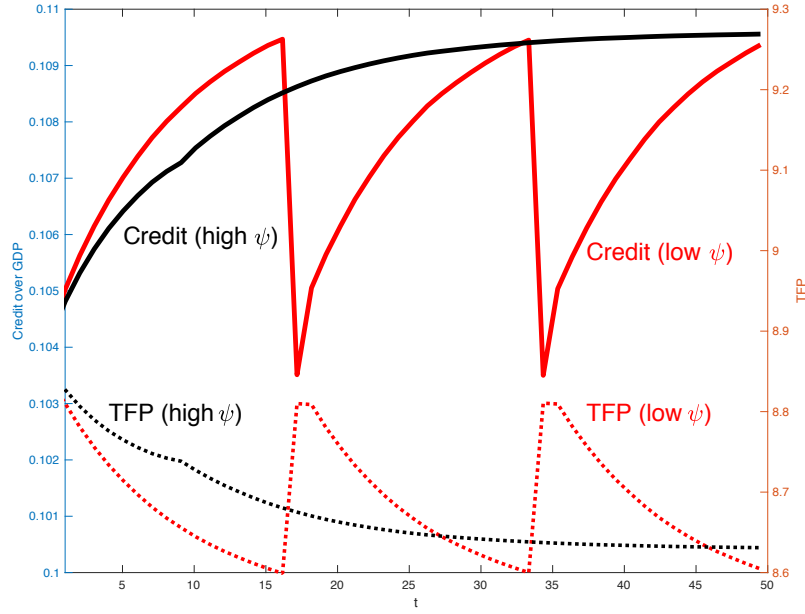
The credit boom generates an endogenous decline in TFP, however we have assumed an exogenous force that compensates this decline in the second case. When the decline in productivity is less severe, crises are less likely (not likely in this illustration), to end in crisis, which is consistent with our main empirical findings. Credit growth is the same in both types of booms, but productivity (and output) are higher during a good boom. This implies that credit over GDP is higher during bad booms. This is however in contrast to the common interpretation of excessive leverage in the literature, as in our model credit grows at the same rate in both cases, but during a bad boom such credit goes to projects that are less productive, which puts pressure for information acquisition and crises. This relation justifies why large credit booms predict crises – they are based on a situation in which credit increases faster than the output it sustains. Note that our setting does not predict the numerator being different across good booms and bad booms but instead that GDP is lower in bad booms, as productivity is lower. We examine this empirically below.

These numerical examples illustrate the rich interactions between productivity and credit in an economy and their implications for its cyclical behavior. An economy

may experience credit booms that take the economy from a low stable output level 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 low stable output level to a sequence of booms and busts that exist even without fundamental changes, which we have denoted as "bad booms".

5 Some Empirical Tests

In this section of the paper we test an assumption we use in the model and two predictions that the model delivers.

The assumption we test is that default is a component of measured TFP. While measured TFP is a residual that may contain several factors, in our model TFP growth is a combination of the growth of the probability of success ($\widehat{q}$) and the growth of output conditional on success (A), as shown in equation (13). We have deliberately constructed the model such that only $\widehat{q}$, not A, affects incentives to examine collateral in credit markets. Then our model is based on the insight that there is a component in our measure of TFP that drives the probability of default and then affects debt markets, while there is another component that determines the gains in case of success (and then repayment) which affects equity markets, not debt markets. Based on this we show that changes in TFP are correlated with changes in a measure of firm fragility (likelihood of failure).

The two predictions we test relate to the different behavior of default frequency and GDP growth during good and bad booms. The first prediction of the model is that firms are increasingly more fragile over bad booms, relative to good booms. The second prediction, as we discussed in the numerical example, is that while the growth in total credit is the same during both types of boom, productivity and output grow less during bad booms, and then credit over GDP grows more during bad booms.

5.1 Test of the assumption that firm default is a component of TFP

Testing the assumption that default is a component of TFP is hard because we do not have bankruptcy data, nor do we have business failures for our panel of countries. We can however 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

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measures the adequacy of a firm's equity cushion relative to its business risk. They show that this is a good proxy for the probability of default and that it can be measured with the inverse of the volatility of a firm's equity returns.[31] We construct $\frac{1}{vol_{j,t}}$ for a country j at year t, based on daily stock price data for all listed companies for each country in our sample. The period for which these data are available differs somewhat across countries. Also, the number of listed firms changes over time. See Table A.5 in the Appendix for details. More specifically, for a given country we calculate the monthly stock return volatility for each listed company based on daily data. We then take the median of the monthly volatilities for each firm in a year. This is the annual measure of firm fragility we use for each country in each year, $vol_{j,t}$.

Note that a decrease in $\frac{1}{vol_{j,t}}$ corresponds to an economy becoming more fragile (as volatility is larger). To test our assumption we examine versions of the following regressions, with and without fixed effects:

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

In Table 10 the results are shown for changes in the variables over different horizons, i.e., $i = 1$ year, 2 years, out to 5 years, confirming that a significant component of measured TFP is firm fragility.

Table 10: Default as a Component of TFP

	($i=1$)		($i=2$)		($i=3$)		($i=4$)		($i=5$)	
α	0.00		0.01		0.02		0.02		0.03	
t-Statistic	3.97		5.32		7.18		8.57		9.49	
β	0.02	0.02	0.02	0.02	0.02	0.03	0.02	0.02	0.02	0.02
t-Statistic	4.10	4.32	3.97	4.33	4.32	4.83	3.43	3.99	2.84	3.50
R^2	0.02	0.07	0.02	0.11	0.02	0.16	0.01	0.19	0.01	0.22
N	871	871	839	839	807	807	775	775	743	743
FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

These results suggest that firms' fragility, which is the productivity component that we highlight in this paper affects credit markets the most, is an important part of TFP. Table

[31]Atkeson, Eisfeldt, and Weill (2013) define the distance-to-insolvency in period t by $DI_t = \left(\frac{V_{At}-V_{Bt}}{V_{At}}\right)\frac{1}{\sigma_{At}}$, where V_{At} and V_{Bt} are the market value of the assets and liabilities future cash flows respectively, while σ_{At} is the standard deviation of innovations to V_{At}. They also define the distance-to-default by $DD_t = \left(\frac{V_{At}-V_A^*}{V_{At}}\right)\frac{1}{\sigma_{At}}$ where V_A^* is the threshold asset value below which the firm defaults. As these components are difficult to measure in the data, they use a structural model of cash flows and show that the inverse of equity volatility is between these two measures, $DI_t \leq \frac{1}{\sigma_{Et}} \leq DD_t$ and that, when creditors are quick in forcing an insolvent firm into default, DI and DD are close to each other and $\frac{1}{\sigma_{Et}}$ is a good proxy of the firm's financial distress.

