Good Booms, Bad Booms*

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Abstract

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

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1 Introduction

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

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

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

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

the postwar period."[3]

In analyzing our panel of countries, we do not use the H-P filter. Rather, we propose a definition of a "credit boom" that is very agnostic. It does not rely on future data or on detrending. As we show, using the H-P filter misses important features of the data in the larger, longer, sample.[4] The phenomena of interest happen at lower frequencies and it seems difficult to separate trend changes from fluctuations. However, changes in technology do seem important. Our evidence suggests that credit booms start with a positive shock to TFP and labor productivity (LP), but that in bad booms the shock dies off rather quickly while this is not the case for good booms. The role of technology over such a longer horizon has been noted by economic historians and growth economists. Indeed, in the long-term, technology has played a central role in understanding growth.[5]

Our finding that credit booms average ten years, and that positive shocks to TFP and LP occur at the start of the boom, is closely related to studies of "Medium-Term Business Cycles," which are also about ten years. Comin and Gertler (2006) find that TFP moves procyclically over the medium term (in U.S. quarterly data from 1948:1-2001:2 – a period without a systemic financial crisis).[6] They do not analyze credit variables however. Drehmann, Borio, and Tsatsaronis (2012) use an analysis of turning points (as well as frequency-based filters) to study six variables for seven countries over the period 1960-2011. In particular, they analyze credit to the private non-financial sector and the ratio of credit to GDP, which is the measure we study. Their main finding is the existence of a medium-term component in credit fluctuations. Also, see Claessens, Motto and Terrones (2011a and 2011b). All of these studies suggest that productivity growth and business cycles are related. We show that there is a difference in the productivity growth and credit booms that end in a financial crisis.

We then develop a simple framework to understand how positive productivity shocks can lead to credit booms which sometimes end with a financial crash. The model be-

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

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

[5]The historical time series of TFP growth has been linked to periods of growth due to technological innovation, such as the steam locomotive, telegraph, electricity or IT (see Kendrick (1961), Abramovitz (1956), Field (2009), Gordon (2010) and Shackleton (2013)).

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

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

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

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

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

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

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

Although there is nothing irrational about the booms and crashes in the model, still there is an externality because of the agents' short horizons, as in Gorton and Ordonez (2014). Here it is also true that a social planner would not let the boom go on as long as the agents, but would not eliminate it either. So, thinking of a boom as an "asset bubble," the perceived bubble could be a good boom, but even if it was a bad boom, still the social planner would not eliminate it. If policymakers could observe TFP or LP growth with a very short lag, then, on average, they could tell whether a boom is good or bad and take action.

In our setting there is arrival of a set of technological opportunities which is exogenous for simplicity. In reality innovation is an endogenous process, but still subject to sudden discoveries. There is news that a new set of technological opportunities as arrived. It is an improvement in technology, but may have the feature that the quality of the projects becomes low as the boom proceeds. The diffusion of technology takes time because firms need financing. As the credit boom develops, more firms get financing and the technology diffuses. The crisis occurs if the lower and lower quality projects diffuse. The innovation runs out of steam (so to say). As in Gorton (1985), Dang, Gorton, and Holmström (2013) and Gorton and Ordonez (2014) the crisis is an information event.

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

2 Good Booms, Bad Booms: Empirical Evidence

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

2.1 Data

We analyze a sample of 34 countries (17 advanced countries and 17 emerging markets) over a 50 year time span, 1960-2010. A list of the countries used in the analysis, together with a classification of the booms (based on the definition given below), is provided in the Appendix.

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

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

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

Once we have computed credit booms and TFP and LP growth over booms, we use the presence of financial crises at the end of the boom to assess the ex-post efficiency of the boom. For this we rely on the classification in Laeven and Valencia (2012), who, by using an extensive cross-country dataset, identify financial crises worldwide since 1960.[7] Their definition of a crisis is given below.

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

2.2 Definition of Credit Booms

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

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

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

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

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

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

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

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

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

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

We define a credit boom as starting whenever we observe at least three years of subsequent positive credit growth with annual growth above a threshold x^s. The boom ends whenever we observe at least three years of credit growth below a threshold x^e. In our baseline experiments we choose $x^s = 5\%$ and $x^e = 0\%$. The choice of thresholds is based on the average credit growth in the sample. Changes in thresholds do not alter the results qualitatively. Later we will compare the results using this classification procedure to one which uses Hodrick-Prescott filtering.

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

We say that a credit boom is accompanied by a financial crisis whenever Laeven and Valencia (2012) classify a crisis in a neighborhood of two years of the end of the boom.[8] Their database covers the period 1970 to 2011. They define a systemic banking

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

crisis as occurring if two conditions are met: (1) there are "significant signs of financial distress in the banking system (as indicated by significant bank runs, losses in the banking system, and/or bank liquidations) and (2) if there are "significant banking policy intervention measures in response to significant losses in the banking system." Significant policy interventions include: (1) extensive liquidity support (when central bank claims on the financial sector to deposits exceeds five percent and more than double relative to the pre-crisis level); (2) bank restructuring gross costs are at least three percent of GDP; (3) significant bank nationalizations; (4) significant guarantees are out in plaice; (5) there are significant asset purchases (at least five percent of GDP); (6) there are deposit freezes and/or bank holidays.

By our definition, there are 88 booms in the sample, of which 33 ended in a financial crisis. The definition of a boom is very inclusive. The Appendix Table A.1 lists the booms and crises. There are very long booms; the longest is in Australia from the 1983 to 2010 (28 years). The definition also results in booms being relative frequent. Of the 1695 years in the sample, 929 were spent in a boom, 55% of the time. On average, over 50 years, a country spent 27 years in a boom and, on average, 9 of those years were spent in a boom that ended in a crisis.[9] This is our first result. Booms are not rare.

Table 1 provides an overview of the booms. (In the Appendix, Table A.1 provides a detailed list of booms and crises.) Table 1 shows average credit growth, average TFP and LP growth, average real GDP growth, average investment growth and the average duration of the booms. The last column shows the t-statistic for the null hypothesis that the mean for each variable is the same for booms that end in a crisis and those that do not. There is no statistical difference between any of these variables. In fact, the means of credit growth, TFP growth and LP growth are essentially the same. Table 2 shows advanced economies and Table 3 shows emerging economies.[10] In emerging economies TFP growth is faster in booms that do not end in a crisis, but LP is essentially the same.[11]

[9] The data are very noisy and are constantly being revised. We remove sample points where the growth rate is greater than 5 percent in absolute value. See Appendix A.2 "Outliers".

[10] The subsamples for crisis and non-crisis booms are small, as shown in Table 1, so there may be concerns about the power of the test. Resampling by randomly selecting pairs (a bootstrap) and repeating the test shows that the null is rejected with more confidence, confirming that the differences in the data do indeed exist.

[11] The classification of countries into advanced or emerging comes from the World Bank. Advanced include the U.S., U.K., Austria, Belgium, Denmark, France, the Netherlands, Japan, Finland, Greece,

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

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

Table 1: Descriptive Statistics - All Economies

	Whole Sample	Booms	Booms with a Crisis	Booms without a Crisis	t-Statistic for Means
Avg. Credit growth (%)	3.61	8.50	7.53	8.83	-1.00
Avg. TFP growth (%)	0.70	0.80	0.76	0.82	-0.35
Avg. rGDP growth (%)	1.72	1.88	1.41	2.08	-4.32
Avg. Inv growth (%)	0.58	0.74	0.49	0.83	-1.74
Avg. LP growth (%)	1.74	1.77	1.57	1.84	-1.82
Avg. Duration (years)	NaN	10.68	9.59	11.31	-1.01
Avg. Time spent in boom	NaN	27.32	9.03	18.29	NaN
Number of Booms	NaN	87	32	55	NaN
Sample Size (years)	1695	929	307	622	NaN

It is instructive to compare our results to results when the HP-filter is used (using a parameter of 100). Tables 4-6 constitute a summary of the results for this boom definition. In this case, there are 44 booms, 21 of which end in a crisis. Of the 1651 years in the sample, only 202 are spent in a boom, 12 percent. The average country spends 6 years in a boom, of which three are in a boom that ends in a crisis. From this

Ireland, Portugal, Spain, Australia, and NZ. Emerging are: Turkey, Argentina, Brazil, Chile, Colombia, Costa Rica, Ecuador, Mexico, Peru, Uruguay, Israel, Korea, Malaysia, Pakistan, the Philippines and Thailand.

Table 2: Descriptive Statistics - Advanced Economies

	Whole Sample	Booms	Booms with a Crisis	Booms without a Crisis	t-Statistic for Means
Avg. Credit growth (%)	5.31	8.33	3.91	9.53	-3.77
Avg. TFP growth (%)	0.66	0.76	0.96	0.71	1.24
Avg. rGDP growth (%)	1.91	2.04	1.87	2.08	-1.07
Avg. Inv growth (%)	0.62	0.87	0.56	0.95	-1.39
Avg. LP growth (%)	2.01	1.88	2.03	1.85	0.96
Avg. Duration (years)	NaN	13.38	13.50	13.35	0.05
Avg. Time spent in boom	NaN	29.00	6.00	23.00	NaN
Number of Booms	NaN	39	8	31	NaN
Sample Size (years)	834	522	108	414	NaN

Table 3: Descriptive Statistics - Emerging Economies

	Whole Sample	Booms	Booms with a Crisis	Booms without a Crisis	t-Statistic for Means
Avg. Credit growth (%)	1.05	8.90	12.84	6.74	3.98
Avg. TFP growth (%)	0.74	0.86	0.64	1.06	-1.73
Avg. rGDP growth (%)	1.49	1.62	1.11	2.07	-4.05
Avg. Inv growth (%)	0.50	0.46	0.41	0.49	-0.26
Avg. LP growth (%)	1.29	1.48	1.07	1.80	-3.05
Avg. Duration (years)	NaN	8.48	8.29	8.67	-0.21
Avg. Time spent in boom	NaN	22.61	11.06	11.56	NaN
Number of Booms	NaN	48	24	24	NaN
Sample Size (years)	861	407	199	208	NaN

point of view, booms are not central to aggregate economic activity. Booms without a crisis have higher labor productivity, but TFP growth is negative, whether the boom ends in a crisis or not. Not much is going on in advanced economies. TFP growth is quite different in emerging economies, but not statistically so.

