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GOOD BOOMS, BAD BOOMS

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ABSTRACT

Credit booms are not rare and usually precede financial crises. However, some end in a crisis (bad booms) while others do not (good booms). We document that credit booms start with an increase in productivity, which subsequently falls much faster during bad booms. We develop a model in which crises happen when credit markets change to an information regime with careful examination of collateral. As this examination is more valuable when collateral backs projects with low productivity, crises become more likely during booms that display large productivity declines. As productivity decays over a boom as an endogenous result of more economic activity, a crisis may be the result of an exhausted boom and not necessarily of a negative productivity shock. We test the main predictions of the model and identify the component of productivity behind crises.

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1 Introduction

The recent financial crisis poses challenges for macroeconomists. There is a need for models displaying financial crises that are preceded by credit booms and that are not necessarily the result of large negative shocks.[1] In this paper we study 34 countries over 50 years and show that credit booms are not rare; that some end in crises (*bad booms*) but others do not (*good booms*).[2] The natural question is whether these two types of booms just differ on how they end or if there are more intrinsic differences in their evolution that may determine how they end. We show that all credit booms start with a *positive shock* to productivity, but that in bad booms this increase dies off rather quickly while this is not the case for good booms.[3] This suggests that a crisis may indeed be the result of an exhausted credit boom.

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. The model begins with the arrival of a new technology. Firms finance projects that use such technology with short-term collateralized debt (e.g. repo). Lenders can at a cost learn the quality of the collateral, but it is not always optimal to do this, in particular when the loan is financing projects that are productive and not very likely to default. If collateral is not examined over time there is a depreciation of information in credit markets 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. So there is a link between the credit boom and the productivity in the economy. We assume decreasing returns such that

[1] There is now a rich body of evidence showing that credit booms precede crises. 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 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), Collyns and Senhadji (2002), Gourinchas, Valdes, and Landerretche (2001), Kaminsky and Reinhart (1999), Hardy and Pazarbasioglu (1991), Goldfajn and Valdez (1997), and Drees and Pazarbasioglu (1998).

[2] We are not the first to note this. Mendoza and Terrones (2008) argue that "not all credit booms end in financial crises, but most emerging markets crises were associated with credit booms." This is also highlighted by Dell'Ariccia et al. (2012) and Herrera, Ordonez, and Trebesch (2014).

[3] 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.

the quality of the marginal project that is financed declines with the total level of economic activity.

As credit booms evolve, the average productivity in the economy declines and lenders have more and more incentives to acquire information about the collateral backing the loan. If at some point the average productivity of the economy decays enough, 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; some firms that used to obtain loans cannot obtain them 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. We characterize the set of parameters under which the economy experiences an 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. This is in contrast with most of the standard literature on real business cycles.

We also show that, if the new technology keeps 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 the change of the information regime is never triggered. If this is the case, the credit boom ends, but not in a crisis – a good boom.

In our setting productivity has two components: the probability that a project succeeds and the productivity conditional on success. In the data productivity is usually measured as a residual, such as total factor productivity (TFP), but the analysis suggests that these 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 upon success and does not affect lenders' incentives to acquire information about collateral, consequently not affecting 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. We show how 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 U.S. to most 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.

Conceptually, the phenomena we find empirically suggests that viewing aggregate fluctuations as deviations from a trend is too stark (see Lucas (1977)). As far as fluctuations that involve financial crises are concerned, changes in the trend of technological change, credit booms and crises are intimately related. Financial crises are not necessarily the result of negative productivity shocks around the trend, but the trend itself determines the likelihood of crises and the cyclical properties of the economy. Cyclical dynamics originate at a lower frequency than is typically studied.

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

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), 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," as in their case, but just as a response to endogenous productivity growth.

Our finding that positive productivity shocks occur at the start of the boom has been already noted by economic historians and growth economists. 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)).[4] Here we show that these technological revolutions can also play a critical role on shaping the cyclical properties and the recurrence of financial crises in certain economies.

Our finding that credit booms average ten years is related to studies of "medium-term business cycles." 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 also 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).[5] They do not analyze credit variables however. Drehmann, Borio, and Tsatsaronis (2012) use an analysis of turning points (as well as frequency-based filters) to study six variables for seven countries over the period 1960-2011. Their main finding is the existence of a medium-term component in credit fluctuations. Similar conclusions are reach 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.

A recent paper that revives the discussion of purely endogenous and deterministic cycles, as we obtain in our setting, is Beaudry, Galizia, and Portier (2015). In their case, cycles are determined by complementarities between aggregate employment and consumption, which induce smooth deterministic cycles. In our case there are complementarities between the volume of credit and the incentives for information acquisition. Since this complementarity is not relevant unless information constraints

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

bind, our model displays deterministic cycles that are not smooth – long booms that suddenly and dramatically end in crises.

In the next section we describe the data and analyze productivity growth, both factor productivity (TFP) and labor productivity (LP), over credit booms, and crises. 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 dynamic implications of information, focusing on endogenous cycles. We test the main predictions of the model in Section 5. In Section 6, we conclude.

2 Good Booms, Bad Booms: Empirical Evidence

Not all credit booms end in a financial crisis. Why do some booms end in a crisis while others do not? To address this question empirically we investigate productivity (total factor productivity and labor productivity) trends during booms. We define a "credit boom" below and analyze the aggregate-level relations between credit, TFP and LP growth and the occurrence of financial crises. We do not test any hypotheses but rather organize the data to develop some preliminary stylized facts.

2.1 Data

There are clearly important data decisions to make when studying credit booms. The stylized facts of business cycles were developed by focusing primarily on the U.S., starting with Kydland and Prescott (1990) who looked at U.S. quarterly data over 1954-1989, using the Hodrick-Prescott (H-P) filter. While the literature by now is very large, it continues to use the H-P filter and typically does not include credit variables. Over the last 25 years or so, longer time series have been used. But, these are only available for a smaller panel of countries. Backus and Kehoe (1992), for example, study ten developed countries where there is at least 100 years of data. Stock and Watson (2003) study seven developed countries over the period 1960-2002. Aguiar and Gopinath (2007) study thirteen middle-income and thirteen developed countries with at least 40 quarters of data. While the focus of this literature was not on credit variables, this has changed since the recent U.S. financial crisis.[6]

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

To focus on financial crises, however, requires facing a trade-off between breadth of countries and length of series, as developed countries provides better data and longer time series, but fewer events of financial distress (see the discussion in Ley and Misch (2014)). 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 the countries we use 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. This variable is defined as the financial resources provided to the private sector, such as loans, purchases of non-equity securities, trade credit and other account receivables, that establish a claim for repayment. For some countries these claims include credit to public enterprises. Gourinchas, Valdes, and Landerretche (2001) and Mendoza and Terrones (2008) measure credit as claims on the non-banking private sector from banking institutions. We choose domestic credit to the private sector because of its breadth – 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.[7] 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

[7] 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.

bank claims on the financial sector to deposits exceeds five percent and more than double relative to the pre-crisis level); (2) bank restructuring gross costs are at least three percent of GDP; (3) significant bank nationalizations; (4) significant guarantees are out in place; (5) there are significant asset purchases (at least five percent of GDP); (6) there are deposit freezes and/or bank holidays.

2.2 Definition and Classification of Credit Booms

There is no consensus in the literature about the definition of a "credit boom." A boom is usually defined by the ratio of credit growth -to-GDP relative to a trend, so there is the issue of how the trend is determined. This choice not only determines whether booms are short or long, but usually discards the initial phase of a sustained increase in credit, which is assigned to the trend. Theory is silent on this issue.

Hodrick and Prescott analyzed U.S. data over a period during which there was no financial crisis in the United States. Separating the growth component from the deviation led to the view that the growth component is driven by technological change, while deviations are due to technological "shocks". Prescott (1986) argues that technology shocks (measured by TFP) are highly procyclical and "account for more than half the fluctuations in the postwar period."[8]

Detrending raises the issue of whether all the data should be used, or only retrospective data. The H-P filter uses all the data. Instead, as we want to impose as few preconceptions as possible, we propose a definition of a "credit boom" that is more agnostic as it does not rely on future data. We define a credit boom as starting whenever a country experiences three consecutive years of positive credit growth that average more than x^s. The boom ends whenever a country experiences at least two years of credit growth not higher than x^e. In our baseline experiments we choose $x^s = 5\%$ and $x^e = 0\%$. The choice of thresholds is based on the average credit growth in the sample. Changes in thresholds do not alter the results qualitatively. 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. Using deviations from a trend implies

[8]Band pass filters are an alternative to the H-P filter. See Baxter and King (1999) and Christiano and Fitzgerald (2003).

that a boom has predetermined maximum length, as a protracted boom would be included in the trend component. We want to avoid this so we do not impose a trend-cycle decomposition on the data. The data will inform us as to whether crises are associated with longer or shorter booms. Second, 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."

We will then compare our results with those obtained by H-P filtering the credit series and will show that indeed detrending misses important features of the data in the larger, longer, sample.[9] The phenomena of interest happen at lower frequencies and it seems difficult to separate trend changes from fluctuations. Changes in technology seem important for the gestation of a financial crisis, but not because of the traditional *contemporaneous negative shock* but because the *past trend* affects the cyclical properties of the economy.

Once we have identified these credit booms, we can classify them between 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.[10] 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

[9]We are not the first to note this problem with the H-P filter. See, e.g., Comin and Gertler (2006).