A.3 in the Appendix we show a scatter plot of this regression for all countries and also specific examples for some countries that illustrates the robustness of this relationship.

5.2 Tests of Model's Predictions.

5.2.1 Firms default more during bad booms

Atkeson, Eisfeldt, and Weill (2013) show that in the U.S. the measure of fragility for the entire economy was uniquely low for the Great Depression, the recession of 1938-39, and the Crisis of 2007. Table 11 below shows that our first prediction is borne out just comparing means. Firms are significantly more fragile, on average, over bad booms compared to good booms.

Table 11: Firm Fragility over Good Booms and Bad Booms

	Whole Sample	Booms	Booms with a Crisis	Booms without a Crisis	t-Statistic for Means
Number of Booms		87	34	53	
1/Volatility	2.75	2.82	2.61	3.03	-4.24

We formalize these results with the following regression, which is a version of regression (2) but using fragility instead of productivity changes.

$$Pr(BadBoom_{j,t})|Boom_{j,t}) = F_L\left(\alpha + \beta\frac{1}{vol_{j,t-1}}\right).$$

Table 12 shows that the coefficient on this variable is significantly negative, meaning that the likelihood of being in a bad boom, conditional on being in a boom, is increasing as the fragility of the firms in the economy increases.

Table 12: $\frac{1}{vol}$, Good Booms and Bad Booms

	Volatility		
	LOGIT	LPM	
α	0.97	0.72	
t-Statistic	3.79	12.56	
β	-34.79	-8.03	-10.40
t-Statistic	-4.04	-4.24	-6.03
Marginal	-0.10	-0.09	-0.12
R^2		0.03	0.66
N	522	522	522
FE	No	No	Yes

5.2.2 GDP grows less during bad booms

In our model, total credit grows at the same rate during both good and bad booms, but productivity and output grow more during a good boom. This implies that credit over GDP grows faster during bad booms, which is confirmed in the first row of Table 2. We can probe into this further by looking at the numerator and the denominator separately. The second row of Table 2 shows that total credit (the numerator) grows in average 13.95% in bad booms and 13.03% in good booms, with this difference not being statistically significant ($t = -0.7$). The third and fourth rows of Table 2 decompose the sources of total credit growth. While corporate credit grows at roughly the same rate in both booms (around 3.6%), credit to households indeed grows less during bad booms (8.5% versus 6.7%), which contradicts the common view that credit booms that end in crises are fueled by particularly strong boosts of credit towards households. In fact, the seventh row of Table 2 shows that real GDP grows in average 2.4% in bad booms and 3.1% in good booms, with this difference being statically significant ($t = 3.28$). So, this model prediction is not only confirmed but also differentiates our model from others that are driven by total credit instead of being driven by what the credit finances. This finding, consistent with our model, suggests that a crisis is more likely to be predicted not by monitoring the growth of total credit but instead the growth of productivity that such increase in credit generates.

Remark on Testing the Informational Mechanism: Even though these empirical results confirm two predictions of the model, we have not directly tested the mechanism of information, under which the crisis is caused by a switch to producing information about collateral from a previous state of not producing information about collateral. Our data limits what we can analyze, but others have produced consistent direct evidence. Benmelech and Bergman (2018) show that when the price of bonds fall, those bonds become very illiquid, corresponding in our model to collateral becoming unusable for borrowing. Benmelech and Bergman (2018) show that the causality runs from prices going down (information being produced) and not the other way around (prices go down in anticipation of future illiquidity). They also show that the effects show a distinct nonlinearity as the value of a bond nears the default point. Their study is not, however, about crises.

In our model, a financial crisis is a sudden switch from information-insensitive debt to information-sensitive debt. Brancati and Macchiavelli (2018) provide evidence for this switch. They find that at the onset of the crisis more analysts are assigned to cover

banks and that these analysts produce significantly more precise information, measured by the standard deviation of their bank ROA forecasts. The precision of the ROA forecasts has a larger impact on bank credit default swap spreads in a crisis compared to non-crisis periods. Also, they show that more precise information has a larger impact on banks that are expected to do poorly, those banks with prior "bad" ROA forecasts. In short, in a crisis more precise information amplifies market expectations of default risk and more precise information increases default risk for banks that are expected to perform poorly. These effects are not present in non-crisis times. Gorton and Holmström (2018) summarize other empirical studies on the mechanism.

Further, as mentioned above, in our model TFP growth is a combination of the growth of the probability of success (q) and the growth of output conditional on success (A). In other words, one component of TFP that drives the probability of default, affecting debt while the other component, which affects the gains in case of success affects equity markets, not debt markets. This is examined by Chousakos, Gorton, and Ordonez (2018). They show, in a large panel of countries, that the amount of information produced in equity markets depends on the state of the macroeconomy. More information is produced (as measured by the standard deviation of the cross section of stock returns) in advance of recessions and particularly in advance of recessions with financial crises. So, while debt displays a switch from information-insensitive to information-sensitive, starting the crisis, information in equity markets is being produced in advance of the crisis.

6   Conclusion

Financial crises are typically preceded by credit booms, but not all credit booms end in a financial crisis. Credit booms are not rare. The average country spends over half its time in a boom, with an average duration of eleven years. The start of a boom is usually preceded by a burst of innovation, but this positive productivity shock dies off faster during booms that end in crises. The seeds of a crisis may be sewn and incubated long before the crisis, which is therefore not necessarily the result of contemporaneous negative shock.

We provided a model that relates productivity, credit booms and financial crises to capture these facts. Investments based on a positive technological shock may be financed by information-insensitive debt that has the potential to generate deterministic business cycles. When technology is good enough there are no incentives to examine the

collateral that backs the debt. As information about collateral decays there is a credit boom that endogenously reduces the quality of projects that are financed and increases the incentives to acquire such information. Once this pressure is large enough, there is a wave of collateral examination, which destroys credit and generates a crash (recession or depression). After this event, the cycle restarts. We do not claim that this informational mechanism is the only plausible explanation of our stylized facts, but it is consistent with those facts without relying on exogenous assumptions about shocks that directly affect credit, such as shocks to collateral constraints.