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

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

Table 7 compares the results of using the HP-filter to detect booms to our results with the agnostic definition of a boom. The first line of the table shows that of the 161 boom-years detected using the HP-filter, 80% of those boom years are in our sample of boom-years. Line 2 shows that of the 40 booms detected with the HP- filter, we detected 91 percent of those boom. The bottom part of the table looks at the overlap of the booms detected with both methods. When do the HP-filter booms start com-

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

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

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

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

pared to our starting date? The table shows that 63 percent of the HP-filter booms started more than three years after our starting point. This, of course, is not surprising because the HP-filter is constraining the data and pushed more of the boom into the trend. So, the HP-filter booms are essentially occurring in the middle of our booms. The average duration of our booms is ten years while the average duration of an HP-filter boom is five years.

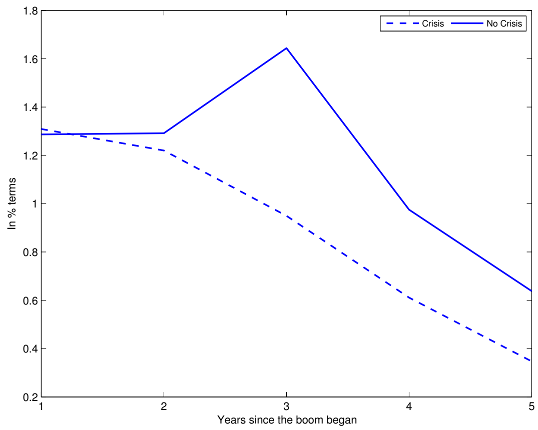
Table 7: Overlap between booms using HP-filter and Gorton and Ordonez (2014)

	Number	As a ratio of HP booms
HP boom-years in GO	161	0.7970
HP booms included in GO	40	0.9091
HP booms	44	1.0000
HP booms included in GO starting		
-in the same year	2	0.0500
-a year later	6	0.1500
-two years later	3	0.0750
-three years later	4	0.1000
-more than three later	25	0.6250

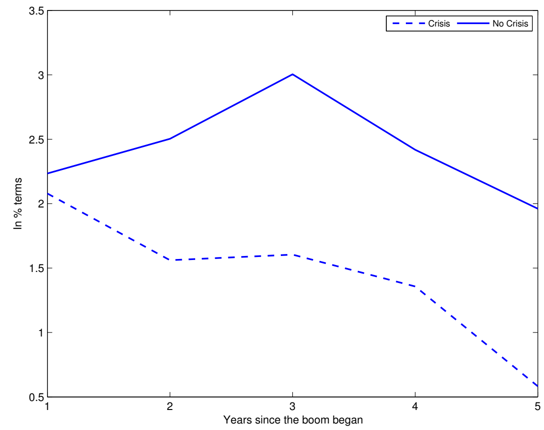
2.3 Booms, Crises and Productivity

The second point we want to make is shown in Figure 1, which shows plots of average growth rates of TFP growth, real GDP, capital formation and labor productivity (LP) for the first five years of booms that ended in a crisis and those that did not. Figure A.1 in the Appendix shows the same variables median growth rates. Note, first that the figures show that a credit boom starts with a positive shock to productivity, but then the paths of these growth rates differ. In the four cases shown in the figures, the positive shock appears. Then, by either measure of productivity, growth seems to die off fairly quickly for booms that end in a crisis compared to booms that do not. Capital formation growth rates and real GDP growth rates are lower for booms that end in a financial crisis.

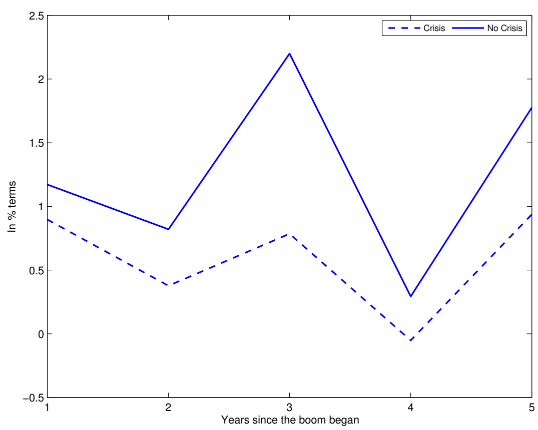
Figure 1: Average Productivity over Good and Bad Booms



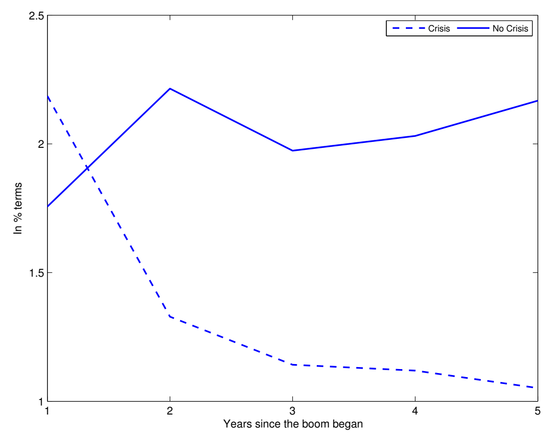
(a) Total Factor Productivity



(b) Real GDP



(c) Capital Formation (Invetsments)



(d) Labor Productivity

We next examine the relationship between financial crises, credit booms, and productivity by looking at whether credit growth predicts crises? And then we ask whether, conditional on credit growth, the growth of productivity has an impact in the likelihood of a crisis. The model is as follows;

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

Finally, we examine the crises in our sample. Our procedure was to start with our definition of a credit boom, apply it each country, and examine Laeven and Valencia (2012) to see if the boom ended in a crisis. Laeven and Valencia have many more countries in their sample then we do, so overall they have more booms. We can reverse this procedure by first identifying all the crises that occur in our sample, based on Laeven and Valencia, and then seeing how they are related to our definition of a boom. Table 8 is a summary of the financial crises in our sample, based on Laeven and Valencia (2012). There are 89 crises in our sample, of which 32 are associated with a boom that ends in one of these crises. There are 41 crises that occur during a boom, but are not at the end of a boom. And there are 16 crises that are in no way associated with a boom; they do not occur during or a boom or at the end of a boom. So, there are good booms and bad booms, but also crises unrelated to booms. Subsequently, in a Probit analysis of what is associated with crises, we will use all of the crises.

Table 8: Financial Crises in the Sample

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

Table 9 shows the results of including credit growth as the sole predictor of crises (that is, imposing the restriction that $\gamma = 0$). There are four parts to the table. The top panel shows the Probit for boom-years and the second looks at booms. In the middle panels, where the sample is booms, the first uses the average growth in credit on the right-hand side. In the other middle panel the boom is measured by the change in credit growth over the boom. Finally, the bottom panel shows the change in credit growth over the five years prior to the observation. This last is closest to the literature and, in fact, does replicate the standard result.[12]

[12] For crises not associated with booms we use the five year rolling credit growth.

Table 9: Credit as Crisis Predictor

boom-years ($N = 929$)	α	β
Coefficient	-0.47	0.34
t-Statistic	-9.85	1.44
booms (averages, $N = 87$)	α	β
Coefficient	-0.70	3.54
t-Statistic	-2.82	1.76
booms (changes, $N = 87$)	α	β
Coefficient	-0.38	0.05
t-Statistic	-1.69	0.24
all data (5 year changes, $N = 1661$)	α	β
Coefficient	-1.62	0.24
t-Statistic	-27.65	2.13

$$Pr(\mathbb{1}_j = 1 | \Delta Credit_j) = \Phi(\alpha + \beta \Delta Credit_j)$$

We are interested in how the growth in TFP and LP are related to the likelihood of a crisis, conditional on credit growth. Tables 10 and 11 add TFP growth and LP growth, respectively, to the same set of Probits. TFP growth mitigates the likelihood of a crisis; the sign is always negative, and significant in two cases. Table 11 showing the results when the growth of LP is added also reveals that this mitigates the likelihood of a crisis. Growth in LP is significant in the same two cases as the growth in TFP, namely, when averages are used and when 5-year changes are used.

This pattern does not arise with HP-filters. In the Appendix, Figures A.2 and A.3 are the counterparts to Figures 1 and A.1 except that they are based on the credit booms determined by HP-filtering. These figures do not display any clear difference between booms that end in a crisis and those that do not. Similarly, there is no predictive power of the growth in productivity on the likelihood of a crisis conditional on credit growth. Tables A.3 and A.4 in the Appendix are the counterparts to the above Tables 10 and 11, except that the booms were determined by HP-filtering.