[10]As dating the start and end of a crisis 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.

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.

2.3 Properties of Good Booms and Bad Booms

Table 2 provides an overview of the booms, with their average duration and average growth in credit, TFP, LP, patents granted and investment. The last column shows the t-statistic for the null hypothesis that the mean for each variable is the same for booms that end in a crisis and those that do not. Our first result is that, given our definition, booms are not rare. Of the 1695 years in the sample, 929 were spent in a boom, 55 percent of the time. On, average, over 50 years, a country spent 27 years in a boom and, on average, 12 of those years were spent in a boom that ended in a crisis. Our second result is that, while credit growth, on average, is the same for good booms and bad booms, productivity growth is higher during good booms, both measured by TFP and LP.[11]

Table 2: Descriptive Statistics - All Economies

	Whole Sample	Booms	Booms with a Crisis	Booms without a Crisis	t-Statistic for Means
Avg. Credit growth (%)	3.83	8.96	9.84	8.30	1.27
Avg. TFP growth (%)	0.83	0.87	0.47	1.17	-3.57
Avg. Pnts Gnt growth (%)	0.17	0.18	-0.68	0.93	-0.50
Avg. LP growth (%)	2.52	2.57	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	929	400	529	

Table 3 shows advanced economies and Table 4 shows emerging economies.[12] Even though it is still the case that TFP and LP growth are significantly larger during good booms, in emerging economies the growth in credit is also significantly higher during bad booms, but not in advanced economies. This difference is consistent with

[11]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.

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

previous literature that finds an asymmetry between boom episodes in emerging and advanced countries. Gourinchas, Valdes, and Landerretche (2001) find that emerging markets are more prone to credit booms. Mendoza and Terrones (2008) find that countries with fixed or managed exchange rates are more subject to credit booms and that in these countries credit booms are more likely to end in a crisis. Herrera, Ordonez, and Trebesch (2014) find that in emerging economies credit booms are usually accompanied by an increase in the government's popularity.

Table 3: Descriptive Statistics - Advanced Economies

	Whole Sample	Booms	Booms with a Crisis	Booms without a Crisis	t-Statistic for Means
Avg. Credit growth (%)	4.26	7.37	7.31	7.42	-0.06
Avg. TFP growth (%)	0.74	0.73	0.37	1.04	-2.91
Avg. Pnts Gnt growth (%)	-2.24	-2.00	-0.74	-3.11	0.72
Avg. LP growth (%)	2.77	2.69	2.25	3.07	-3.73
Avg. Duration (years)		13.38	15.93	11.79	1.25
Avg. Time spent in boom		29.00	13.28	15.72	
Number of Booms		39	15	24	
Sample Size (years)	834	522	239	283	

Table 4: Descriptive Statistics - Emerging Economies

	Whole Sample	Booms	Booms with a Crisis	Booms without a Crisis	t-Statistic for Means
Avg. Credit growth (%)	3.40	11.00	13.60	9.31	2.95
Avg. TFP growth (%)	0.91	1.06	0.63	1.33	-2.00
Avg. Pnts Gnt growth (%)	3.40	4.17	-0.57	8.38	-1.28
Avg. LP growth (%)	2.13	2.32	1.54	2.76	-2.42
Avg. Duration (years)		8.48	8.47	8.48	-0.00
Avg. Time spent in boom		22.61	8.94	13.67	
Number of Booms		48	19	29	
Sample Size (years)	861	407	161	246	

Table 5 shows the same summary statistics for the first five years of booms, and in addition to the previous results, we see a difference in patents granted over good booms and bad booms.[13] The growth of patents granted is positive in good booms and negative in bad booms, with a significant difference between them, consistent with technological change dying out over the bad booms, as reflected in lower TFP and LP growth. This result suggests that a large component of the difference between good and bad booms arises at the initial phase of the credit boom, the first five years.

Figure 1 shows plots of the average growth rates for TFP, LP, real GDP, and capital formation, for both good booms and bad booms. Figure A.2 in the Appendix shows

[13] Patent data is from the World Intellectual Property Organization. For details see http://www.wipo.int/ipstats/en/statistics/patents/

Table 5: Descriptive Statistics (first 5 years of boom) - All Economies

	Whole Sample	Booms	Booms with a Crisis	Booms without a Crisis	t-Statistic for Means
Avg. Credit growth (%)	3.83	11.05	13.84	9.25	1.98
Avg. TFP growth (%)	0.83	1.31	0.76	1.66	-3.05
Avg. Pnts Gnt growth (%)	0.17	-0.14	-5.06	3.66	-1.87
Avg. LP growth (%)	2.52	2.83	1.96	3.37	-3.98
Number of Booms		87	34	53	
Sample Size (years)	1695	407	160	247	

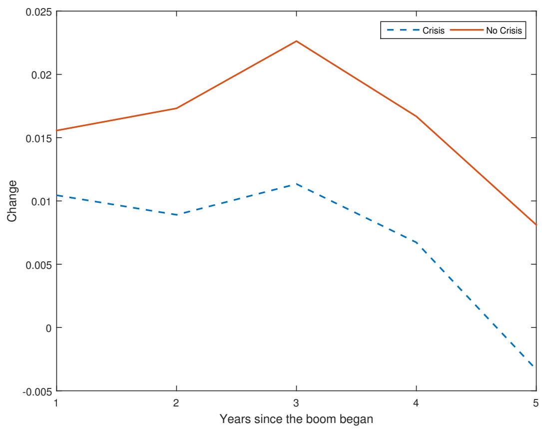
the median growth rates for the same variables. The figure shows that a credit boom starts with a positive shock to productivity, but then the paths of growth rates differ for good booms and bad booms. In bad booms, the productivity growth rates die off as do the growth rates for real GDP and capital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

Next we confirm that the different patterns between good booms and bad booms that are evident in panels (a) and (b) of Figure 1 are also significant. To do this we ask whether the changes in TFP and LP predict the type of boom, by running the following regression.

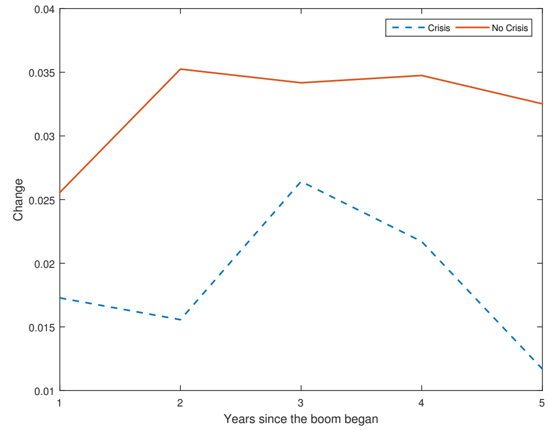
$$Logit\left(BadBoom_{j,t}|Boom_{j,t}\right) = \Phi\left(\alpha + \beta\Delta X_{j,t}\right).$$

$BadBoom_{j,t}$ is the odds ratio of being in a bad boom conditional on being in a boom in country j at period t, defined by $ln[Pr(BadBoom_{j,t})/(1-Pr(BadBoom_{j,t}))]$, where $Pr(BadBoom_{j,t})$ is the probability a boom in country j at period t has been identified as bad. The variable $\Delta X = \{\Delta TFP, \Delta LP\}$ represents the change in the respective measure of productivity in country j at period t.

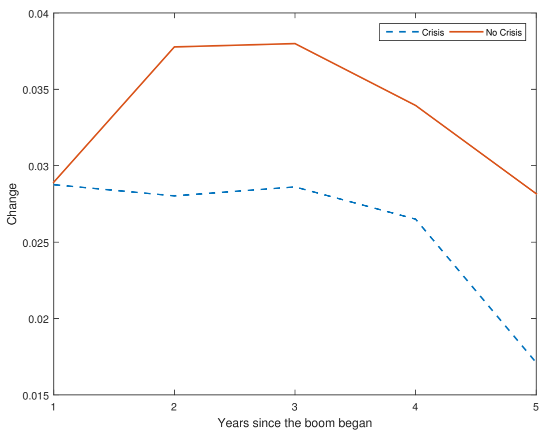
Figure 1: Average Productivity over Good and Bad Booms



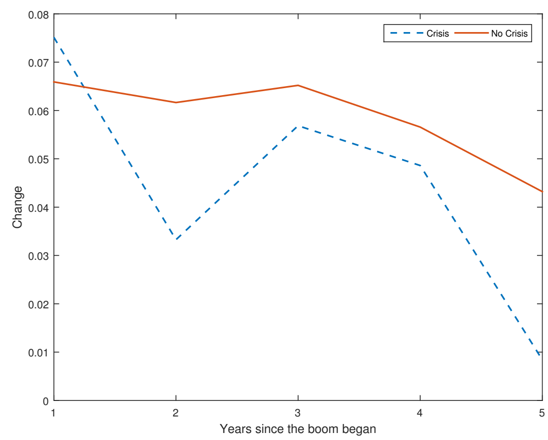
(a) Total Factor Productivity



(b) Labor Productivity



(c) Real GDP



(d) Capital Formation (Investment)

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.[14] We see exactly this pattern in Table 6, for both our measures of productivity change.[15]

Table 6: Productivity 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		0.20	0.59
N	929	929	929	761	761	761
FE	No	No	Yes	No	No	Yes

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 variable. The first column of Table 6, 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%.[16]

The patterns for the change in real GDP and investment also significantly differ across good booms and bad booms. Table 7 shows the results of the previous regression but using investment and real GDP instead. On average a decline in investment and real GDP also are more likely to happen during bad booms.