The business cycle we obtain 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.

In our setting the change of technological opportunities is exogenous for simplicity. In reality innovation is an endogenous process, usually subject to sudden discoveries. The diffusion of technology takes time because firms need financing, as the credit boom develops, more firms get financing and the technology diffuses. But, if over time there is decreasing productivity of marginal projects, then a crisis will eventually occur. The innovation runs out of steam, so to say. This endogenous process is outside the scope of the paper, but a fruitful path for future research is to understand how endogenous growth and financial crises relate.

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A   Additional Tables and Figures

Our analysis uses data on the countries listed in Table A.1 and the variables defined in Table A.2. 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.3 and Figure A.1 show our classification of the booms.

Table A.1: Frequency of Booms

Country	Booms	Bad Booms	Frequency of Boom Periods	Average Time Between Booms
US	1	1	0.52	
UK	3	1	0.58	7.00
Austria	1	0	0.68	
Belgium	3	1	0.68	9.00
Denmark	2	1	0.30	14.00
France	2	1	0.68	13.00
Netherlands	1	1	1.00	
Sweden	3	2	0.62	10.00
Japan	3	1	0.48	8.50
Finland	2	1	0.40	10.00
Greece	2	1	0.62	14.00
Ireland	2	1	0.50	11.00
Portugal	3	1	0.76	6.00
Spain	3	2	0.72	8.00
Turkey	4	2	0.40	10.00
Australia	2	0	0.76	10.00
New Zealand	3	0	0.70	3.00
Argentina	4	2	0.34	8.67
Brazil	3	1	0.38	13.50
Chile	2	1	0.52	11.00
Colombia	4	2	0.38	9.33
Costa Rica	2	0	0.32	31.00
Ecuador	4	2	0.58	6.33
Mexico	3	1	0.36	14.50
Peru	4	1	0.48	6.00
Uruguay	3	2	0.42	11.00
Israel	3	1	0.64	5.50
Egypt	2	0	0.44	7.00
India	2	0	0.78	12.00
Korea	4	0	0.52	7.00
Malaysia	2	1	0.62	8.00
Pakistan	1	0	0.18	
Philippines	3	2	0.60	4.50
Thailand	1	1	0.62	

Table A.2: Data Definitions

Variable	Definition	Source
A. Macroeconomic data		
Domestic credit to private sector	Domestic credit to private sector refers to financial resources provided to the private sector by financial corporations, such as through loans, purchases of nonequity securities, and trade credits and other accounts receivable, that establish a claim for repayment. For some countries these claims include credit to public enterprises.	IMF-IFS, World Bank and OECD GDP estimates
Total factor productivity	Total factor productivity calculated using the PWT6.2 dataset	Kose, Prasad, and Terrones (2008)
Real GDP	Total PPP Converted GDP, G-K method, at current prices - PWT 7.1	Penn World Tables 7.1
Per capita investment	Per capita investment, PWT 7.0	Penn World Tables 7.0
Labor Productivity	Labor productivity per hour worked in 2014 US$ (converted to 2014 price level with updated 2011 PPPs)	The Conference Board Total Economy Database
Equity Premium	Excess stock returns computed as the difference of country equity total return indices and country risk free rates	Global Financial Data
Patents Granted	Counts are based on the grant date	WIPO Statistics Database, December 2011
Patent applications	Counts are based on the filing date	WIPO Statistics Database, December 2011
Distance to Insolvency	The measure is computed as 1/Vol. Vol is the median annual firm level volatility computed using daily stock return data	Thomson Reuters DataStream
B. Financial Crises and Credit Booms		
Financial Crises	A systemic banking crisis occurs if (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.	Laeven and Valencia (2012)
Credit Boom	A credit boom begins whenever a country experiences three consecutive years of positive credit growth that average more than 5%, and it ends whenever a country experiences at least two years of credit growth not higher than zero	Gorton and Ordonez
Good Boom	A credit boom that does not end with a financial crisis	Gorton and Ordonez
Bad Boom	A credit boom that ends with a financial crisis occurring within a window of $(t-3, t+3)$, where t is the end of the boom	Gorton and Ordonez