Table 10: Credit and TFP Growth as Crises Predictors

boom-years ($N = 929$)

	α	γ	β
Coefficient	-0.46	-1.62	0.34
t-Statistic	-9.47	-1.39	1.44

booms (averages, $N = 87$)

	α	γ	β
Coefficient	-0.48	-19.35	2.59
t-Statistic	-1.75	-2.26	1.19

booms (changes, $N = 87$)

	α	γ	β
Coefficient	-0.35	-1.35	0.12
t-Statistic	-1.52	-1.44	0.61

all data (5 year changes, $N = 1661$)

	α	γ	β
Coefficient	-1.59	-1.05	0.25
t-Statistic	-26.64	-1.99	2.18

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

2.4 Productivity, Investment and Real GDP Growth over the Boom

Next we turn to examining the paths of the growth rates of TFP, LP, capital formation and real GDP growth over the boom. We run the following regression over the boom years, starting with the year after the boom begins:

$$\Delta X_{n,t} = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + \alpha_3 t^3 + \mathbb{1}_n(\beta_0 + \beta_1 t + \beta_2 t^2) + \beta_3 t^3) + \epsilon_{n,t} \quad (2)$$

where $X \in \{TFP, LP, INV, RGDP\}$ and ΔX is growth in X over boom n in year t after the boom has started. $\mathbb{1}_n$ is an indicator that takes the value 1 if boom n is followed by a financial crisis. If the pattern of the growth rate of X is unrelated to crises, then the betas should be insignificantly different from zero. If any beta is significantly different from zero, then it would show that the level (or slope, or curvature) of the growth of X over crisis booms is different from X growth over non-crisis booms.

The first two panels in Table 12 show the results for TFP growth and for LP growth. The results show little for TFP growth, but LP growth is marginally different over the two boom types. The last two panels in Table 12 show the results for capital formation and real GDP growth. No statistical significance in for either variable. Nevertheless,

Table 11: Credit and LP Growth as Crises Predictors

boom-years ($N = 929$)			
	α	γ	β
Coefficient	-0.55	-1.79	0.19
t-Statistic	-8.29	-1.19	0.76
booms (averages, $N = 87$)			
	α	γ	β
Coefficient	-0.33	-16.55	2.62
t-Statistic	-0.98	-2.06	1.30
booms (changes, $N = 87$)			
	α	γ	β
Coefficient	-0.10	-0.96	-0.11
t-Statistic	-0.39	-1.51	-0.48
all data (5 year changes, $N = 1661$)			
	α	γ	β
Coefficient	-1.50	-1.66	0.12
t-Statistic	-15.48	-2.73	0.85

$$Pr(\mathbb{1}_j = 1|\Delta LP_j, \Delta Credit_j) = \Phi(\alpha + \gamma\Delta LP_j + \beta\Delta Credit_j)$$

the fitted values from these regressions are revealing. Figure 2 shows the fitted values. The patterns are clearly different. Figure A.4 in the Appendix shows the fitted values based on the HP filtering of booms (the regression results are omitted for the sake of space). What is interesting about Figure A.4 is that LP shows the same pattern, although it is essentially looking at the middle of one of our credit booms. The other panels are uninformative.

Table 12: Trend of TFP Growth over Booms

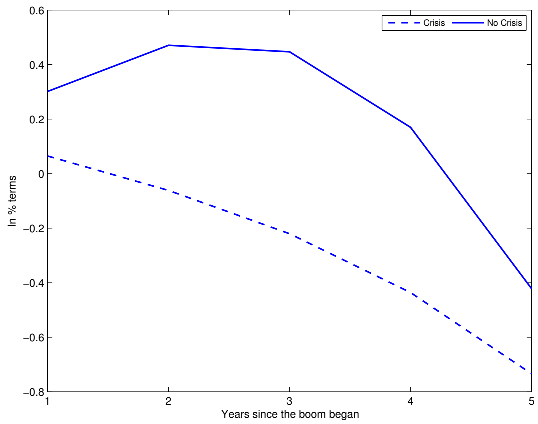
TFP	α_1	α_2	α_3	β_0	β_1	β_2	β_3
Coefficient	0.35	-0.04	-0.01	0.18	-0.47	0.04	0.01
t-Statistic	0.19	-0.05	-0.13	0.08	-0.15	0.04	0.05

LP	α_1	α_2	α_3	β_0	β_1	β_2	β_3
Coefficient	1.22	-0.42	0.04	3.70	-5.24	1.83	-0.20
t-Statistic	1.68	-1.26	1.02	1.96	-1.94	1.71	-1.60

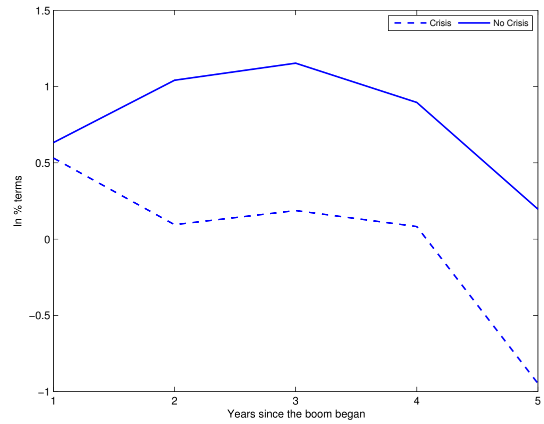
INV	α_1	α_2	α_3	β_0	β_1	β_2	β_3
Coefficient	1.65	-0.72	0.09	-0.23	0.28	-0.24	0.02
t-Statistic	1.30	-1.24	1.21	-0.06	0.06	-0.12	0.07

RGDP	α_1	α_2	α_3	β_0	β_1	β_2	β_3
Coefficient	0.72	-0.08	-0.01	2.22	-3.28	1.07	-0.11
t-Statistic	0.70	-0.18	-0.24	1.31	-1.34	1.11	-0.98

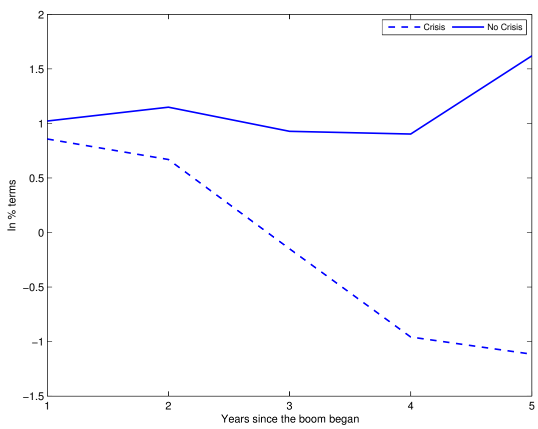
Figure 2: Fitted Values of Measures of Productivity over Good and Bad Booms



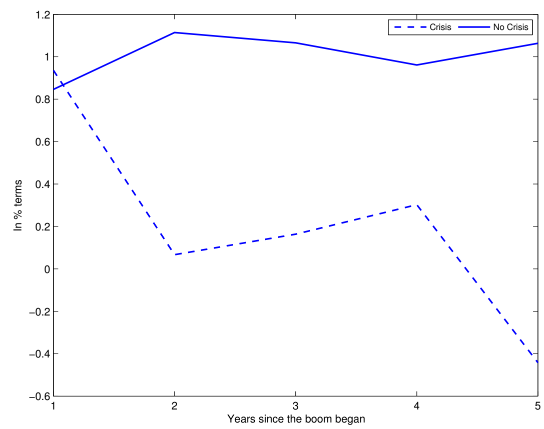
(a) Total Factor Productivity



(b) Real GDP



(c) Capital Formation (Invetsments)



(d) Labor Productivity

2.5 Summary

We take the following points from this empirical study:

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

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

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

3 The Model

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

3.1 Setting

The economy is characterized by two overlapping generations – young and old – each a continuum of agents with mass 1, and two types of goods – *numeraire* and *"land"*. Each generation is risk neutral and derives utility from consuming numeraire at the end of each period. Numeraire is non-storable, productive and reproducible – it can be used as *"capital"* to produce more numeraire, hence we denote it by K. Land is storable, but non-productive and non-reproducible.

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

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

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

Households and firms not only differ in their managerial skills, but also in their initial endowments. Firms are born with an endowment of numeraire $\overline{K}_f < \widehat{K}^*$, not enough to sustain optimal production in the economy. Similarly, households are born with an endowment of numeraire $\overline{K} > K^* \equiv \widehat{K}^* - \overline{K}_f$, such that there is enough endowment in the economy to sustain optimal production.

Even when non-productive, land potentially has an intrinsic value. If land is *"good"*, it can delivers C units of K, but only once. If land is *"bad"*, it does not deliver anything.

We assume a fraction $\hat{p}$ of land is good. At the beginning of the period, different units of land i can potentially be viewed differently, with respect to their quality. We denote these priors of being good p_i and assume they are commonly known by all agents.[13] Observing the quality of land costs γ_b units of numeraire to land holders (young borrowers), and γ_l units of numeraire to land non-holders (lenders).

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

In this simple setting, resources are in the wrong hands. Households only have numeraire while firms have managerial skills but less numeraire than needed. Since production is efficient, if output was verifiable it would be possible for households to lend the optimal amount of numeraire K^* to firms using state contingent claims. In contrast, if output is non-verifiable, firms would never repay and households would never be willing to lend.

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

The perception about the quality of collateral then becomes critical in facilitating loans. To be precise, we will assume that $C > K^*$. This implies that land that is known to be good can sustain the optimal loan, K^*. Contrarily, land that is known to be bad is not able to sustain any loan. We refer to firms that have land with a positive probability of being good ($p > 0$) as *active firms*. In contrast to firms that are known to hold bad land, these firms can actively participate in the loan market to raise funds to start their projects.[14]

[13] 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.

[14] The assumption that active firms are those for whom $p > 0$ is just imposed for simplicity, and

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

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

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

3.2 Optimal loan for a single firm

We now turn to the two-sided information acquisition, which is the second extension of Gorton and Ordonez (2014). To start we study the optimal short-term collateralized debt for a single firm, with a project that has a probability of success q and when there is a total mass of active firms η. Both borrowers and lenders may want to produce information about its collateral, which is good with probability p.[15] Loans that trigger information production (information-sensitive debt) are costly – either borrowers acquire information at a cost γ_b or have to to compensate lenders for their information cost γ_l. However, loans that do not trigger information production (information-insensitive debt) may be infeasible because they introduce the fear

is clearly not restrictive. If we add a fixed cost of operation, then it would be necessary a minimum amount of funding to operate, and firms having collateral with small but strictly positive beliefs p would not be considered active either.