2.4 Comparison with an H-P Based Definition of Credit Booms

The results above show significant differences between good and bad booms, in particular at the initial phase of the boom. This was the reason we decided not to detrend

[14] 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.

[15] 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.

[16] 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 7: Investment and Real GDP as an Indicator of Bad Booms

	Investments			Real GDP		
	LOGIT	LPM		LOGIT	LPM	
α	-0.22	0.45		-0.06	0.48	
t-Statistic	-3.14	26.19		-0.72	23.94	
β	-1.58	-0.38	-0.21	-7.87	-1.86	-1.51
t-Statistic	-2.85	-2.89	-2.16	-4.20	-4.33	-4.63
Marginal	-0.05	-0.05	-0.03	-0.07	-0.07	-0.06
R^2		0.01	0.47		0.02	0.48
N	929	929	929	929	929	929
FE	No	No	Yes	No	No	Yes

credit when defining a boom, as by construction this procedure tends to shorten the length of the boom by excluding the initial increase of credit and assigning it to the trend. Table 8 compares the results of using the H-P filter to detect booms (using a smoothing parameter of 100 and following the Mendoza and Terrones (2008) definition that a boom occurs when credit to the private sector grows by more than a typical business cycle expansion) to our results with the agnostic definition of a boom. The first line of the table shows that of the 161 boom-years detected using the H-P filter, 80% of those boom years are in our sample of boom-years. Line 2 shows that of the 40 booms detected with the H-P filter, we detected 91 percent of those booms. The bottom part of the table shows that 63 percent of the H-P filter booms starts more than three years after booms start according to our definition. This, of course, is not surprising because the H-P filter is constraining the data and pushing more of the boom into the trend. So, the H-P filter booms are essentially occurring in the middle of our booms. The average duration of our booms is ten years while the average duration of an H-P filter boom is five years, also by construction.

Tables 9, 10 and 11 constitute a summary of the previous comparisons using this boom definition. In this case, there are 44 booms, 21 of which end in a crisis. Of the 1651 years in the sample, only 202 are spent in a boom, 12 percent. From this point of view, booms are not central to aggregate economic activity. Good and bad booms are not statistically different in their evolution of productivity, and this is the case both for advanced and emerging economies.

In the Appendix, Figures A.3 and A.4 are the counterparts to Figures 1 and A.2 with credit booms determined by H-P filtering. Again, these figures do not display any

Table 8: Overlap between booms using H-P filter and Gorton and Ordonez (2015)

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

Table 9: Descriptive Statistics (with H-P filter) - All Economies

	Whole Sample	Booms	Booms with a Crisis	Booms without a Crisis	t-Statistic for Means
Avg. Credit growth (%)	5.83	7.37	7.50	7.14	0.21
Avg. TFP growth (%)	0.69	-0.11	-0.03	-0.23	0.58
Avg. Pnts Gnt growth (%)	0.22	-0.41	-0.60	-0.02	-0.08
Avg. LP growth (%)	1.75	1.15	1.00	1.43	-1.26
Avg. Duration (years)		4.59	4.64	4.50	0.36
Avg. Time spent in boom		6.31	4.06	2.25	
Number of Booms		44	28	16	
Sample Size (years)	1651	202	130	72	

Table 10: Descriptive Statistics (with H-P filter) - Advanced Economies

	Whole Sample	Booms	Booms with a Crisis	Booms without a Crisis	t-Statistic for Means
Avg. Credit growth (%)	5.69	6.96	6.93	7.01	-0.04
Avg. TFP growth (%)	0.64	-0.12	0.04	-0.40	1.10
Avg. Pnts Gnt growth (%)	-2.28	-6.06	-4.42	-9.09	0.76
Avg. LP growth (%)	2.00	1.31	1.17	1.59	-1.32
Avg. Duration (years)		4.58	4.80	4.22	0.96
Avg. Time spent in boom		6.47	4.24	2.24	
Number of Booms		24	15	9	
Sample Size (years)	806	110	72	38	

Table 11: Descriptive Statistics (with H-P filter) - Emerging Economies

	Whole Sample	Booms	Booms with a Crisis	Booms without a Crisis	t-Statistic for Means
Avg. Credit growth (%)	5.97	7.86	8.20	7.28	0.29
Avg. TFP growth (%)	0.75	-0.08	-0.13	-0.02	-0.18
Avg. Pnts Gnt growth (%)	3.45	7.23	4.27	13.76	-0.68
Avg. LP growth (%)	1.31	0.68	0.50	0.99	-0.53
Avg. Duration (years)		4.60	4.46	4.86	-0.78
Avg. Time spent in boom		5.75	3.63	2.13	
Number of Booms		20	13	7	
Sample Size (years)	845	92	58	34	

clear difference between booms that end in a crisis and those that do not.

2.5 The Effect of Productivity Growth on Crises

We now 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), has converged on the growth in credit as a 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

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

$Crisis_{j,t}$ is the odds ratio of a crisis, defined by $ln[Pr(Crisis_{t,j})/(1 - Pr(Crisis_{t,j}))]$, 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 12 . 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%.

Table 12: 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.

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

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

Table 13: Credit and TFP Growth as Crises Predictors

	5Ychange			5YchangeMA		
	LOGIT	LPM		LOGIT	LPM	
α	-3.99	0.02		-3.90	0.02	
t-Statistic	-19.67	3.88		-18.60	3.81	
β	0.80	0.04	0.04	0.90	0.04	0.04
t-Statistic	4.15	4.61	4.74	3.30	3.47	3.63
Marginal	0.01	0.02	0.02	0.01	0.01	0.02
γ	-2.29	-0.06	-0.06	-0.98	-0.03	-0.04
t-Statistic	-1.34	-1.51	-1.67	-0.48	-0.65	-0.76
Marginal	-0.00	-0.01	-0.01	-0.00	-0.00	-0.00
R^2		0.02	0.03		0.01	0.02
N	1525	1525	1525	1389	1389	1389
FE	No	No	Yes	No	No	Yes

Table 14: Credit and LP Growth as Crises Predictors

	5Ychange			5YchangeMA		
	LOGIT	LPM		LOGIT	LPM	
α	-3.70	0.02		-3.70	0.02	
t-Statistic	-12.79	3.63		-11.69	3.18	
β	0.66	0.03	0.03	0.70	0.03	0.03
t-Statistic	3.11	3.41	3.51	2.25	2.36	2.49
Marginal	0.01	0.01	0.01	0.01	0.01	0.01
γ	-2.41	-0.06	-0.08	-1.23	-0.04	-0.06
t-Statistic	-1.43	-1.66	-2.11	-0.70	-0.87	-1.24
Marginal	-0.01	-0.01	-0.01	-0.00	-0.00	-0.01
R^2		0.21	0.22		0.21	0.22
N	1217	1217	1217	1097	1097	1097
FE	No	No	Yes	No	No	Yes

The results are shown in Tables 13 and 14. Growth in TFP appears unrelated to crises although TFP growth is higher on average in booms that do not end in a crisis (as seen in the previous Tables).[17] Further, credit growth remains significant. Table 14

[17] Results for TFP are fragile. Small changes in the data, i.e. data revisions or new data at the end of

shows the results when growth in LP is used as a predictor. Here the results show that growth in LP marginally reduces the likelihood of a crisis occurring at the end of the boom. Tables A.4 and A.5 are the counterparts of Tables 13 and 14 showing that productivity does not affect the likelihood of crises when credit is H-P filtered, reinforcing our previous result that detrending misses all these findings.

2.6 Summary

We take the following points from this empirical study:

1. Credit booms are not rare and occur in both advanced and emerging economies.
2. Booms are ten years long in average.
3. Booms start with a positive shock to TFP and LP growth. The subsequent dynamics of productivity growth differ between good and bad booms, declining quickly in bad booms.
4. Crises are less likely with larger productivity growth during the boom.
5. These findings are not found when applying H-P filtering.

Point 1 emerges when we adopt the agnostic boom definition, without detrending credit. The results then show that booms are an important part of aggregate economic activity. Point 2 is the connection with the economic history literature which looks at average TFP and LP growth over longer periods, usually ten years, which is the average duration of a boom in our data. Point 3 suggests a link between technological change and aggregate cyclical behavior, in particular financial crises, showing that the paths of productivity differ over booms which end in a crisis and those that do not. This is also reflected in the growth rate of patent activity, which declines during bad booms and rises during good booms. Point 4 highlights that the likelihood of a financial crisis is higher when LP growth is lower. H-P filtering misses these findings

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

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the sample period make TFP growth sometimes significant.

3 The Model

3.1 Setting

The model builds on Gorton and Ordonez (2014). Time is discrete and denoted by $t \in \{0, 1, ...\}$. The economy is characterized by two overlapping generations – young and old – each a continuum of agents with mass 1, and three types of goods – *numeraire*, *land* and *managerial skills*. 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. Managerial skills are non-transferrable and their use does not generate disutility.