Figure A.1: Credit Booms and Crises

Table A.3: Booms in the Sample
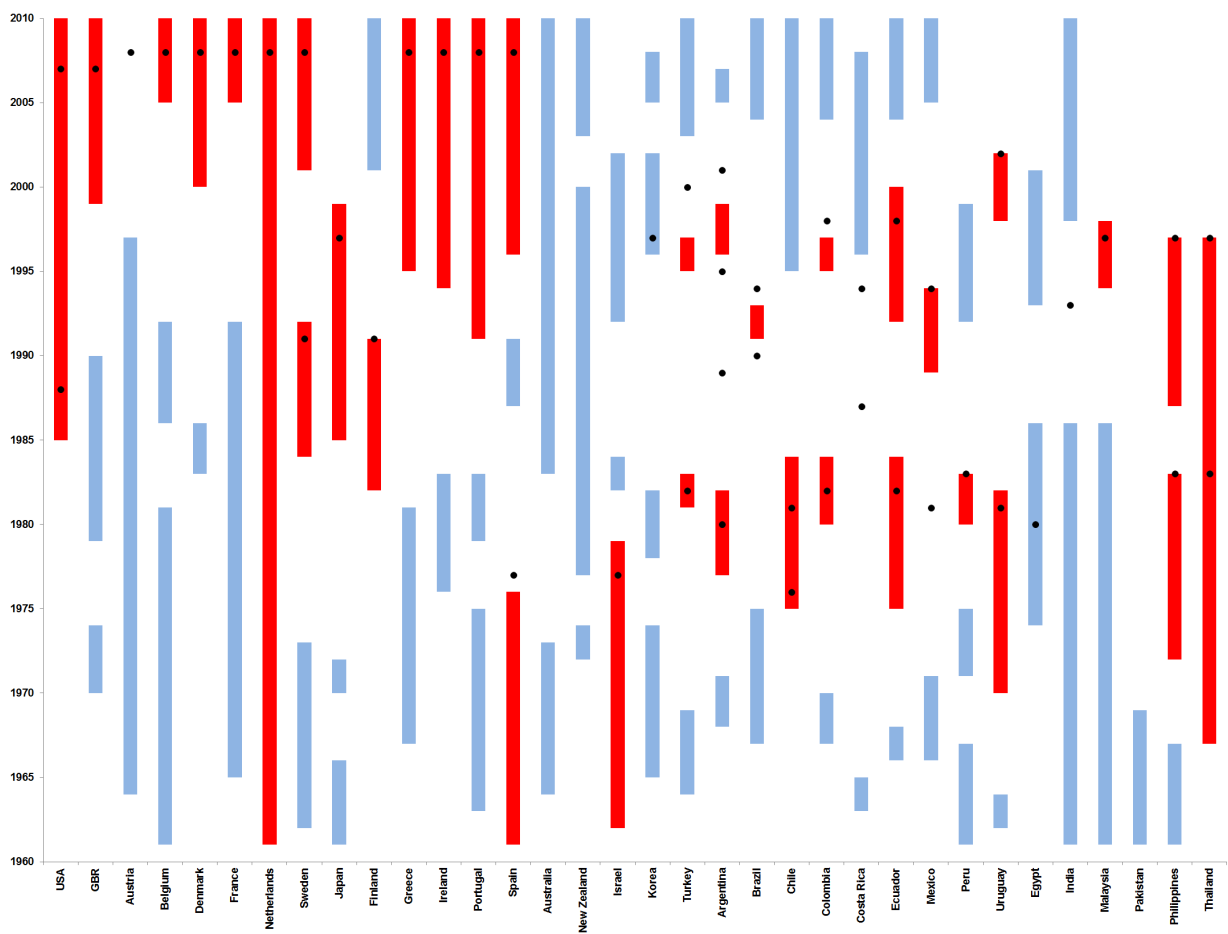
	Country	Years	Classification
1	US	1985-2010	crisis
2	UK	1970-1974	no crisis
3	UK	1979-1990	no crisis
4	UK	1999-2010	crisis
5	Austria	1964-1997	no crisis
6	Belgium	1961-1981	no crisis
7	Belgium	1986-1992	no crisis
8	Belgium	2005-2010	crisis
9	Denmark	1983-1986	no crisis
10	Denmark	2000-2010	crisis
11	France	1965-1992	no crisis
12	France	2005-2010	crisis
13	Netherlands	1961-2010	crisis
14	Sweden	1962-1973	no crisis
15	Sweden	1984-1992	crisis
16	Sweden	2001-2010	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	no crisis
23	Greece	1995-2010	crisis
24	Ireland	1976-1983	no crisis
25	Ireland	1994-2010	crisis
26	Portugal	1963-1975	no crisis
27	Portugal	1979-1983	no crisis
28	Portugal	1991-2010	crisis
29	Spain	1961-1976	crisis
30	Spain	1987-1991	no crisis
31	Spain	1996-2010	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	no crisis
65	Peru	1980-1983	crisis
66	Peru	1992-1999	no 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	no crisis
72	Israel	1992-2002	no crisis
73	Egypt	1974-1986	no 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	no crisis
84	Philippines	1961-1967	no crisis
85	Philippines	1972-1983	crisis
86	Philippines	1987-1997	crisis
87	Thailand	1967-1997	crisis

Table A.4: BIS Data Description

Country	Credit	Corporate Credit	Household Credit
United States	1960	1960	1960
United Kingdom	1960	1976	1966
Austria	1960	1995	1995
Belgium	1960	1980	1980
Denmark	1960	1994	1994
France	1960	1977	1977
Netherlands	1960	1990	1990
Sweden	1960	1980	1980
Japan	1960	1964	1964
Finland	1960	1970	1970
Greece	1960	1994	1994
Ireland	1960	NA	NA
Portugal	1960	1979	1979
Spain	1960	1980	1980
Turkey	1960	1986	1986
Australia	1960	1977	1977
New Zealand	1960	1998	1990
Argentina	1960	1994	1994
Brazil	1960	1995	1995
Chile	1960	NA	NA
Colombia	1960	NA	NA
Costa Rica	1960	NA	NA
Ecuador	1960	NA	NA
Mexico	1960	1994	1994
Peru	1960	NA	NA
Uruguay	1960	NA	NA
Israel	1960	1992	1992
Egypt	1965	NA	NA
India	1960	NA	NA
Korea	1960	1962	1962
Malaysia	1960	NA	NA
Pakistan	1960	NA	NA
Philippines	1960	NA	NA
Thailand	1960	1991	1991

Table A.5: Number of Firms per Year for the Countries of with Available Daily Firm Level Data

| Country	1965	1966	1967	1968	1969	1970	1971	1972	1973	1974	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986	1987
Argentina																							
Australia									78	78	80	83	84	84	85	86	88	89	94	104	107	115	140
Austria									24	23	17	13	16	20	18	17	21	19	21	20	29	34	37
Belgium									36	40	40	40	41	41	41	41	42	41	44	48	50	88	93
Brazil																							
Chile																							
Colombia																							
Denmark									31	31	32	31	25	30	30	33	33	37	39	40	44	45	45
Ecuador																							
Egypt																							
Finland																							
France									67	71	84	88	88	90	90	94	99	101	101	105	108	112	134
Greece																							
India																							
Ireland	26	23	28	29	34	29	36	40	46	46	46	46	45	47	45	42	45	44	41	44	41	43	56
Israel																						165	182
Japan									753	763	770	779	793	793	825	831	844	860	885	905	908	910	1036
Malaysia																						199	213
Mexico																							
Netherlands									97	103	104	103	104	108	108	108	108	113	113	118	124	140	154
New Zealand																							17
Pakistan																							
Peru																							
Philippines																							
Portugal																							16
South Korea																				293	308	335	374
Spain																							46
Sweden																		34	40	48	53	61	69
Thailand																							97
Turkey																							
United Kingdom	570	583	592	610	1227	1247	1324	1417	1460	1461	1458	1456	1481	1505	1517	1542	1577	1571	1585	1624	1633	1663	1679
United States									731	737	802	803	808	816	822	867	916	947	1054	1102	1188	1357	1495