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

of asymmetric information – they introduce incentives for either the borrower or the lender to deviate and acquire private information to take advantage of its counterparty. The magnitude of this fear determines the information-sensitivity of the debt and, ultimately the volume and dynamics of information in the economy.

3.2.1 Information-Sensitive Debt

Lenders can learn the true value of the borrower's land by using γ_l of numeraire. Borrowers can learn the value of their own land by using γ_b of numeraire. Since borrowers have to divert numeraire from production to discover the quality of the collateral, their opportunity cost is $\gamma_b qA$.

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

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

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

In this setting debt is risk-free, that is firms will pay the same in the case of success or failure. If $R^l_{IS} > x^l_{IS}C$, firms always default, handing in the collateral rather than repaying the debt. Contrarily, if $R^l_{IS} < x^l_{IS}C$ firms always sell the collateral directly at a price C and repay lenders R^l_{IS}. This condition pins down the fraction of collateral posted by a firm, as 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 interest rates and the fraction of collateral that has to be posted do not depend on q because debt is risk-free, firms cannot signal their q by offering to pay different interest rates. Intuitively, since collateral prevents default completely, the loan cannot be used to signal the probability of default.

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

Expected total profits are $p(qAK - x^l_{IS}C) + \bar{K}_f(qA-1) + pC$. Then, plugging x^l_{IS} in equilibrium, *expected net profits* (net of the land value pC and net of production using own numeraire $\bar{K}_f(qA-1)$) from information-sensitive debt when lenders acquire information are

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

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

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

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

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

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

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

$$E(\pi|p,q,IS) = \max\left\{pK^*(qA-1) - \min\{\gamma_b(qA-1), \gamma_l\}, 0\right\}. \tag{3}$$

3.2.2 Information-Insensitive Debt

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

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

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

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

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

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

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

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

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

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

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

Similarly, borrowers want to deviate if the expected gains from acquiring information, evaluated at x_{II} and R_{II}, are greater than the losses γ_b from acquiring information. Specifically, if borrowers acquire information, their expected benefits, net of the costs of information, are $pK^*(qA-1)+(1-p)K(qA-1)-\gamma_b(qA-1)$ (with probability p they find the land is good, disclose it and obtain a loan for K^* and with probability $1-p$ they find the land is bad, do not disclose it and obtain a loan at the original contract K). If borrowers do not acquire information, their benefits are $K(qA-1)$. Hence borrowers do not acquire information if

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

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

$$K > K^* - \frac{\gamma_b}{p}. \tag{5}$$

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

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

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

Hence, the loan size from information-insensitive debt is

$$\begin{aligned} K(p|\widehat{q}(\eta), II) &= \min\left\{K^*, \frac{\gamma_l}{(1-p)(1-\widehat{q}(\eta))}, pC\right\} \\ s.t.\ \ \frac{\gamma_l}{(1-p)(1-\widehat{q}(\eta))} &> K^* - \frac{\gamma_b}{p} \end{aligned} \tag{7}$$

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

$$E(\pi|p,q,II) = K(p|\widehat{q}(\eta), II)(qA-1). \tag{8}$$

3.2.3 Borrowing Inducing Information or Not?

Figure 3 shows the ex-ante expected profits in both regimes (information sensitive and insensitive) for a firm with private information about its own probability of success q, net of the expected value of land and net of the production that can be funded with own numeraire, for each possible p, assuming $\gamma_b(qA-1) \leq \gamma_l$ for $q \in [q_L, q_H]$.[17]

The dotted blue line shows the net expected profits in the information-sensitive regime (equation 3), while the solid black function shows the net expected profits in the information-insensitive regime (equation 8). The solid black concave curve shows the left hand side of the constraint in equation (6) while the dashed green convex curve shows the right hand side of the constraint.[18] Since the information insensitive regime is infeasible when the concave curve is smaller than the convex curve, the red solid function, which represent the net expected profits of borrowers subject to constraint (6) is equal to the information-sensitive expected profits in the IS range and to the information-insensitive expected profits in the II range.

The cutoffs highlighted in Figure 3 are determined in the following way:

1. The cutoff p^H is the belief under which firms reduce borrowing, under optimal K^*, to prevent information production, from equation (4)

$$p^H = 1 - \frac{\gamma_l}{K^*(1-\widehat{q}(\eta))}. \tag{9}$$

The cutoff p^L is also obtained from equation (4), where the value of collateral is more restrictive than the possibility of information deviation,[19]

$$p^L = \frac{1}{2} - \sqrt{\frac{1}{4} - \frac{\gamma_l}{C(1-\widehat{q}(\eta))}}. \tag{10}$$

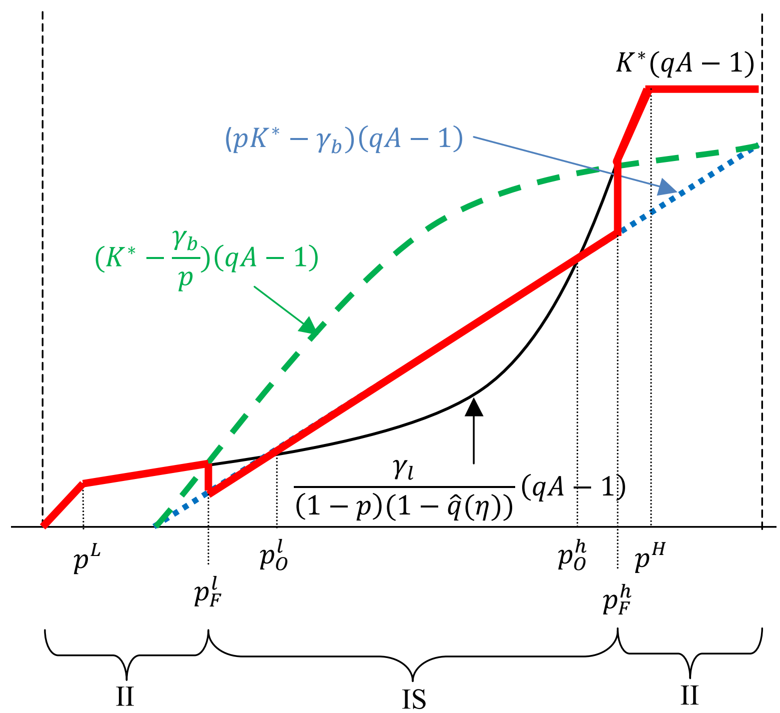
2. Cutoffs p_O^l and p_O^h show the beliefs at which firms optimally change from one regime to the other, and are obtained from equalizing expected profits of information-

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

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

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

Figure 3: Information-Sensitivity with Two-Sided Acquisition



sensitive and insensitive loans and solving the quadratic equation

$$pK^* - \gamma_b = \frac{\gamma_l}{(1-p)(1-\widehat{q}(\eta))}. \tag{11}$$

3. Cutoffs p^l_F and p^h_F show the beliefs at which information-insensitive debt becomes infeasible and are obtained from condition (6)

$$K^* - \frac{\gamma_b}{p} = \frac{\gamma_l}{(1-p)(1-\widehat{q}(\eta))}. \tag{12}$$

Whenever $\gamma_b(qA-1) \leq \gamma_l$, as is clear from equations (11) and (12), and shown in the figure, $p^l_F < p^l_O$ and $p^h_F > p^h_O$. This implies that there are regions of beliefs $[p^l_F, p^l_O]$ and $[p^h_O, p^h_F]$ for which the firm would prefer information-insensitive debt, but it is simply infeasible. There is a cost of information γ_b large enough with respect to γ_l such that $p^l_F > p^l_O$ and $p^h_F < p^h_O$. In this case the non-feasibility of information-insensitive debt becomes irrelevant since, even when feasible, firms prefer paying the cost of information production rather than reducing borrowing to discourage information production.

We can summarize the expected loan sizes for different beliefs p, graphically represented in red/bold in Figure 3, by

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

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

It is also simple to see that $K(p)$ increases with q in the intermediate range, increases with $\widehat{q}(\eta)$ in the second and fourth ranges and is independent of q in the first and last ranges. Furthermore, as is clear from equations (9) and (10), the range in which information-insensitive loans are infeasible, $[p_F^l, p_F^h]$ shrinks as $\widehat{q}(\eta)$ increases.

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

3.3 Aggregation

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

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

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

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

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

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

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

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

4 Dynamics

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

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

Specifically, we assume that initially (at period 0) there is perfect information about which collateral is good and which is bad, a situation that we denote by *"symmetric information"*. In every period, with probability λ the true quality of each unit of land remains unchanged and with probability $(1-\lambda)$ there is an idiosyncratic shock that changes its type. In this last case, land becomes good with a probability $\hat{p}$, independent of its current type. Even when the shock is observable, the realization of the new quality is not, unless some numeraire good $\min\{\gamma_b, \gamma_l\}$ is used to learn about it.[20]

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

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

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

Proposition 1 *Constant Symmetric Information - Constant Consumption.*

If $\widehat{q}(\chi)$ is such that $p_F^l(\widehat{q}(\chi)) < \hat{p} < p_F^h(\widehat{q}(\chi))$, from equation (12), then there is information acquisition for collateral suffering idiosyncratic shocks and consumption is constant every

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

period,

$$\overline{W}(\hat{p}) = \overline{K} + (\overline{K}_f + \hat{p}K^* - (1-\lambda)\gamma_b)(q_H A - 1). \tag{13}$$

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

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

Since $K(0) = 0$, $K(1) = K^*$ and $K(\hat{p}) = \hat{p}K^* - \gamma_b$. Then consumption is constant (equation (13)) at the level at which information is reacquired every period. Q.E.D.

Maintaining the assumption that $\hat{p}$ is relatively high, the incentives to acquire information depend on the evolution of the relevant threshold for information acquisition, given by p_F^h in Figure 3. As is clear from equation (12), this threshold depends on $\widehat{q}(\eta)$. The next Lemma discusses these effects.