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

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

The first important difference with Gorton and Ordonez (2014) is the following. The quality of technology is given by q, which will be subject to exogenous shocks but also driven endogenously by the size of the credit boom. We assume the technology is determined by a limited supply of projects in the economy, also with mass 1. There are two types of projects that are available: A fraction ψ has *high* probability of success, q_H, and the rest have a *low* probability of success, q_L. We assume all projects are efficient, i.e., $q_H A > q_L A > 1$, which implies that the optimal scale of numeraire in production is $K^* = L^*$ for all projects, independent of their success probability $q \in \{q_L, q_H\}$. For now we assume the average quality of the projects, ψ, is fixed, but later we allow for shocks to it. An increase in ψ will be interpreted, for instance, as a technological improvement.

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

Even though non-productive, land potentially has an intrinsic value. If land is *"good"*, it can 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. At the beginning of the period, different units of land i can potentially be viewed differently, with respect to their quality. We denote these priors of being good p_i and assume they are commonly known by all agents in the economy.

Privately observing the quality of land costs γ_l units of numeraire to households and γ_b units of managerial skills to firms. We assume households only have numeraire at the beginning of the period and using γ_l for monitoring diverts its use for consumption. Similarly, firms only have managerial skills at the beginning of the period and using γ_b for monitoring diverts their use from production.

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

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

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

The perception about the quality of collateral then becomes critical in facilitating loans. To be precise, we further assume that $C > K^*$. This implies that land that is known to be good can sustain the optimal loan, K^*. Contrarily, land that is known to be bad is not able to sustain any loan. We refer to firms that have land with a positive probability of being good ($p > 0$) as *active firms*, since in contrast to firms that are known to hold bad land, they can actively participate in the loan market and raise funds to start their projects.[18]

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. We assume that lenders know (or can infer in equilibrium) the mass of active firms in the economy, which we denote by η, but not each firm's position in the queue. This implies that only firms know their individual project quality, q, but lenders just know the average productivity of projects among active firms, which we denote by $\widehat{q}(\eta)$. Lenders' beliefs of the probability of success for any single firm are then

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

This implies that the average productivity of projects in the economy weakly declines with the mass of active firms, η, and reaches the minimum when all firms are active (i.e, when $\eta = 1$).

Remark on the interpretation of collateral: As in Gorton and Ordonez (2014), for simplicity we abstract from including financial intermediaries in the model and instead we have households lending directly to firms. The debt we have in mind is short-term debt like sale and repurchase agreements ("repo") or other money market instruments. In these cases, the collateral is either a specific bond or a portfolio of bonds and loans. The backing collateral is hard to value as it does not trade in centralized markets where prices are observable. But, we can also think of the debt as longer term. For example, Chaney, Sraer, and Thesmar (2012) show that firms, in fact, use land holdings as the basis for borrowing.[19]

[18] 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.

[19] Firms use their land as pledgeable assets for borrowing. In 1993, 59 percent of U.S. firms reported

3.2 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.[20] Both borrowers and lenders may want to produce information about the collateral type.[21] 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-insensitivity and, ultimately, the volume and dynamics of information in the economy.

3.2.1 Information-Sensitive Debt

Lenders can learn the true value of the borrower's land by using γ_l of numeraire. Borrowers can learn the true value of their own land by using γ_b of managerial skills, 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.

We assume lenders are competitive. If they are the ones acquiring information, as they are risk neutral,[22]

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

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).

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

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

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

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

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

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

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

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

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

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

Similarly, we can compute these expected net profits in the case borrowers acquire information directly at a cost γ_b in terms of managerial skills. Regardless of what the borrower finds, the firm will only have $L^* - \gamma_b$ managerial skills remaining for using in the project. If the borrower finds out that the land is good he will then just borrow $K^* - \gamma_b$ to operate at the, now lower, optimal scale.

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

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

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

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

Then, expected profits from information-sensitive debt effectively are

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

where

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

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.

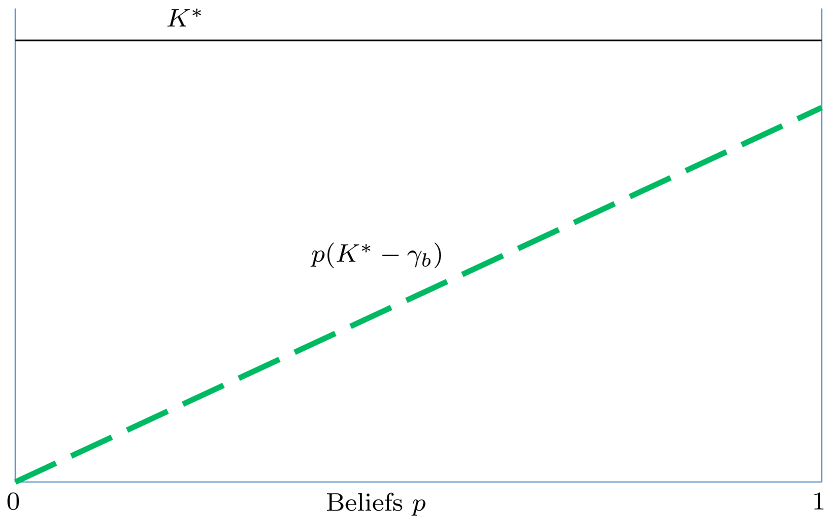
In Figure 2 we show the expected information-sensitive loan for the case in which $\gamma_b p(qA - 1) < \gamma_l$ for all p. As can be seen the loan is declining in p as the project is less likely to be financed when the collateral is less likely to be good, and it is always below the optimal loan size, K^*, as managerial skills are inefficiently wasted in monitoring the quality of land.[23]

3.2.2 Information-Insensitive Debt

Another possibility for firms is to borrow such that there is no information acquisition. Information acquisition is private, however, and there may be incentives to deviate. We assume information is private immediately after being obtained and becomes public at the end of the period. Still, the agent can credibly disclose his private information immediately if it is beneficial to do so. This introduces incentives for both

[23] 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).

Figure 2: Expected Loan Size with Information-Sensitivity Debt



lenders and borrowers to obtain information before the loan is negotiated and to take advantage of such private information before it becomes common knowledge.

As lenders break even in equilibrium

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

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

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

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

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

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

More specifically, 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,

$$K < \frac{\gamma_l}{(1-p)(1-\widehat{q}(\eta))}. \tag{2}$$

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 (2), information-insensitive loans are such that

$$K < K^l(p|\widehat{q}(\eta), II) \equiv \min\left\{K^*, \frac{\gamma_l}{(1-p)(1-\widehat{q}(\eta))}, pC\right\} \tag{3}$$

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

Similarly, borrowers want to deviate if the expected gains from acquiring information, evaluated at x_{II} and R_{II}, are greater than the losses γ_b from acquiring information. Specifically, if borrowers acquire information, their expected benefits are $p(K^*-\gamma_b)(qA-1)+(1-p)\min\{K, K^*-\gamma_b\}(qA-1)$. With probability p land is good and the firm borrows $K^*-\gamma_b$ as there are only $L^*-\gamma_b$ managerial skills remaining. With probability $1-p$ land is bad and the firm borrows the minimum between the original contract K or the optimum conditional on having 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

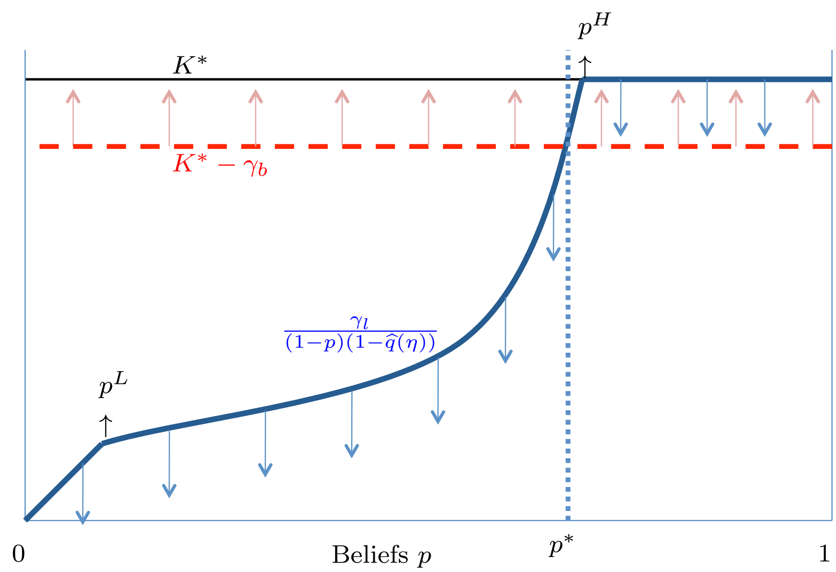
$$p(K^*-\gamma_b)(qA-1)+(1-p)\min\{K, K^*-\gamma_b\}(qA-1) < K(qA-1).$$

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,

$$K > K^b(p|\widehat{q}(\eta), II) \equiv K^* - \gamma_b. \tag{4}$$

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

Figure 3: Expected Loan Size with Information-Insensitive Debt



Combining the two conditions (3) and (4), 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 (3) and (4). Then

$$p^* = \max\left\{1 - \frac{\gamma_l}{(K^* - \gamma_b)(1 - \widehat{q}(\eta))}, \frac{K^* - \gamma_b}{C}\right\}. \tag{5}$$

It is clear from inspecting equation (5) that the region in which information-insensitive debt is feasible widens with information costs (as p^* decreases with γ_b and γ_l) and shrinks with the mass of active firms (as p^* decreases with $\widehat{q}$, which decreases with η).