| Country	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Argentina	16	16	18	20	30	84	92	88	91	89	84	81	80	72	76	79	79	78	75	82	81	74	79
Australia	269	387	429	455	476	521	611	648	944	999	1021	1069	1185	1260	1278	1316	1415	1520	1690	1866	1874	1832	1854
Austria	31	54	68	72	83	87	90	99	98	106	104	109	126	122	106	108	99	97	102	111	115	105	108
Belgium	96	98	107	110	111	115	137	135	152	182	214	229	232	221	214	201	205	211	223	237	244	237	234
Brazil			20	43	51	64	83	79	106	113	135	166	165	147	146	170	180	179	193	270	265	256	266
Chile		111	130	144	154	171	181	183	190	194	195	187	177	174	169	170	169	174	188	174	172	172	168
Colombia									77	79	73	54	52	58	52	56	59	69	62	68	67	50	54
Denmark	172	180	192	217	235	240	242	245	259	265	267	256	248	234	204	197	190	183	197	217	221	211	207
Ecuador						7	13	14	13	17	16	17	17	9	10	13	14	19	19	16	21	16	25
Egypt							8	9	61	64	74	110	110	112	129	167	173	152	145	139	141	144	141
Finland	35	48	58	60	63	68	110	118	132	144	159	179	186	177	171	167	160	154	160	159	151	145	142
France	194	476	578	594	609	627	701	740	908	1008	1128	1013	1074	1060	1027	964	926	920	953	997	978	928	899
Greece	89	93	131	152	158	170	214	230	252	254	274	309	343	355	354	349	351	344	321	310	302	291	277
India		904	904	1014	1164	1552	2028	2994	3067	3066	2728	2696	2719	2394	2194	2201	2203	2671	2710	2962	3086	3121	3331
Ireland	60	67	68	65	65	62	58	57	58	59	62	66	62	63	61	57	54	56	64	68	67	62	56
Israel	184	191	199	200	260	451	540	554	565	569	600	644	678	658	632	582	572	586	604	647	628	610	602
Japan	1618	1949	2226	2459	2514	2618	2797	2986	3148	3288	3359	3431	3590	3690	3758	3765	3849	3914	4030	4060	4010	3913	3787
Malaysia	221	236	272	317	362	405	471	526	619	707	733	738	771	774	832	887	943	1013	1037	1043	1000	972	971
Mexico	63	71	84	112	158	211	229	204	201	205	184	188	158	150	132	123	131	130	125	126	117	115	124
Netherlands	159	167	170	174	177	180	185	194	205	219	244	253	250	221	198	184	170	161	166	167	164	151	141
New Zealand	56	59	64	69	79	95	110	114	121	120	119	120	129	131	131	141	163	164	158	155	149	137	132
Pakistan				25	135	163	194	201	221	261	301	379	393	373	361	358	366	328	305	290	273	266	256
Peru				24	52	76	102	107	119	108	111	116	120	126	137	131	139	135	146	149	149	141	128
Philippines	16	65	96	123	123	147	180	215	231	240	226	223	226	217	215	210	219	229	229	238	226	230	233
Portugal	86	104	114	121	133	138	139	142	141	140	142	123	116	95	87	79	73	70	70	67	61	62	62
South Korea	479	590	633	651	660	670	700	726	945	1062	1048	1193	1406	1475	1582	1616	1646	1692	1715	1800	1851	1897	1908
Spain	55	88	101	108	114	123	124	122	131	147	176	187	190	190	193	174	159	154	163	173	167	163	164
Sweden	108	169	192	196	202	218	250	271	303	373	407	457	481	456	425	400	408	428	477	519	542	532	537
Thailand	133	165	206	266	302	349	398	428	468	468	431	382	355	347	364	396	446	487	505	520	528	540	547
Turkey	59	64	96	123	133	149	171	200	224	252	271	272	302	292	293	288	294	299	313	317	313	311	335
United Kingdom	1658	1629	1572	1468	1405	1403	1409	1434	1532	1599	1599	1539	1616	1581	1627	1609	1803	2065	2228	2214	2144	1918	1797
United States	1553	1596	1634	1741	1915	2144	2406	2655	2937	3176	3047	2997	2794	2583	2581	2640	2764	2889	3037	3222	3296	3346	3479

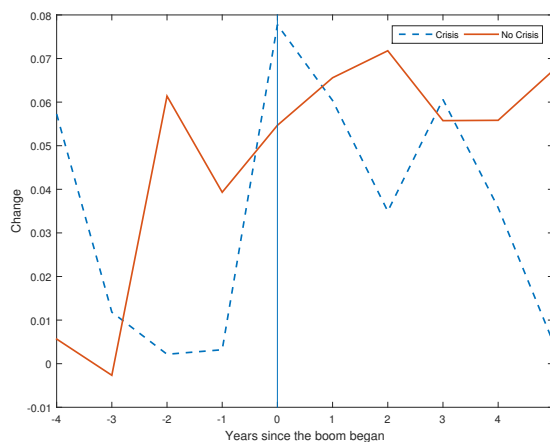Figure A.2: Median Productivity over Good and Bad Booms
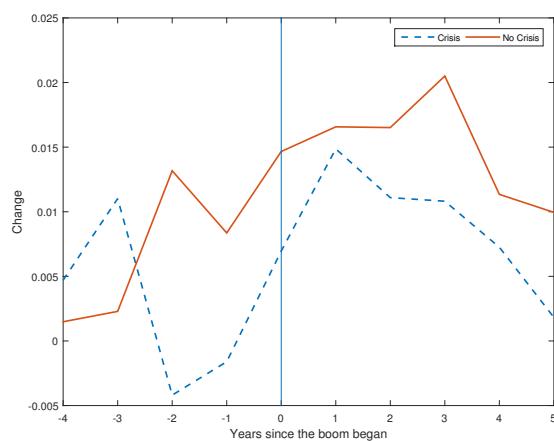
(a) Total Factor Productivity
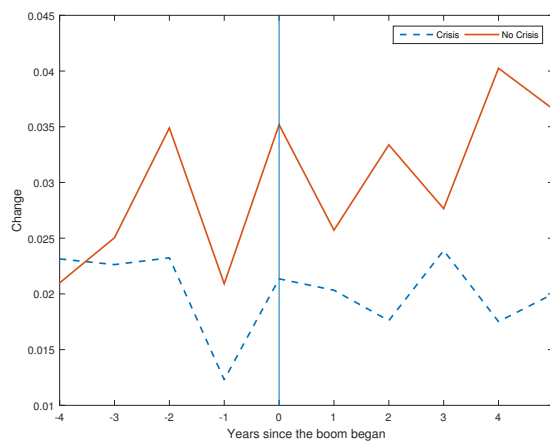
(b) Labor Productivity
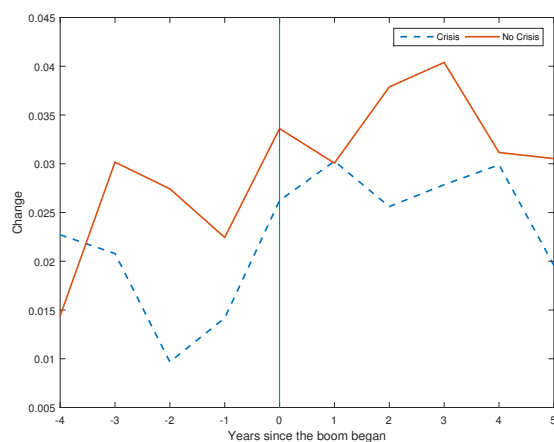
(c) Real GDP