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

Proof From equation (12), it is clear that the right hand side increases with $\hat{q}(\eta)$, then decreasing the range of information-insensitive debt, this is decreases $p^h(\hat{q}(\eta))$ and increases $p^l(\hat{q}(\eta))$. Q.E.D.

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

Proposition 2 *Information Cycles.*

If $\widehat{q}(\chi)$ *is such that* $\hat{p} > p_F^h(\widehat{q}(\chi))$ *and* $\hat{q}(1)$ *is such that* $\hat{p} < p_F^h(\hat{q}(1))$*, from equation (12), then there are information cycles. Under the conditions for consumption growth in the previous proposition, there is a length of the boom* t^* *at which consumption crashes to the symmetric information consumption, restarting the cycle.*

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

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

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

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

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

4.1 Productivity Shocks

In this section we explore the evolution of credit and production in the presence of shocks to aggregate productivity $\widehat{q}A$. Interestingly, shocks to the two different components of measured productivity, the probability of success, $\widehat{q}$, and productivity conditional on success, A, affect credit booms and busts very differently, since only $\widehat{q}$ matters for credit markets. We constructed the model such that it has this property and we can disentangle different types of productivity changes.

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

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

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

Proposition 3 *Productivity shocks and likelihood of crises.*

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

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

From equation (12), the cutoff $p_F^h(\widehat{q})$ always decreases with ψ' since the left hand side does not change, while the right hand side increases with ψ'. Q.E.D.

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

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

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

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

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

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

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

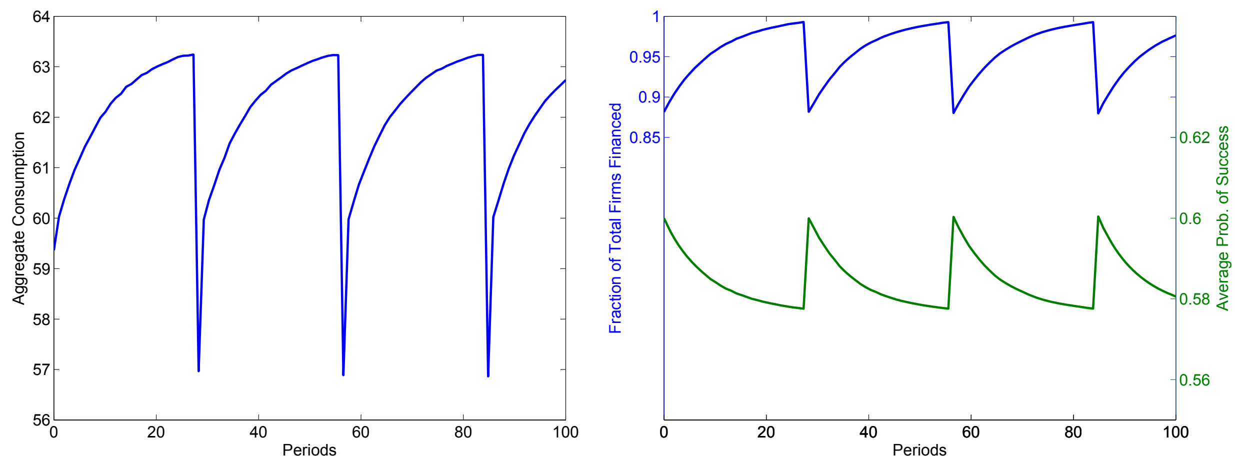
It is an interesting avenue for future empirical research to disentangle the effects of productivity shocks into the real effects highlighted by the standard literature and the effects on real activity through the incentives for information acquisition that affect the functioning of credit markets.

4.2 Numerical Illustration

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

We simulate 100 periods, starting from a situation of symmetric information, in which all collateral is known to be either good or bad. In this situation of symmetric information all projects operate with $q_H = 0.6$. Figure 4 shows that over time, as information decays, a larger fraction of firms obtain funds, which implies more projects in the economy. When the projects that obtain funds exceed $\hat{p}$, they have to operate with projects of lower productivity, $q_L = 0.4$, which decreases the marginal productivity in the economy. This decline generates a gradual increase in the cutoff $p_F^h(\widehat{q}(\eta_t))$ over time. When $p_F^h(\widehat{q}(\eta_t)) > \hat{p}$, then information is produced and only good collateral (a fraction $\hat{p}$) gets credit; there is a collapse in output and consumption and the cycle starts again. Here the dynamics are completely endogenous, generated by an endogenous increase in cutoffs p_F^h and p^H rather than by an exogenous reduction in the expected quality of collateral $\hat{p}$ or in productivity.

Figure 4: Purely Endogenous Cycles



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

4.3 Policy Implications

There is a clear externality in our setting. When firms decide to take an information-insensitive loan, it does not internalize the effect in reducing the average productivity in the economy. Since the incentives to acquire information increase when such average productivity declines, firms do not internalize the effect on the feasibility of a "symmetric ignorance" regime.

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

5 Conclusions

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

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

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

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

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

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

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

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A Appendix

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

Table A.1: Booms in the Sample

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

Table A.2 shows the number of booms, number of bad booms, the frequency of boom periods and the average time between booms for each country in our sample. If there was only one boom, then the average time between booms is not available (NA). Otherwise it is computed as the average number of years from a boom end to the subsequent boom start.

Table A.2: Frequency of Booms

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

A.1 Robustness

Table A.3: HP-filtered Credit and TFP Growth as Crises Predictors

boom-years ($N = 202$)

	α	γ	β
Coefficient	-0.10	-4.03	0.23
t-Statistic	-0.88	-1.65	0.30

booms (averages, $N = 44$)

	α	γ	β
Coefficient	-0.09	-22.13	-1.99
t-Statistic	-0.24	-1.76	-0.46

booms (changes, $N = 44$)

	α	γ	β
Coefficient	-0.18	-5.34	-0.21
t-Statistic	-0.48	-1.89	-0.23

all data (5 year changes, $N = 1624$)

	α	γ	β
Coefficient	-1.70	-1.51	0.42
t-Statistic	-21.35	-2.27	2.52

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

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

boom-years ($N = 202$)

	α	γ	β
Coefficient	-0.14	-2.66	-0.18
t-Statistic	-1.15	-0.74	-0.21

booms (averages, $N = 44$)

	α	γ	β
Coefficient	0.18	-6.53	-3.70
t-Statistic	0.35	-0.49	-0.67

booms (changes, $N = 44$)

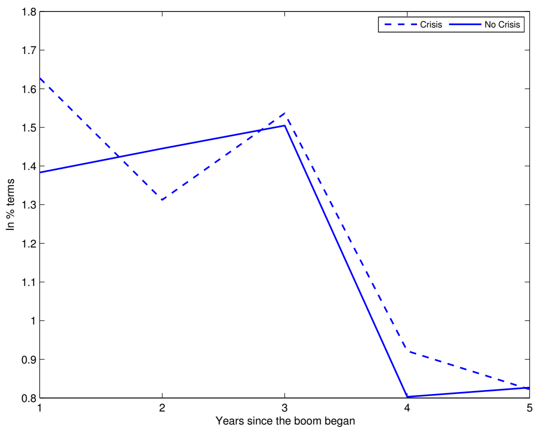
	α	γ	β
Coefficient	0.16	-2.08	-0.69
t-Statistic	0.34	-0.69	-0.60

all data (5 year changes, $N = 1624$)

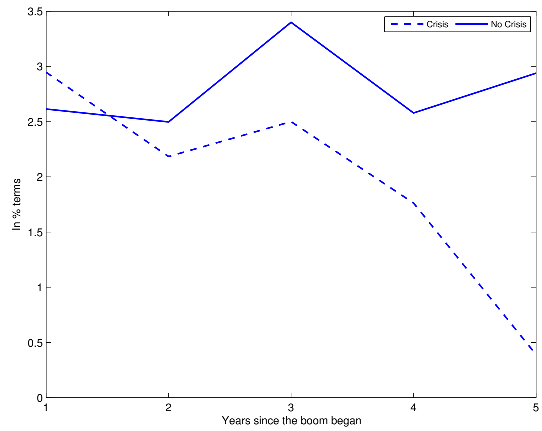
	α	γ	β
Coefficient	-1.67	-2.71	0.52
t-Statistic	-11.96	-2.79	1.93

$$Pr(\mathbb{1}_j = 1 | \Delta LP_j, \Delta Credit_j) = \Phi(\alpha + \gamma \Delta LP_j + \beta \Delta Credit_j)$$

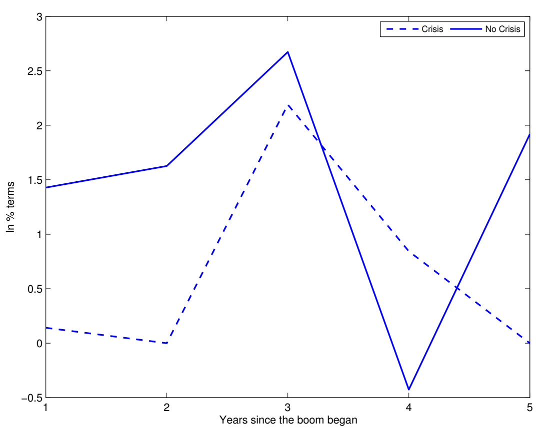
Figure A.1: Median Productivity over Good and Bad Booms