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 (3). Then

$$p^H = 1 - \frac{\gamma_l}{K^*(1-\widehat{q}(\eta))}. \tag{6}$$

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 (3). Then [24]

$$p^L = \frac{1}{2} - \sqrt{\frac{1}{4} - \frac{\gamma_l}{C(1-\widehat{q}(\eta))}}. \tag{7}$$

3.2.3 Loans With or Without Information?

Figure 4 shows the ex-ante expected profits in both regimes (information-sensitive and information-insensitive debt) for a firm with private information about its own probability of success q, net of the expected value of land, for each possible p, assuming $\gamma_b(qA-1) \leq \gamma_l$ for $q \in [q_L, q_H]$.[25]

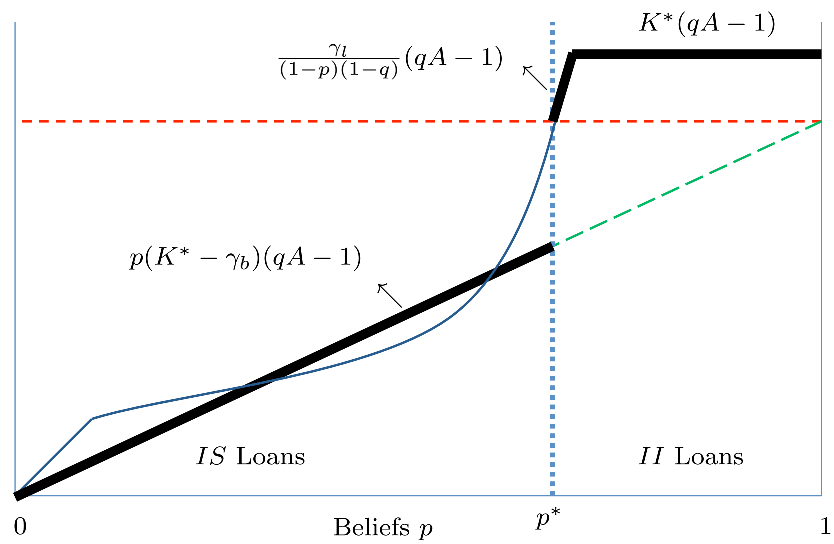
We can summarize the expected loan sizes for different beliefs p, graphically represented with a wide black discontinuous function in Figure 4, by

$$K(p|\widehat{q}(\eta)) = \begin{cases} K^* & \texttt{if } p^H < p \\ \frac{\gamma_l}{(1-p)(1-\widehat{q}(\eta))} & \texttt{if } p^* < p < p^H \\ p(K^* - \gamma_b) & \texttt{if } \quad p < p^*. \end{cases} \tag{8}$$

[24]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.

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

Figure 4: Expected Profits in Equilibrium



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.

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 $\widehat{q}(\eta)$.

3.3 Aggregation

The expected consumption of a household that lends to a firm with land that is good with probability p, conditional on an expected probability of default $\widehat{q}(\eta)$, is $\overline{K}-K(p|\widehat{q}(\eta))+E_q\{E(repay|p,q,\eta)\}$. The expected consumption of a firm that borrows using land that is good with probability p and has a privately known probability of success q is $E(K'|p,q,\eta)-E(repay|p,q,\eta)$ (recall this is 0 for inactive firms). Then, the ex-ante (before observing its position in the queue for projects) aggregate consumption of firms is $E_q\{E(K'|p,q,\eta)-E(repay|p,q,\eta)\}$. Expected aggregate consumption is the sum of the consumption of all households and firms. Since $E(K'|p, q, \eta) = qAK(p|\widehat{q}(\eta))$, with $K(p|\widehat{q}(\eta))$ given in (8), then $E_q\{E(K'|p, q, \eta)\} = \widehat{q}(\eta)AK(p|\widehat{q}(\eta))$,

$$W_t = \overline{K} + \int_0^1 K(p|\widehat{q}(\eta))(\widehat{q}(\eta)A - 1)f(p)dp \tag{9}$$

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

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

$$W^* = \overline{K} + K^*(\widehat{q}(1)A - 1). \tag{10}$$

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

4 Dynamics

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

We impose a specific process of idiosyncratic mean reverting shocks that are useful in characterizing analytically the endogenous dynamics of information production. First, we assume idiosyncratic shocks are observable, but their realization is not observable, unless information is produced. Second, we assume that the probability that land faces an idiosyncratic shock is independent of its type. Finally, we assume the probability that a unit of land becomes good, conditional on having an idiosyncratic shock, is also independent of its 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 collateral type.

We assume that initially (initial condition) there is perfect information about which collateral is good and which is bad, a situation that we denote by *"symmetric information"*. In every period, with probability λ the true quality of each unit of land remains unchanged and with probability $(1-\lambda)$ there is an idiosyncratic shock that changes its type. In this last case, land becomes good with a probability $\widehat{p}$, independent of its current type. Even when the shock is observable, the realization of the new quality is not, unless managerial skills are used to learn about it.[26]

With this simple stochastic process for idiosyncratic shocks, 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 Deterministic Technology

Here we study a deterministic economy with fixed technology (the fraction of high quality projects, ψ) and characterize the stationary equilibrium. Define by $\chi \equiv \lambda\widehat{p} + (1-\lambda)$ the fraction of active firms after a single round of idiosyncratic shocks starting from a symmetric information situation. That is, a fraction $(1-\lambda)$ of all collateral suffers the shock and their perceived quality, absent information acquisition, is $\widehat{p}$ while a fraction λ of collateral known to be good (a fraction $\widehat{p}$ of all collateral) remain with such a perception. These are the active firms, $\eta = \chi$.

[26]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 $\lambda K^*(\underline{\widehat{q}}(1)A-1) > (1-\lambda)C$. Furthermore they should have enough resources to buy good collateral, this is $\overline{K} > C$.

When $\eta = \chi$, average productivity is $\widehat{q}(\chi|\psi) = \frac{\psi}{\chi}q_H + \left(1 - \frac{\psi}{\chi}\right)q_L$. From equation (5), given $\widehat{p}$, there is a technology level $\underline{\psi}$ such that $\widehat{p} = p^*(\widehat{q}(\chi|\underline{\psi}))$. Similarly, when $\eta = 1$ and all firms are active, average productivity is $\widehat{q}(1|\psi) = \psi q_H + (1-\psi)\,q_L$. From equation (5), given $\widehat{p}$, there is technology level $\overline{\psi}$ such that $\widehat{p} = p^*(\widehat{q}(1|\overline{\psi}))$. Finally, when $\eta = 1$, from equation (6), given $\widehat{p}$, there is 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 (5), 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 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 acquisition about collateral and constant consumption in every period at,

$$\overline{W}(\widehat{p}) = \overline{K} + \widehat{p}(K^* - \gamma_b(1-\lambda))(\widehat{q}(\widehat{p})A - 1) < W^*. \tag{11}$$

Proof In this case, as $\psi < \underline{\psi}$ then $\widehat{p} < p^*(\widehat{q}(\chi|\psi))$. If the economy starts from a symmetric information state $\eta = \chi$ after the first round of idiosyncratic shocks. Then $f(1) = \lambda\widehat{p}$, $f(\widehat{p}) = (1-\lambda)$ and $f(0) = \lambda(1-\widehat{p})$. Since $\widehat{p}$ is in the region where information-insensitive debt is not feasible,

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

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 (11)), which is less than the optimal consumption from equation (10). 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 renovation of information in the economy. In this case, as there are no exogenous shocks, 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, this 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.

Proof In this case, as $\psi \in [\underline{\psi}, \overline{\psi}]$ then $\widehat{p} \geq p^*(\widehat{q}(\chi|\psi))$ and $\widehat{p} \leq p^*(\widehat{q}(1|\psi))$. Starting from an initial condition with symmetric information about collateral, in the first period $\eta_1 = \chi$, 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 $W^{II}_{t^*} > W^{II}_0$, 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 restarts.

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 are generated by an endogenous evolution of the distribution of collateral beliefs in credit markets as time goes on.

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

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 (10).

Proof In this case, as $\psi > \overline{\psi}$ then $\widehat{p} > p^*(\widehat{q}(1|\psi))$. Starting from a situation of perfect information (initial condition), in the first period $\eta_1 = \chi$, and if $\widehat{q}(\chi)$ is such that $\widehat{p} > p^*(\widehat{q}(\chi))$ there are no incentives to acquire information about the collateral with beliefs $\widehat{p}$, and there is no information acquisition in the first period. Since by assumption $\widehat{p} > p^*(\widehat{q}(1))$ and p^* reaches its maximum level when all firms are active, the process converges to all firms obtaining loans in the steady state. 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 (10). Q.E.D.

In this last region, when technology is high, there are no incentives to acquire information about collateral. As over time all collateral looks alike, the economy converges to a situation in which all firms obtain a loan and produces without spending resources on information acquisition. If 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.

4.2 Stochastic Technology

The previous section describes the steady state of the economy when technology ψ is fixed. In this section we discuss how the economy reacts to sudden changes in ψ and then how our model also captures crises that do not happen during booms and crises that may arise because of negative contemporaneous shocks to productivity, more in line with standard views of crises.