(d) Capital Formation (Investment)

Table A.6: Median Productivity Growth by Country

|	TFP	LP	TFP	LP	TFP		LP	
Country	Booms		No Booms		Bad B.	Good B.	Bad B.	Good B.
United States	0.90%	2.11%	0.24%	1.47%	1.16%	0.73%	1.92%	2.93%
United Kingdom	1.11%	2.61%	-0.79%	2.43%	1.07%	1.76%	2.49%	4.19%
Austria	1.12%	2.93%			1.12%		2.93%	
Belgium	0.90%	2.98%	-0.94%	1.14%	0.80%	1.07%	0.92%	3.66%
Denmark	0.84%	2.11%	0.42%	2.44%	0.84%	0.63%	0.96%	2.95%
France	0.79%	2.80%	-0.30%	2.06%	0.04%	1.24%	1.15%	3.86%
Netherlands	0.93%	1.98%	0.77%	2.28%	0.80%	1.66%	1.43%	4.23%
Sweden	0.81%	2.58%	-0.15%	1.96%	0.81%		2.58%	
Japan	0.51%	3.02%	0.33%	2.33%		0.51%		3.02%
Finland	1.46%	3.20%	2.95%	3.52%	1.53%	0.17%	3.39%	2.18%
Greece	1.01%	3.36%	-2.72%	-2.70%	0.93%	1.55%	2.94%	3.41%
Ireland	2.85%	4.63%	-0.40%	3.78%	1.98%	3.24%	4.63%	5.24%
Portugal	0.90%	2.90%	2.40%	4.65%	0.70%	3.34%	1.73%	7.58%
Spain	-0.55%	0.86%	-1.20%	4.85%	-1.12%	0.96%	0.83%	1.42%
Turkey	2.66%	4.76%	-1.49%	1.25%	1.96%	2.69%	4.08%	4.99%
Australia	0.73%	2.08%	-0.93%	1.22%		0.73%		2.08%
New Zealand	0.68%	1.49%	1.09%	3.42%		0.68%		1.49%
Argentina	2.69%	2.75%	-3.33%	-1.14%	2.33%	2.69%	3.16%	0.50%
Brazil	1.05%	3.12%	-1.49%	0.75%	0.52%	1.32%	3.70%	2.71%
Chile	2.14%	2.81%	0.47%	0.63%	2.07%	2.21%	2.22%	3.16%
Colombia	0.48%	1.35%	0.08%	1.07%	-0.05%	0.84%	0.72%	1.97%
Costa Rica	-0.24%	1.37%	0.06%	0.83%		-0.24%		1.37%
Ecuador	2.05%	4.03%	-0.63%	0.59%	2.15%	2.05%		4.03%
Mexico	-0.03%	1.55%	1.03%	0.18%	-0.38%	0.03%	0.08%	2.50%
Peru	2.17%	2.40%	-1.04%	-1.04%	-0.19%	2.34%	1.07%	3.08%
Uruguay	2.27%	0.22%	0.21%	4.63%	2.23%	3.16%	-0.20%	1.61%
Israel	0.85%	0.77%				0.85%		0.77%
Egypt	0.79%		1.97%		1.34%	0.61%		
India	2.04%		0.50%			2.04%		
Korea	1.86%	5.59%	0.24%	4.29%		1.86%		5.59%
Malaysia	1.86%	4.06%	2.13%	3.07%	2.20%	0.59%	4.15%	-0.13%
Pakistan	2.77%		0.29%			2.77%		
Philippines	0.01%		0.96%		0.01%	0.35%		
Thailand	2.61%	3.76%	0.81%	1.60%	2.64%	2.56%	3.73%	3.79%

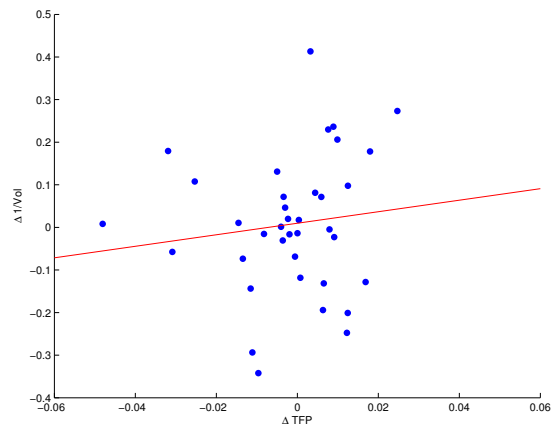# Figure A.3: Changes in Default and Productivity
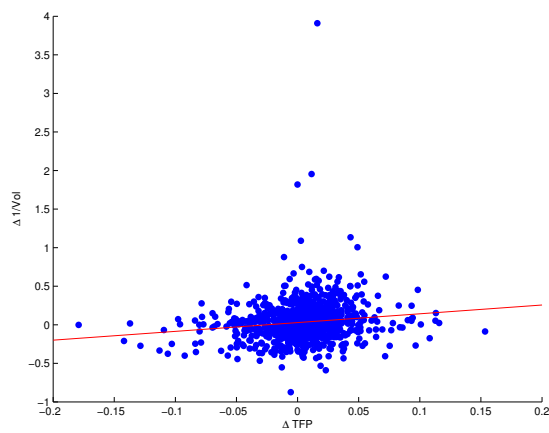
(a) Whole Sample
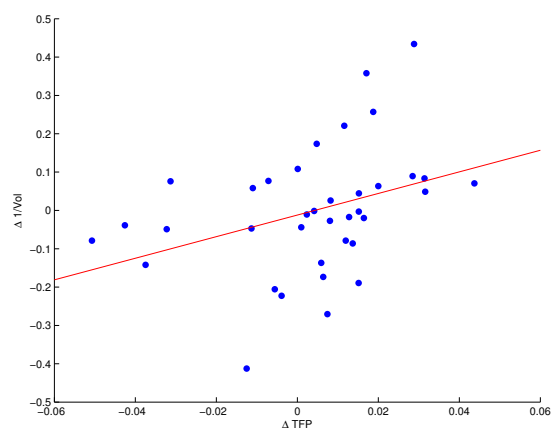
(b) United States
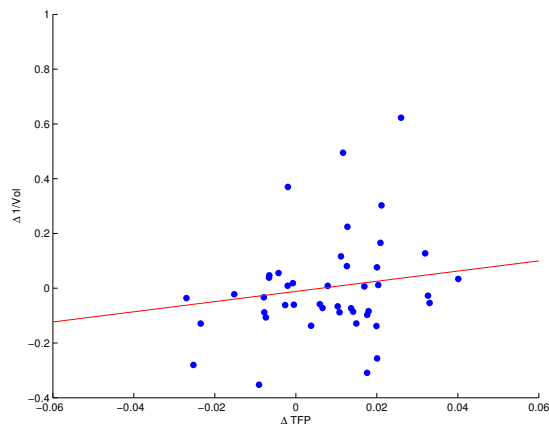
(c) United Kingdom