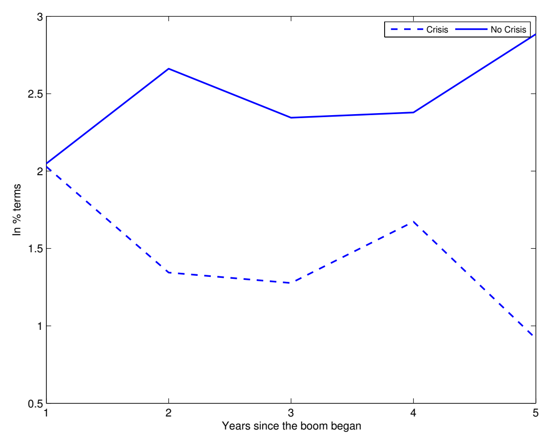
(a) Total Factor Productivity



(b) Real GDP

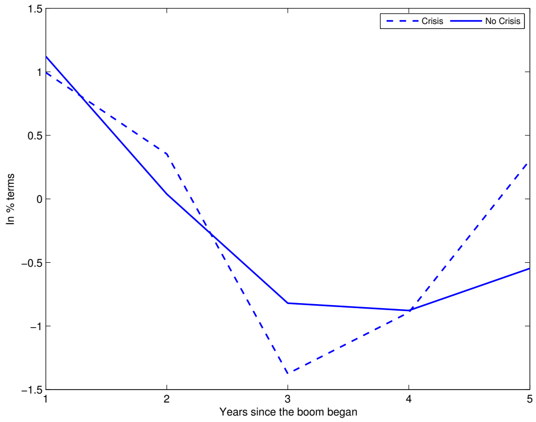


(c) Capital Formation (Invetsments)

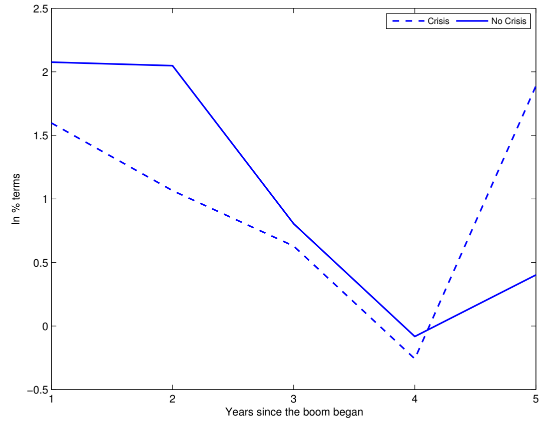


(d) Labor Productivity

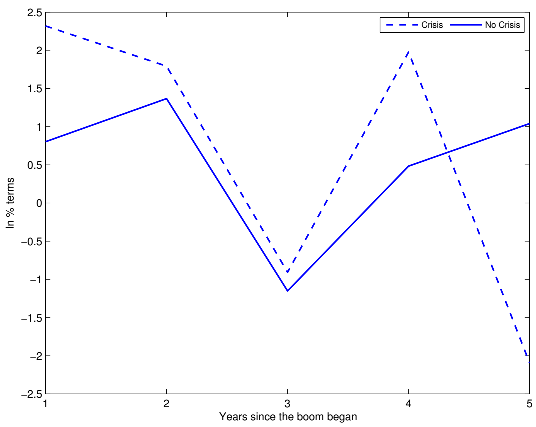
Figure A.2: Average Productivity over Good and Bad Booms (H-P filter)



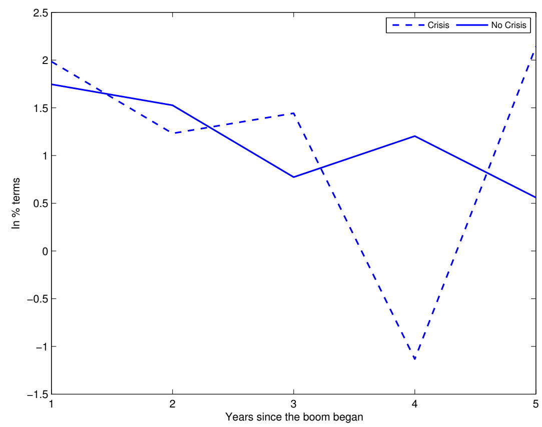
(a) Total Factor Productivity



(b) Real GDP

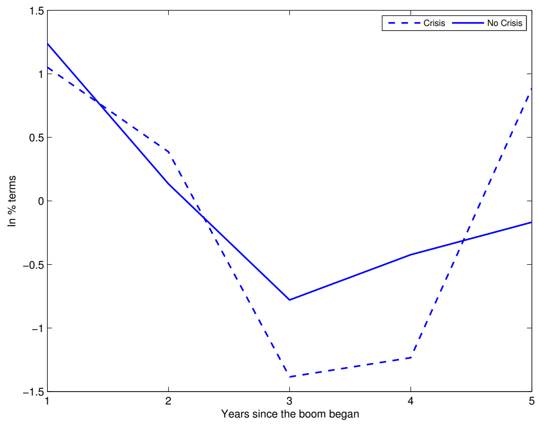


(c) Capital Formation (Invetsments)

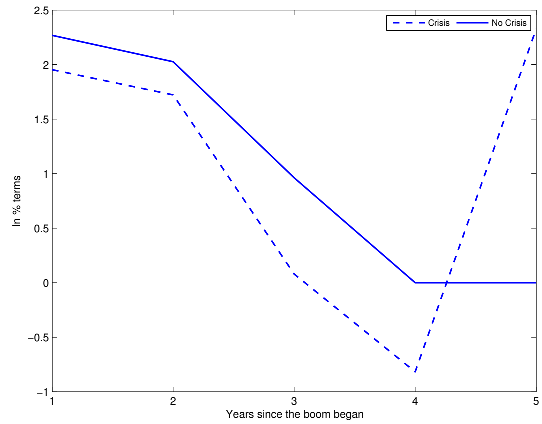


(d) Labor Productivity

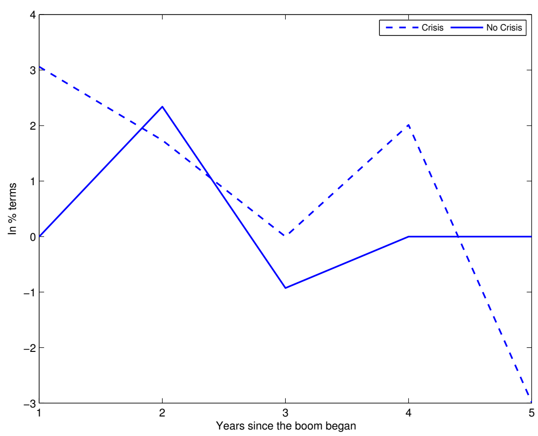
Figure A.3: Median Productivity over Good and Bad Booms (H-P filter)



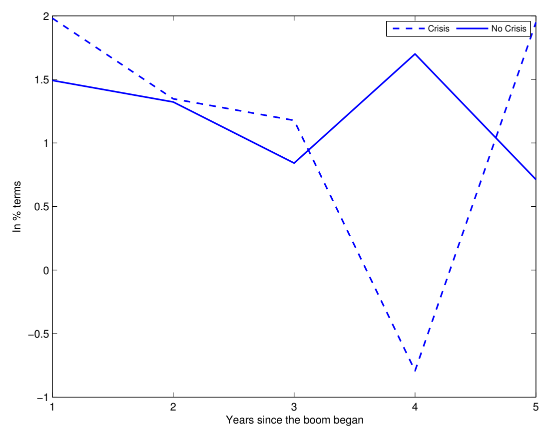
(a) Total Factor Productivity



(b) Real GDP

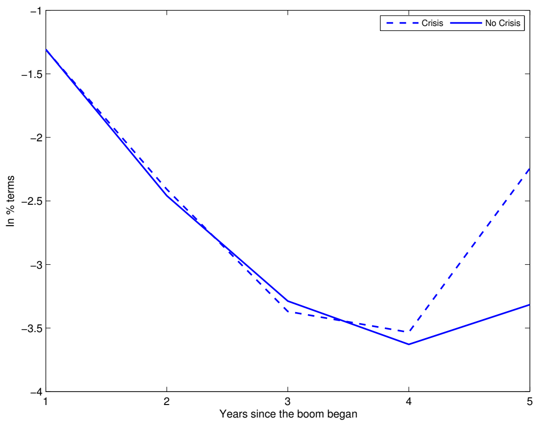


(c) Capital Formation (Invetsments)

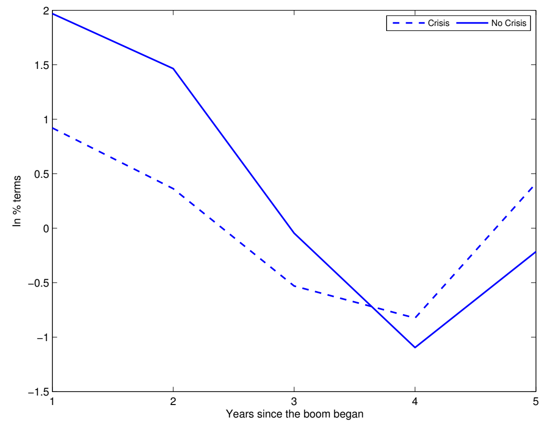


(d) Labor Productivity

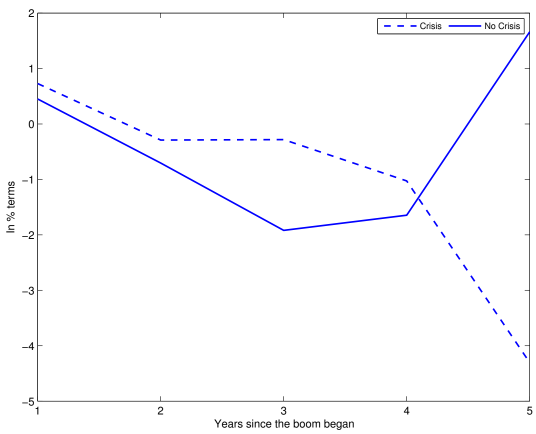
Figure A.4: Fitted Values of Measures of Productivity over Good and Bad Booms (H-P filter)