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 symmetric information regime to a 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. 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.

If technology is high enough and the economy had experienced a good boom, it does not imply that the economy cannot suffer a negative technological shock. 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 longer boom. Then, a negative shock can induce a crisis even in the absence of a preceding boom. This type of crisis is more in line with standard real business cycles. In our setting, however, this negative contemporaneous shock induces an otherwise stable credit situation to collapse. This effect complements the ones highlighted by the real business cycles literature since real negative shocks in productivity feeds back into credit markets and causes a magnification of real shocks.

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

4.3 Numerical Illustration

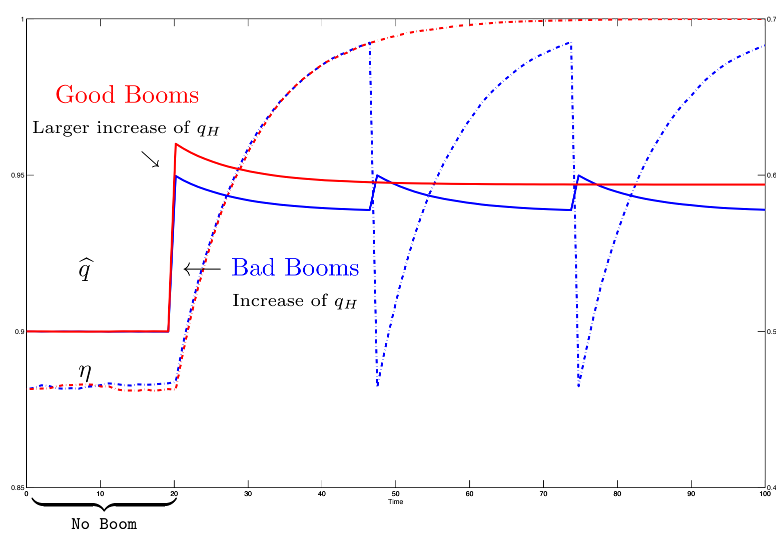
In this section we illustrate how small differences in the exogenous process of productivity can lead to large differences in the cyclical behavior of measured credit, productivity and output. We assume an economy that is originally in an "information-sensitive" regime, with low stable output (low technology state). We then introduce an exogenous permanent productivity shock that increases the average probability of project success. We show that if this shock is not large enough (from low to intermediate technology), the economy may enter in a regime with deterministic credit booms followed by crises – a sequence of bad booms. When the shock is larger (from low to high technology) 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. We then discuss how the same result arises from an initial shock of the same size but with a different subsequent growth rate of technology. When the initial shock is not sustained, then the economy is more likely to enter a regime with deterministic cycles. Both cases are consistent with our empirical findings.

More precisely, we assume idiosyncratic shocks happen with probability $(1-\lambda) = 0.1$ per period, in which case the collateral becomes good with probability $\widehat{p} = 0.88$. We also assume $L^* = K^* = 7$, $\bar{K} = 20$ (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 managerial skills. With respect to the decreasing expected productivity of projects, we assume a fraction $\psi = 0.3$ of projects have a probability of success $q_H = 0.7$ and the rest can only operate with a lower probability of success, $q_L = 0.4$. Finally, we assume an initial productivity of $A = 15$, which grows exogenously at a 0.3% rate per period.

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

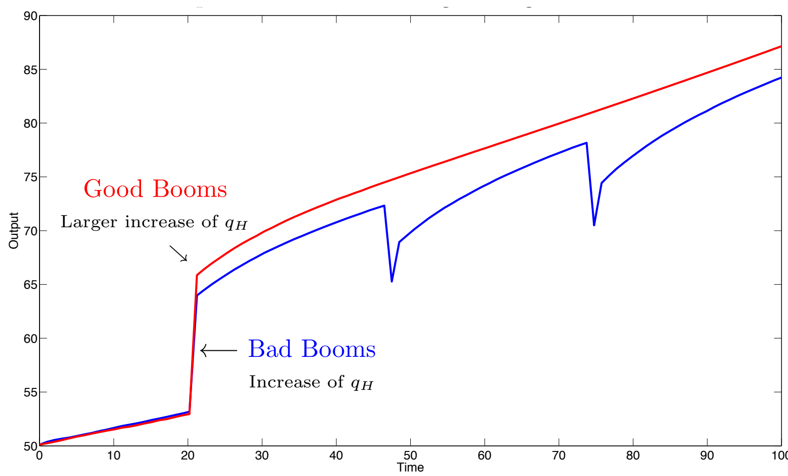
We assume that in period 20 the economy experiences an exogenous shock that increases the probability of success of "good quality" projects from $\psi = 0.5$ to a permanently higher level, $\psi' > \psi$. We assume this shock is large enough for the economy to initially escape the information-sensitive regime. More formally, we assume two possible shocks. One leads to $\psi' = 0.586$ such that $\widehat{q}$ in the symmetric information state goes from 0.5 to 0.6 (from low to intermediate technology). This is represented by the lower curve in Figure 5. The other, slightly larger shock, leads to $\psi' = 0.645$ such that $\widehat{q}$ in the symmetric information state goes from 0.5 to 0.62 (from low to high technology). This is represented by the upper curve in Figure 5. It is clear that the shocks are very similar in terms of their impact to the expected probability of default. Yet, they will have very different effects in terms of the cyclical behavior of the economy.

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



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

Figure 6: Positive Shocks of Different Size - Output



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

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

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

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

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

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

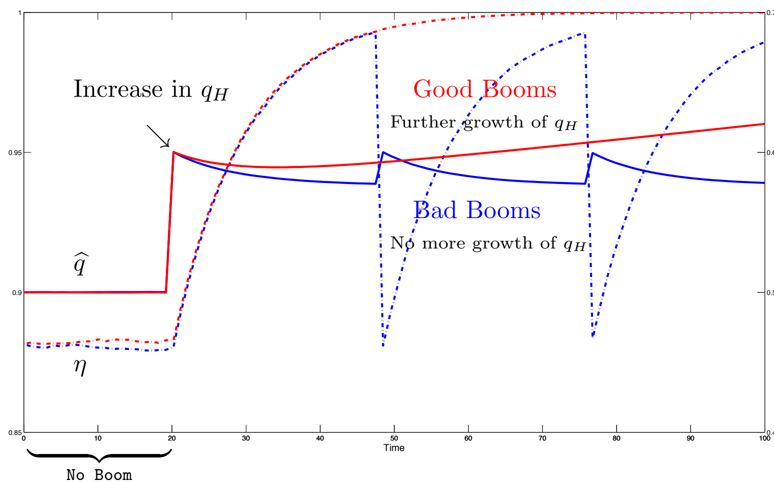
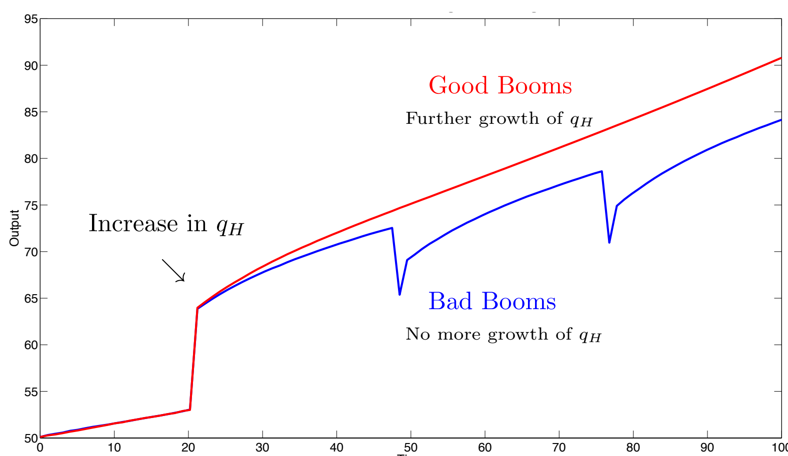


Figure 8: Positive Shocks with Different Growth Rates- Output



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 Testable Predictions

In this section of the paper we test two of the main predictions of the model.

The driving force of the model is the assumption that during booms firms are increasingly using projects with a lower probability of realizing output. So, over booms firms should be increasingly risky and firm failures should increase. That firms are increasingly fragile, leading up to recessions and crises, has a long history, going back at least to Burns and Mitchell (1946) who show that the liabilities of failed nonfinancial businesses is a leading indicator of recession. Also, see Zarnowitz and Lerner (1961).[27] Further, Gorton (1988) using this variable shows that during the banking panics of the U.S. National Banking Era, every time an unexpected increase in this indicator exceeded a threshold there was a panic; there was never a panic without the threshold being exceeded and the threshold was never exceeded without a panic. The first prediction of the model is that firms are increasingly more fragile over bad booms, relative to good booms.

The second prediction concerns the pro-cyclicality of TFP. Measured TFP is a residual which can contain many factors, as has been argued in the literature. In our model average TFP is $\widehat{q}A$, hence a combination of the probability of success and the output in case of success. We have deliberately constructed the model such that only $\widehat{q}$, not A, affects incentives to examine collateral in credit markets. Then our model highlights that in our measure of TFP there is a component 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.

[27]The financial press during the National Banking Era regularly discussed this statistic. See Gorton (2012), p. 75-77.