(d) France

B The Roaring Twenties: Example of a Bad Boom

To understand the role of credit granted to households and to corporations during a credit boom ending in a crisis, we briefly look at the Roaring Twenties in the United States, the famous credit boom leading up to the Great Depression. The Roaring Twenties illustrates the variety of credit granted during a boom and also shows the decline or maturing of the technological innovation that started at the beginning of that decade, leading up to the crisis, which we will subsequently model as a decline in average productivity over a bad boom.

The Roaring Twenties was also an investment boom, as more generally shown in Table 2. It was a period of intense technological innovation, deemed by Field (2003) to be "the most technologically progressive decade of the century". There seems to have been a sharp upward movement in TFP at the start of this era, a technology shock. In Solomon Fabricant's introduction to John Kendrick's (1961) study of productivity trends in the U.S., he noted: "A distinct change in trend appeared sometime after World War I. By each of our measures, productivity rose, on the average, more rapidly after World War I than before....The change in trend...is one of the most interesting facts before us" (p. xliii). David and Wright (1999) also note "A marked acceleration of productivity growth in U.S. manufacturing occurred after World War I".

According to Field (2006), "Manufacturing contributed almost all 83 percent of the growth of total factor productivity in the U.S. private non-farm economy between 1919 and 1929" (p. 203). "The extraordinary TFP growth in manufacturing in the 1920s was largely driven by floor space savings and improved materials flow associated with newly laid out factories. The rearrangements were made possible by the removal of the straightjacket previously imposed by a mechanical distribution of internal power" (p. 227). There was also a large increase in the use of electric power. See Devine (1983). Other examples of this burst of innovation include the radio and other electrical appliances, assembly-line production for cars, petrochemicals, new materials like Teflon and Nylon. See Field (2003 and 2006) and Raff (1991). Further, the National Research Council data show that between 1919 and 1928 inclusive, companies founded an average of 66 R&D labs per year. See Field (2003). According to Gordon (1951): "The rise in output of cars, trucks, and accessories accounted for roughly a third of the total increase in the flow of finished commodities between 1909-13 and 1923-1929. Comparing the flow of finished commodities from the automobile industry with the total flow of all finished commodities, both in producers' 1913 prices, for selected years between 1909 and 1929, we find that by 1920, the output of the motor industry had already expanded some 2 billion, in 1913 prices, since 1990" (p. 189). Smiley (2008), Oshima (1984), and Soule (1947) provide further overviews of technological change prior to and during the Roaring Twenties.

What types of credit were granted during the Roaring Twenties? Table B.1 shows the changes in the quantity of different types of credit granted during the twenties. The percentage changes, in the last column, show that real estate loans, including urban home mortgages, had the highest growth. Commercial mortgages also grew a lot. Non-real estate loans and corporate bond issuance also grew, but not by as much. The credit

boom, it seems, consisted of a variety of different types of credit, but mortgages were the largest component. Although, as Gordon (1951) points out: "It is difficult to say to what extent the housing boom should be considered an independent influence in the '20's. In part it arose out of the changes created by the automobile. This was true also of commercial building. In part the housing boom was due to the war, which tended to push forward into the '20's a good deal of private investment that otherwise would have occurred earlier" (p. 212).

Table B.1: Credit During the Roaring Twenties

Changes in the Quantity of Credit by Type during the Roaring Twenties			
Amount (millions of dollars)			
Type of Credit	Change 1920-1924	Change 1925-1929	Change 1920-1929 (in %)
Total Loans and Investments	841	7566	17%
Real Estate Loans	2723	2600	114%
Non-Real Estate Loans	841	7566	34%
Domestic Corporate Bond Issuance	10138	13739	35%
Urban Home Mortgages	20	41.5	108%
Urban Commercial Mortgages	16.3	31.6	94%

Note 1: Total, Real and non-Real Estate Loans from All Bank Statistics (1959), Board of Governors of the Federal Reserve System.
Note 2: Domestic Corporate Bond Issuance from Moore (1956), citing Hickman (1957) Corporate Bond Characteristics and Investor Experience, NBER.
Note 3: Urban Home and Commercial Mortgages from Moore (1956), citing Morton (n.d.), Urban Lending: Comparative Markets and Experience, and Linter (1948), Mutual Savings Banks in the Savings and Mortgage Markets, Harvard. These studies are based on samples of loans made by life insurance companies, commercial banks, savings and loan associations, and mutual savings banks, all in Massachusetts.

The Roaring Twenties is also an illustration of the technological change slowing or "maturing." Gordon (1951) put it this way:

> ". . . the investment boom of the '20's resulted from a concentrated flowering of investment opportunities, created by the rapid maturing of a series of new industries and new services. . . . The 'gestation period' for the new industries of the '20's was short compared with that of the railroads or steel in an earlier period. By 1929 automobiles, electric power, road-building, the new service industries, and so on were at or near maturity; they no longer needed, for replacement or for further growth, the same volume of investment as formerly" (p. 211).