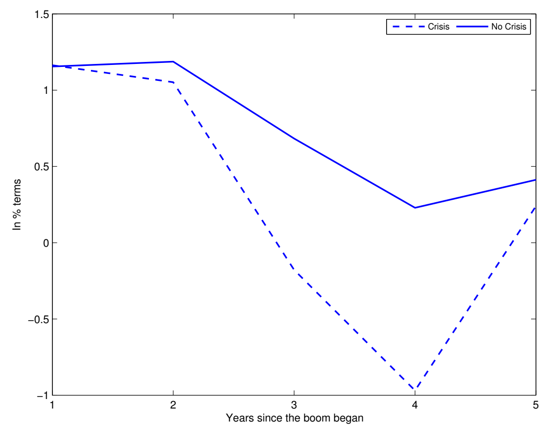
(a) Total Factor Productivity



(b) Real GDP



(c) Capital Formation (Invetsments)



(d) Labor Productivity

A.2 Outliers

Table A.5: TFP Outliers

	Year	Country	TFP	Credit	Classification	Advanced
1	1961	Japan	8.14	1.03	no crisis	Advanced
2	1964	Japan	6.94	-3.57	no crisis	Advanced
3	1970	Japan	5.02	41.04	no crisis	Advanced
4	1969	Greece	7.04	3.17	crisis	Advanced
5	1970	Greece	5.38	6.74	crisis	Advanced
6	1995	Ireland	6.57	55.50	no crisis	Advanced
7	1997	Ireland	6.93	12.41	no crisis	Advanced
8	1983	Portugal	-8.73	1.61	crisis	Advanced
9	1961	Spain	11.15	3.74	crisis	Advanced
10	1962	Spain	6.96	9.28	crisis	Advanced
11	1963	Spain	6.20	3.15	crisis	Advanced
12	1966	Turkey	7.62	4.57	no crisis	Developing
13	2007	Turkey	11.32	13.70	no crisis	Developing
14	1977	New Zealand	-5.21	5.40	no crisis	Advanced
15	1969	Argentina	6.27	15.24	no crisis	Developing
16	1978	Argentina	-5.32	11.83	crisis	Developing
17	1981	Argentina	-8.46	32.12	crisis	Developing
18	1999	Argentina	-5.62	3.06	crisis	Developing
19	2005	Argentina	5.76	9.38	no crisis	Developing
20	2007	Argentina	5.05	8.45	no crisis	Developing
21	1968	Brazil	6.38	15.50	no crisis	Developing
22	1970	Brazil	5.62	16.49	no crisis	Developing
23	1971	Brazil	6.21	20.74	no crisis	Developing
24	1992	Brazil	-6.26	87.04	crisis	Developing
25	1975	Chile	-17.24	36.93	crisis	Developing
26	1977	Chile	7.87	24.29	crisis	Developing
27	1978	Chile	6.23	44.62	crisis	Developing
28	1979	Chile	6.47	25.23	crisis	Developing
29	1995	Chile	9.02	3.40	no crisis	Developing
30	1997	Colombia	15.34	3.26	crisis	Developing
31	1965	Costa Rica	6.26	2.22	no crisis	Developing
32	1991	Mexico	-17.91	19.90	crisis	Developing
33	2005	Mexico	11.28	8.08	no crisis	Developing
34	2009	Mexico	-9.77	9.28	no crisis	Developing
35	1982	Peru	-5.16	12.77	crisis	Developing
36	1983	Peru	-18.02	18.12	crisis	Developing
37	1994	Peru	9.84	14.92	crisis	Developing
38	1999	Uruguay	-5.67	7.59	crisis	Developing
39	2002	Uruguay	-14.92	30.94	crisis	Developing
40	1966	Israel	-5.69	17.19	crisis	Developing
41	1974	Egypt	-7.00	25.37	crisis	Developing
42	1976	Egypt	12.98	0.96	crisis	Developing
43	1978	Egypt	5.21	-0.78	crisis	Developing
44	1965	India	-5.05	8.59	no crisis	Developing
45	1999	India	7.54	7.37	no crisis	Developing
46	1966	Korea	6.86	8.70	no crisis	Developing
47	1969	Korea	6.63	25.11	no crisis	Developing
48	1980	Korea	-10.26	14.43	no crisis	Developing
49	1998	Korea	-10.29	9.19	no crisis	Advanced
50	1999	Korea	9.31	8.71	no crisis	Advanced
51	1998	Malaysia	-12.86	0.08	crisis	Developing
52	1963	Pakistan	5.21	15.95	crisis	Developing
53	1965	Pakistan	5.91	4.69	crisis	Developing
54	1970	Thailand	6.14	14.49	crisis	Developing

Table A.6: LP Outliers

	Year	Country	LP	Credit	Classification	Advanced
1	1971	UK	5.19	4.93	no crisis	Advanced
2	1964	Austria	6.90	5.23	no crisis	Advanced
3	1966	Austria	7.44	5.46	no crisis	Advanced
4	1967	Austria	5.63	1.58	no crisis	Advanced
5	1968	Austria	5.54	1.24	no crisis	Advanced
6	1961	Belgium	5.45	7.90	no crisis	Advanced
7	1963	Belgium	5.05	12.31	no crisis	Advanced
8	1964	Belgium	6.91	-0.68	no crisis	Advanced
9	1965	France	5.10	5.46	no crisis	Advanced
10	1967	France	5.95	7.95	no crisis	Advanced
11	1968	France	5.83	8.13	no crisis	Advanced
12	1969	France	9.03	0.92	no crisis	Advanced
13	1964	Netherlands	6.59	-0.69	no crisis	Advanced
14	1963	Sweden	5.25	6.44	no crisis	Advanced
15	1964	Sweden	8.48	39.55	no crisis	Advanced
16	1961	Japan	10.37	1.03	no crisis	Advanced
17	1962	Japan	8.67	30.63	no crisis	Advanced
18	1963	Japan	7.87	9.92	no crisis	Advanced
19	1964	Japan	9.86	-3.57	no crisis	Advanced
20	1965	Japan	5.04	3.85	no crisis	Advanced
21	1970	Japan	10.04	41.04	no crisis	Advanced
22	1972	Japan	8.39	7.88	no crisis	Advanced
23	1988	Japan	5.18	5.21	crisis	Advanced
24	1967	Greece	7.22	7.03	crisis	Advanced
25	1968	Greece	8.36	5.72	crisis	Advanced
26	1969	Greece	10.75	3.17	crisis	Advanced
27	1970	Greece	8.54	6.74	crisis	Advanced
28	1971	Greece	7.25	9.06	crisis	Advanced
29	1997	Greece	5.81	3.70	no crisis	Advanced
30	1977	Ireland	6.29	4.10	no crisis	Advanced
31	1978	Ireland	6.97	11.71	no crisis	Advanced
32	1980	Ireland	5.96	-1.28	no crisis	Advanced
33	1995	Ireland	5.42	55.50	no crisis	Advanced
34	1996	Ireland	5.52	6.37	no crisis	Advanced
35	1997	Ireland	8.26	12.41	no crisis	Advanced
36	1963	Portugal	6.92	5.96	no crisis	Advanced
37	1964	Portugal	7.58	6.41	no crisis	Advanced
38	1965	Portugal	8.45	4.49	no crisis	Advanced
39	1966	Portugal	5.26	1.98	no crisis	Advanced
40	1967	Portugal	8.91	-2.05	no crisis	Advanced
41	1961	Spain	12.62	3.74	crisis	Advanced
42	1962	Spain	10.74	9.28	crisis	Advanced
43	1963	Spain	9.43	3.15	crisis	Advanced
44	1964	Spain	9.20	7.40	crisis	Advanced
45	1965	Spain	5.76	8.77	crisis	Advanced
46	1966	Turkey	10.85	4.57	no crisis	Developing
47	1968	Turkey	6.69	0.99	no crisis	Developing
48	1997	Turkey	8.28	15.21	crisis	Developing
49	2003	Turkey	6.10	0.17	no crisis	Developing
50	2004	Turkey	8.71	18.78	no crisis	Developing
51	2005	Turkey	5.12	28.77	no crisis	Developing
52	1967	Australia	5.03	3.19	no crisis	Advanced
53	1977	New Zealand	-6.11	5.40	no crisis	Advanced
54	1969	Argentina	7.59	15.24	no crisis	Developing
55	1978	Argentina	-5.11	11.83	crisis	Developing
56	1979	Argentina	5.48	17.02	crisis	Developing
57	1981	Argentina	-5.35	32.12	crisis	Developing
58	1968	Brazil	6.00	15.50	no crisis	Developing
59	1969	Brazil	5.77	59.00	no crisis	Developing
60	1970	Brazil	6.80	16.49	no crisis	Developing
61	1975	Chile	-9.36	36.93	crisis	Developing
62	1977	Chile	5.38	24.29	crisis	Developing
63	1978	Chile	7.47	44.62	crisis	Developing
64	1979	Chile	6.43	25.23	crisis	Developing
65	1995	Chile	8.07	3.40	no crisis	Developing
66	1997	Chile	6.92	24.27	no crisis	Developing
67	1999	Costa Rica	5.04	9.57	no crisis	Developing
68	2008	Ecuador	7.84	3.62	no crisis	Developing
69	1961	Peru	7.27	8.83	no crisis	Developing
70	1962	Peru	5.87	2.37	no crisis	Developing
71	1964	Peru	5.39	0.23	no crisis	Developing
72	1965	Peru	5.07	6.02	no crisis	Developing
73	1975	Peru	5.71	0.93	crisis	Developing
74	1983	Peru	-17.28	18.12	crisis	Developing
75	1994	Peru	7.14	14.92	crisis	Developing
76	1998	Uruguay	11.72	56.42	crisis	Developing
77	2002	Uruguay	-7.78	30.94	crisis	Developing
78	1966	Korea	9.86	8.70	no crisis	Developing
79	1968	Korea	5.36	50.88	no crisis	Developing
80	1969	Korea	9.92	25.11	no crisis	Developing
81	1979	Korea	5.84	8.27	no crisis	Developing
82	1996	Korea	5.37	6.54	no crisis	Advanced
83	1997	Korea	6.20	9.83	no crisis	Advanced
84	1999	Korea	8.46	8.71	no crisis	Advanced
85	2007	Korea	5.64	6.02	no crisis	Advanced