Testing the first prediction that there should be more firms defaulting over a bad boom is hard because we do not have bankruptcy data, nor do we have business failures, for our panel of countries. We can use, however, equity data to produce a measure of firm fragility recently introduced and studied by Atkeson, Eisfeldt, and Weill (2013). As a measure of firm fragility, they introduce Distance-to-Insolvency (DI), based on Merton (1975) and Leland (1994). DI measures the adequacy of a firm's equity cushion relative to its business risk. They show that this is a good proxy for the probability of default and that can be measured with the inverse of the volatility of a firm's equity returns.

We construct $\frac{1}{vol_{j,t}}$ for each country j and each 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.6 in the Appendix. For a given country we calculate the monthly volatility for each listed company based on daily data. We then take the median of the monthly volatilities for each year. This is the annual measure of firm fragility we use for each country.

Note that a decrease in $\frac{1}{vol_{j,t}}$ corresponds to an economy becoming more fragile (as volatility is larger). Atkeson, Eisfeldt, and Weill (2013) show that in the U.S. this measure for the entire economy was uniquely low for the Great Depression, the recession of 1938-39, and the Crisis of 2007. Table 15 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 15: 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 can formalize this with the following regression

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

Table 16 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 16: $\frac{1}{vol}$, 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		0.45	0.80
N	522	522	522
FE	No	No	Yes

The second prediction of the model is related to the composition of TFP. In our model, as time goes on, bad booms are more likely when firms become increasingly prone to default (that is, $\widehat{q}$ decreases) but not if the productivity conditional on success declines (that is, if A decreases). 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 17 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 estimate TFP is firm fragility (which differs over good booms and bad booms).

Table 17: 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	0.93	0.64	0.92	0.68	0.92	0.72	0.91	0.74	0.91	0.75
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.

6 Conclusions

Financial crises and credit booms are inherent parts of macroeconomic activity. Financial crises are typically preceded by a credit boom, but not all credit booms end in financial crises. Credit booms are not rare. The average country spends over half its time in a boom, with an average duration of ten 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 long before the crisis, so not all crises are the result of contemporaneous negative shocks.

We provided a model that relate productivity, credit booms and financial crises to capture these facts. A technological shock can induce investments based on information-insensitive debt that have 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.

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. If the diffusion of technology takes time because firms need financing, as the credit boom develops, more firms get financing and the technology diffuses, which would endogenously increase productivity and compensating the effect of a decreasing productivity of marginal projects. In this case, a crisis would occur if lower and lower quality projects diffuse. 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 to understand how endogenous growth and financial crises relate.

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A Appendix

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

Table A.3 shows the classification of the booms identified by our algorithm.

Table A.1: Frequency of Booms

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

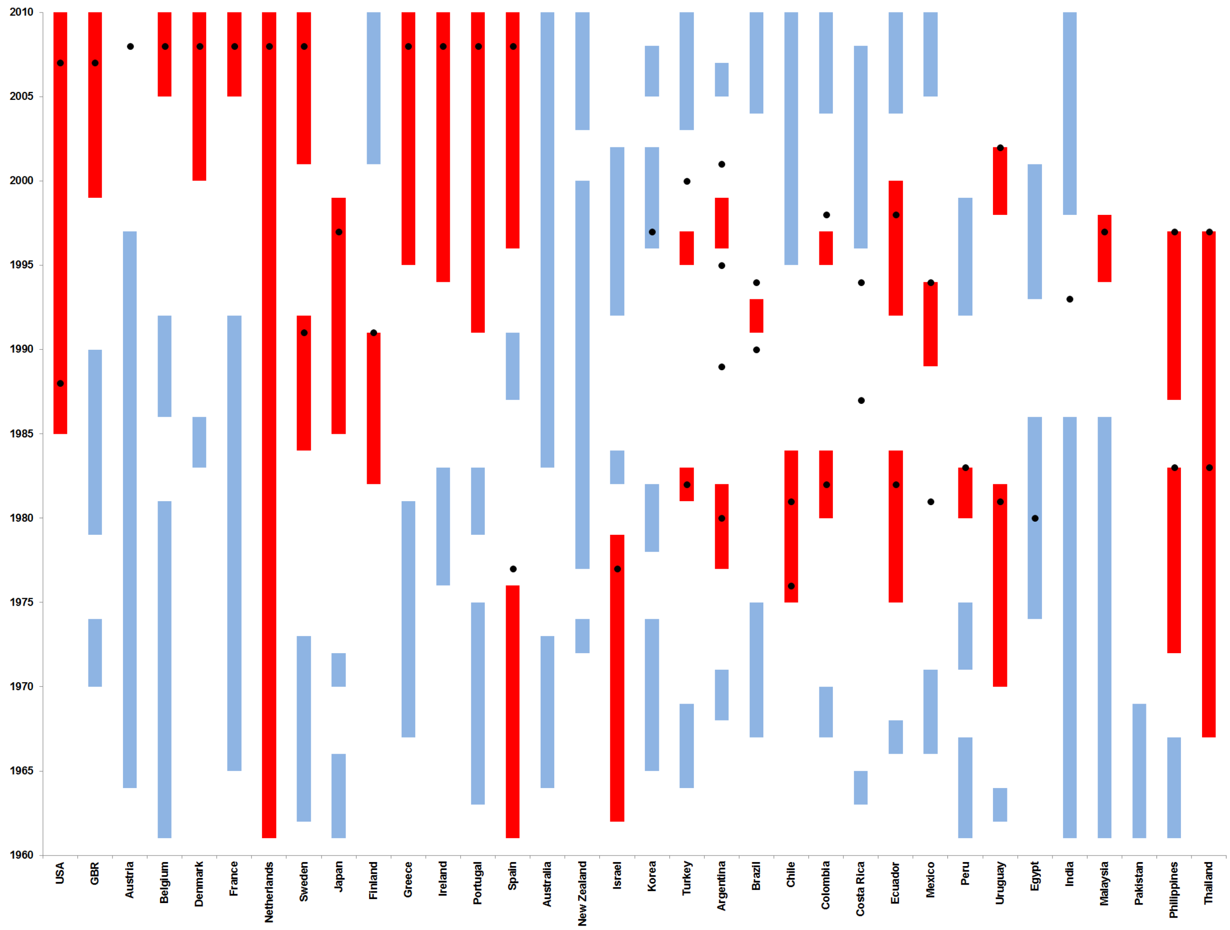


Table A.3: Booms in the Sample

	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: H-P filtered Credit and TFP Growth as Crises Predictors

	5Ychange			5YchangeMA		
	LOGIT	LPM		LOGIT	LPM	
α	-4.19	0.01		-4.13	0.01	
t-Statistic	-19.19	1.87		-17.95	2.17	
β	0.44	0.03	0.04	0.56	0.03	0.04
t-Statistic	4.24	7.09	7.75	3.54	4.82	5.53
Marginal	0.01	0.03	0.03	0.01	0.02	0.02
γ	-0.99	-0.05	-0.06	0.24	-0.04	-0.05
t-Statistic	-0.51	-1.50	-1.69	0.10	-0.74	-0.88
Marginal	-0.00	-0.01	-0.01	0.00	-0.00	-0.00
R^2		0.03	0.05		0.02	0.04
N	1481	1481	1481	1345	1345	1345
FE	No	No	Yes	No	No	Yes

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

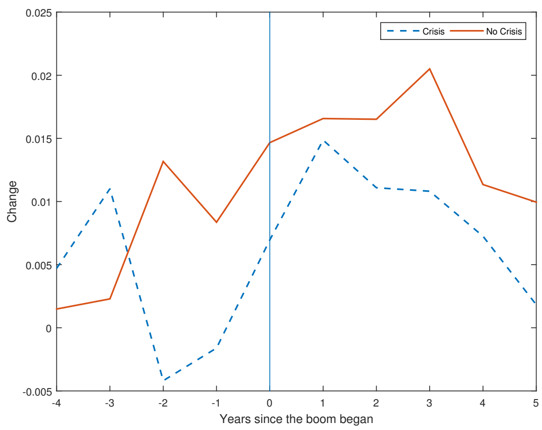
	5Ychange			5YchangeMA		
	LOGIT	LPM		LOGIT	LPM	
α	-4.02	0.01		-3.97	0.02	
t-Statistic	-12.14	2.28		-11.18	2.28	
β	0.39	0.03	0.03	0.49	0.03	0.04
t-Statistic	3.77	5.72	6.32	3.00	3.90	4.50
Marginal	0.00	0.02	0.03	0.01	0.02	0.02
γ	-1.35	-0.05	-0.09	-0.91	-0.05	-0.10
t-Statistic	-0.69	-1.57	-2.18	-0.44	-1.19	-1.79
Marginal	-0.00	-0.01	-0.01	-0.00	-0.01	-0.01
R^2		0.24	0.25		0.23	0.24
N	1168	1168	1168	1048	1048	1048
FE	No	No	Yes	No	No	Yes

Table A.6: Number of Firms per Year for the Countries of with Available Daily Firm Level Data