In other words, the new technologies ran out of steam, resulting in a crisis, the Great Depression. The Roaring Twenties are an example of a Bad Boom.[32]

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[32]This view is consistent with Eichengreen and Michener (2003) whose paper is entitled "The Great Depression as a Credit Boom Gone Wrong."

C Alternative Model with Mortgages

Consider a single period economy, with a mass 1 of risk-neutral households and deep-pocket lenders. Households have an exogenous endowment c of numeraire good at the beginning of the period and can work during the period to obtain a wage w at the end of the period. The lender verifies that the household is employed at the beginning of the period, but employment is uncertain. With probability q the household maintains his work and with probability $(1 - q)$ he is laid-off. Households obtain utility from home ownership. A house of size K (in terms of the price in units of numeraire) generates marginal utility $A > 1$ for $K \leq K^*$, and 0 for $K > K^*$. This assumption just guarantees an optimal housing size of K^*.

If labor income were verifiable, state contingent contracts would implement the optimal consumption of housing. In this case, households would borrow $K^* - c$ from lenders, promising 0 in case of being unemployed and $\frac{K^* - c}{q}$ in case of being employed. As long as $w > \frac{K^* - c}{q}$, lenders break even and all households would consume housing of size K^*, obtaining an expected utility of

$$E(U)_{opt} = K^* A + q \left(w - \frac{K^* - c}{q} \right) = c + qw + K^*(A - 1)$$

If labor income were non-verifiable, households can use the house they buy as collateral. We assume that a lender who seizes a house of size K in case of default can resell it at K with probability p, but cannot resell it at all with probability $1 - p$ (then generating 0 to the lender, as the lender does not obtain any utility from holding the house). We assume the lender can analyze the housing market to determine the value of the house at a cost γ_l in terms of the numeraire good. Households can also endeavor in such analysis at a cost γ_b in terms of housing. As in the main text, the question is whether there is information about the (marketability of the) house or not at the time of issuing the mortgage.

Information-Sensitive Mortgage

Lenders are competitive and they break even when

$$p[qR_{IS} + (1 - q)x_{IS}K] = p(K - c) + \gamma,$$

with $\gamma = \min\{\gamma_l, \gamma_b\}$. As in the main text, truth telling implies that households should pay the same in case of success or failure, $R_{IS} = x_{IS}K$. Then $x_{IS} = \frac{p(K-c)+\gamma}{pK} \leq 1$. Expected total utility of households (both from consumption and housing) is $c + qw + p(KA - x_{IS}K)$. Then, plugging x_{IS} in equilibrium, and as households buy a house of size K^* when obtaining a mortgage, *expected net utility* (net of the endowment and expected labor income $c + qw$) from an information-sensitive mortgage is

$$E(U|p, q, IS) = \max\{pK^*(A - 1) - \gamma, 0\}.$$

Intuitively, with probability p the households can obtain a mortgage for K^*, which generates a net utility of $K^*(A-1)$ of housing services, and with probability $(1-p)$ the house does not have any resale value and then the household cannot obtain a mortgage. Notice this is almost identical to the expected profits from information-sensitive loans we derived in the main text.

Information-Insensitive Mortgage

Another possibility for households is to borrow such that there is no information acquisition about the house that will serve as collateral. As in the text, information acquisition is private. Lenders break even when

$$qR_{II} + (1-q)x_{II}pK = K - c,$$

subject to truth-telling, $R_{II} = x_{II}pK$. Then $x_{II} = \frac{K-c}{pK} \le 1$.

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 before the loan is negotiated and to take advantage of such private information before it becomes common knowledge. Lenders want to deviate because they can lend at beneficial contract provisions if the house has a market for sure, and not lend at all if the house cannot be resold. Borrowers want to deviate because they can borrow at beneficial contract provisions if the house cannot be resold and they can renegotiate even better conditions if the house can be resold.

Formally, lenders do not want to deviate if the expected gains from acquiring information, evaluated at x_{II} and R_{II}, are smaller than the private losses, γ_l, from acquiring information,

$$p[qR_{II} + (1-q)x_{II}K - (K-c)] < \gamma_l \qquad \Rightarrow \qquad K < c + \frac{\gamma_l}{(1-p)(1-q)}.$$

As mortgages are never larger than K^*,

$$K < K^l(p|q, II) \equiv \min\left\{K^*, c + \frac{\gamma_l}{(1-p)(1-q)}\right\} \tag{15}$$

Similarly, borrowers do not want to deviate if the expected gains from acquiring information, evaluated at x_{II} and R_{II}, are smaller than the losses from acquiring information. Specifically, if borrowers acquire information, their expected benefits are $p(K^*(A-1) - \gamma_b) + (1-p)K(A-1)$. With probability p the house has a resale value and the household borrows K^*. Recall that for simplicity we have assumed that the information cost is in terms of housing and then it only applies if the house can be resold, with probability p. With probability $1-p$ the house does not have any resale value and the household borrows the original contract K. If borrowers do not acquire information, their benefits are $K(A-1)$. Hence borrowers do not acquire information

if

$$K > K^b(p|q, II) \equiv K^* - \frac{\gamma_b}{(A-1)}. \tag{16}$$

An information-insensitive mortgage is only feasible when both conditions (15) and (16) are satisfied. In this case the expected net utility of households becomes

$$E(U|p, q, II) = \max\{K^l(p|q, II), K^b(p|q, II)\}(A-1).$$

Notice again that the problem is almost identical in structure to the one in the main text. In particular constraint (16) does not depend on q, while constraint (15) does. This implies that, as q declines, the range of p for which an information insensitive mortgage is feasible shrinks, making crises more likely for a given average resaleability of houses $\widehat{p}$.

Dynamics The same dynamics as in the paper holds in this case. Denote by η the volume of mortgages in the economy, this is the leverage and indebtedness of households for home ownership. One possibility is that the increase in household indebtedness in the economy increases labor supply by a dominating wealth effect, reducing the likelihood of finding a job for each individual, reducing q. Our setting has the same dynamic implications as in the main text as long as $q(\eta)$ declines with household leverage. Another possibility is that the increase in household leverage reduces the probability a house can be resold in average. If $\widehat{p}(\eta)$ is a decreasing function of η, information-insensitive mortgages are more difficult to sustain and then the system is also more prone to suffer a crisis.