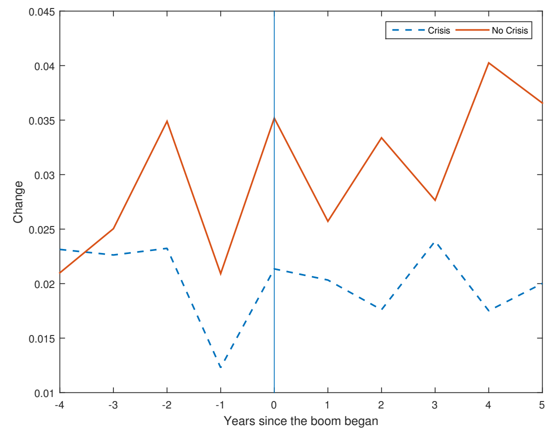
Country	1965	1966	1967	1968	1969	1970	1971	1972	1973	1974	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986	1987
Argentina																							
Australia									78	78	80	83	84	84	85	86	88	89	94	104	107	115	140
Austria									24	23	17	13	16	20	18	17	21	19	21	20	29	34	37
Belgium									36	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																							16
Portugal																							
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	167	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					48	48	81	86	77	79	73	54	52	58	52	56	59	69	62	68	52	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	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

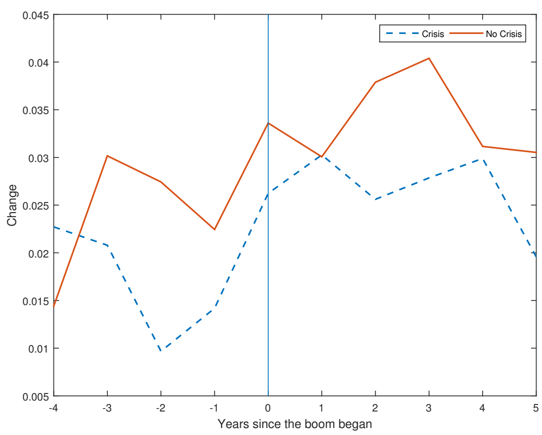
Figure A.2: Median Productivity over Good and Bad Booms



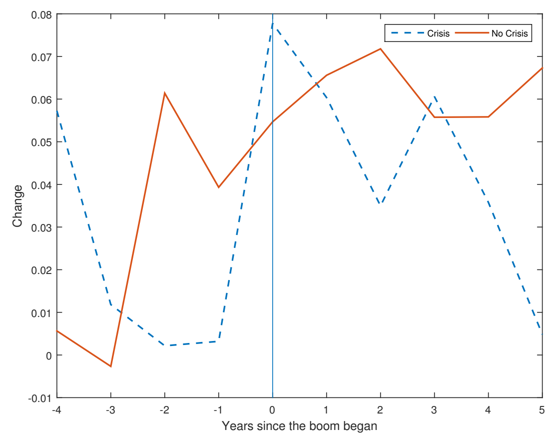
(a) Total Factor Productivity



(b) Labor Productivity

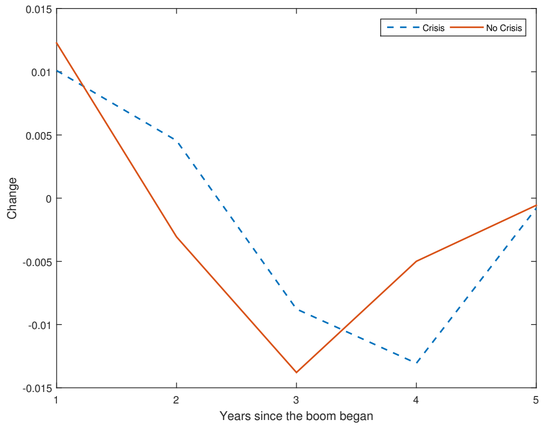


(c) Real GDP

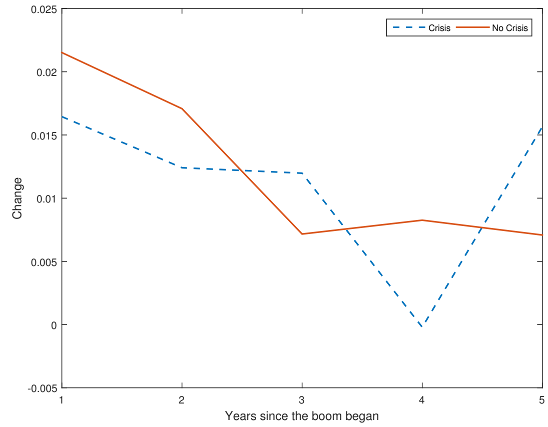


(d) Capital Formation (Investment)

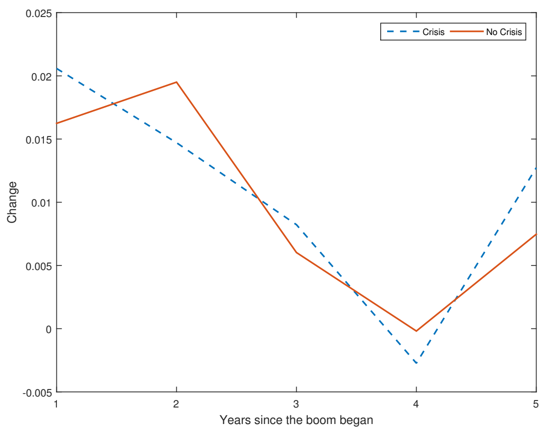
Figure A.3: Average Productivity over Good and Bad Booms (H-P filter)



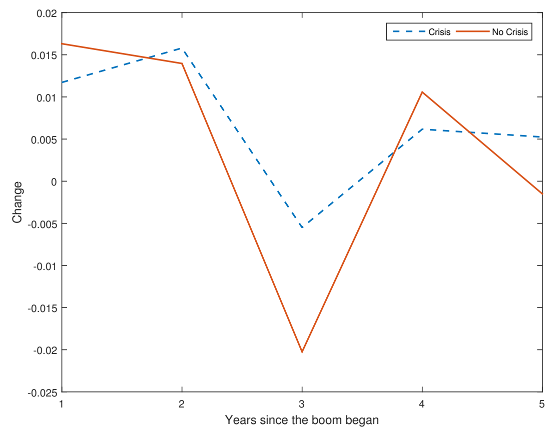
(a) Total Factor Productivity



(b) Labor Productivity

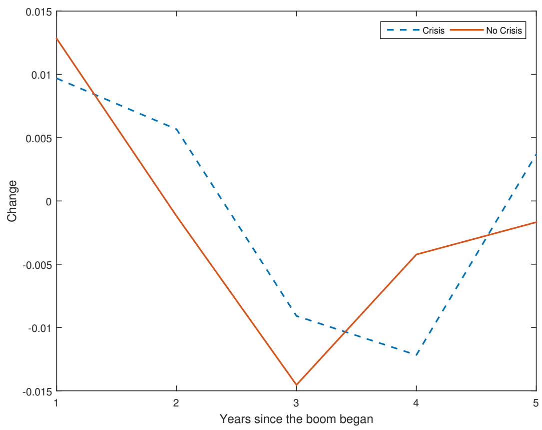


(c) Real GDP

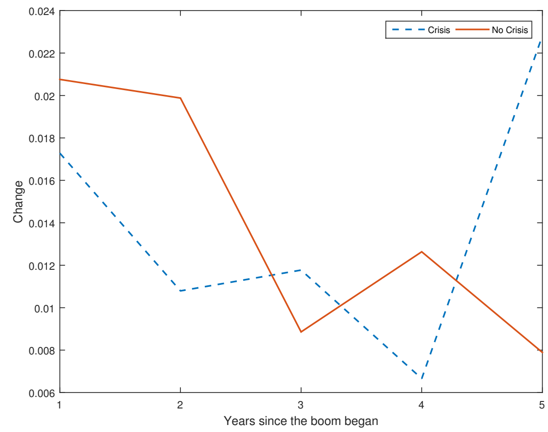


(d) Capital Formation (Investment)

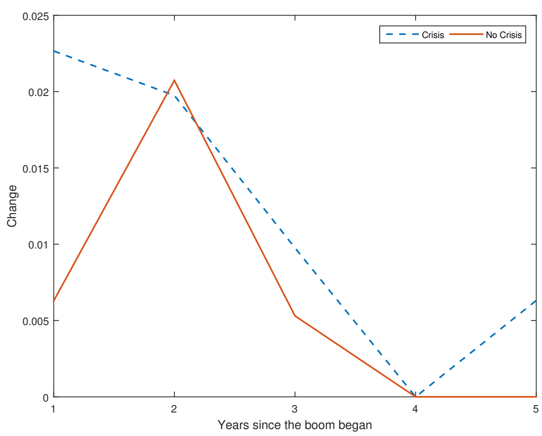
Figure A.4: Median Productivity over Good and Bad Booms (H-P filter)



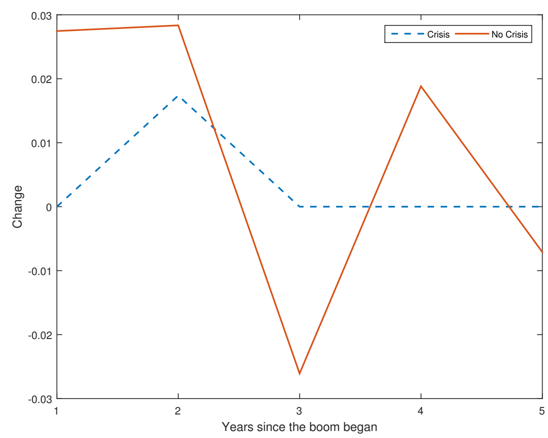
(a) Total Factor Productivity



(b) Labor Productivity



(c) Real GDP



(d) Capital Formation (Investment)