Continued on next page

Table A.6 – *Continued from previous page*

	Year	Country	LP	Credit	Classification	Advanced
86	1994	Malaysia	6.66	2.59	crisis	Developing
87	1996	Malaysia	5.51	13.84	crisis	Developing
88	1998	Malaysia	-7.33	0.08	crisis	Developing

Table A.7: INV Outliers

	Year	Country	INV	Credit	Classification	Advanced
1	1973	UK	18.41	18.01	no crisis	Advanced
2	1974	UK	-6.80	3.94	no crisis	Advanced
3	1980	UK	-15.40	1.70	no crisis	Advanced
4	1981	UK	-9.21	18.56	no crisis	Advanced
5	1982	UK	10.48	10.24	no crisis	Advanced
6	1983	UK	10.39	9.12	no crisis	Advanced
7	2003	UK	5.09	3.25	crisis	Advanced
8	1964	Austria	17.69	5.23	no crisis	Advanced
9	1966	Austria	11.27	5.46	no crisis	Advanced
10	1961	Belgium	13.80	7.90	no crisis	Advanced
11	1964	Belgium	19.50	-0.68	no crisis	Advanced
12	1986	Belgium	5.53	3.43	no crisis	Advanced
13	1987	Belgium	9.15	7.07	no crisis	Advanced
14	1988	Belgium	18.70	10.85	no crisis	Advanced
15	1989	Belgium	10.26	16.19	no crisis	Advanced
16	1990	Belgium	7.33	-0.63	no crisis	Advanced
17	2005	Belgium	7.82	3.61	no crisis	Advanced
18	2007	Belgium	6.92	10.80	no crisis	Advanced
19	2009	Belgium	-9.33	3.82	no crisis	Advanced
20	1984	Denmark	18.91	6.30	no crisis	Advanced
21	1985	Denmark	12.09	6.86	no crisis	Advanced
22	1986	Denmark	17.66	25.04	no crisis	Advanced
23	2000	Denmark	11.15	288.11	no crisis	Advanced
24	2004	Denmark	5.72	4.31	no crisis	Advanced
25	1966	France	8.19	6.15	no crisis	Advanced
26	1968	France	5.15	8.13	no crisis	Advanced
27	1969	France	11.38	0.92	no crisis	Advanced
28	2007	France	6.20	7.26	no crisis	Advanced
29	2009	France	-15.98	2.56	no crisis	Advanced
30	1964	Netherlands	25.12	-0.69	no crisis	Advanced
31	1964	Sweden	11.82	39.55	no crisis	Advanced
32	1965	Sweden	5.10	3.38	no crisis	Advanced
33	1984	Sweden	10.98	0.95	crisis	Advanced
34	1985	Sweden	10.64	1.70	crisis	Advanced
35	1987	Sweden	6.29	-13.70	crisis	Advanced
36	1988	Sweden	6.61	13.42	crisis	Advanced
37	2005	Sweden	13.25	6.44	no crisis	Advanced
38	1961	Japan	26.56	1.03	no crisis	Advanced
39	1962	Japan	5.89	30.63	no crisis	Advanced
40	1963	Japan	11.24	9.92	no crisis	Advanced
41	1964	Japan	15.53	-3.57	no crisis	Advanced
42	1970	Japan	18.99	41.04	no crisis	Advanced
43	1972	Japan	8.32	7.88	no crisis	Advanced
44	1985	Japan	8.15	1.67	crisis	Advanced
45	1987	Japan	5.92	10.99	crisis	Advanced
46	1988	Japan	14.41	5.21	crisis	Advanced
47	1989	Japan	8.14	4.25	crisis	Advanced
48	2005	Finland	16.30	11.02	no crisis	Advanced
49	1968	Greece	10.71	5.72	crisis	Advanced
50	1969	Greece	24.48	3.17	crisis	Advanced
51	1970	Greece	11.35	6.74	crisis	Advanced
52	1971	Greece	10.78	9.06	crisis	Advanced
53	1995	Greece	5.18	8.39	no crisis	Advanced
54	1996	Greece	8.27	3.28	no crisis	Advanced
55	1997	Greece	6.45	3.70	no crisis	Advanced
56	1998	Greece	9.97	6.02	no crisis	Advanced
57	1999	Greece	9.09	21.26	no crisis	Advanced
58	1976	Ireland	15.39	0.55	no crisis	Advanced
59	1977	Ireland	15.29	4.10	no crisis	Advanced
60	1978	Ireland	8.88	11.71	no crisis	Advanced
61	1979	Ireland	14.51	2.64	no crisis	Advanced
62	1980	Ireland	-16.07	-1.28	no crisis	Advanced
63	1994	Ireland	11.51	3.86	no crisis	Advanced
64	1995	Ireland	23.46	55.50	no crisis	Advanced
65	1996	Ireland	16.28	6.37	no crisis	Advanced
66	1997	Ireland	19.28	12.41	no crisis	Advanced
67	1998	Ireland	13.90	6.16	no crisis	Advanced
68	1963	Portugal	14.09	5.96	no crisis	Advanced
69	1964	Portugal	10.77	6.41	no crisis	Advanced
70	1965	Portugal	16.27	4.49	no crisis	Advanced
71	1979	Portugal	7.18	12.32	crisis	Advanced
72	1980	Portugal	10.09	0.20	crisis	Advanced
73	1983	Portugal	-19.19	1.61	crisis	Advanced

Continued on next page

Table A.7 – *Continued from previous page*

	Year	Country	INV	Credit	Classification	Advanced
74	1993	Portugal	-9.07	5.87	no crisis	Advanced
75	1994	Portugal	11.48	2.24	no crisis	Advanced
76	1995	Portugal	5.62	10.06	no crisis	Advanced
77	1961	Spain	28.04	3.74	crisis	Advanced
78	1962	Spain	21.33	9.28	crisis	Advanced
79	1963	Spain	9.72	3.15	crisis	Advanced
80	1964	Spain	6.49	7.40	crisis	Advanced
81	1965	Spain	14.74	8.77	crisis	Advanced
82	1987	Spain	12.40	4.72	no crisis	Advanced
83	1988	Spain	14.33	9.54	no crisis	Advanced
84	1989	Spain	11.08	5.06	no crisis	Advanced
85	1990	Spain	5.88	-1.25	no crisis	Advanced
86	1998	Spain	11.93	8.82	no crisis	Advanced
87	1999	Spain	10.89	5.23	no crisis	Advanced
88	1966	Turkey	31.60	4.57	no crisis	Developing
89	1968	Turkey	7.97	0.99	no crisis	Developing
90	1981	Turkey	33.34	22.51	crisis	Developing
91	1982	Turkey	-14.95	11.03	crisis	Developing
92	1995	Turkey	29.78	15.97	crisis	Developing
93	1997	Turkey	10.00	15.21	crisis	Developing
94	2003	Turkey	9.12	0.17	no crisis	Developing
95	2004	Turkey	15.64	18.78	no crisis	Developing
96	2005	Turkey	16.67	28.77	no crisis	Developing
97	2006	Turkey	11.68	16.60	no crisis	Developing
98	1964	Australia	16.05	4.30	no crisis	Advanced
99	1968	Australia	15.95	3.91	no crisis	Advanced
100	1983	Australia	8.59	6.45	no crisis	Advanced
101	1984	Australia	8.23	5.26	no crisis	Advanced
102	1986	Australia	-5.24	8.76	no crisis	Advanced
103	1987	Australia	9.51	6.05	no crisis	Advanced
104	1973	New Zealand	28.36	25.65	no crisis	Advanced
105	1974	New Zealand	20.38	16.27	no crisis	Advanced
106	1977	New Zealand	-11.74	5.40	no crisis	Advanced
107	1978	New Zealand	-14.86	6.81	no crisis	Advanced
108	1979	New Zealand	12.93	2.90	no crisis	Advanced
109	1980	New Zealand	-7.75	-0.82	no crisis	Advanced
110	1981	New Zealand	20.07	0.39	no crisis	Advanced
111	2003	New Zealand	11.28	5.24	no crisis	Advanced
112	2004	New Zealand	7.13	3.44	no crisis	Advanced
113	2006	New Zealand	-5.40	7.66	no crisis	Advanced
114	2007	New Zealand	7.00	4.35	no crisis	Advanced
115	1968	Argentina	7.30	26.70	no crisis	Developing
116	1969	Argentina	21.20	15.24	no crisis	Developing
117	1971	Argentina	6.30	2.75	no crisis	Developing
118	1977	Argentina	18.87	35.54	crisis	Developing
119	1978	Argentina	-14.25	11.83	crisis	Developing
120	1979	Argentina	5.02	17.02	crisis	Developing
121	1981	Argentina	-16.40	32.12	crisis	Developing
122	1996	Argentina	11.81	1.13	crisis	Developing
123	1997	Argentina	15.24	8.65	crisis	Developing
124	1999	Argentina	-17.83	3.06	crisis	Developing
125	2005	Argentina	13.89	9.38	no crisis	Developing
126	2006	Argentina	16.70	9.98	no crisis	Developing
127	2007	Argentina	13.26	8.45	no crisis	Developing
128	1967	Brazil	-8.60	16.13	no crisis	Developing
129	1968	Brazil	16.20	15.50	no crisis	Developing
130	1969	Brazil	36.16	59.00	no crisis	Developing
131	1971	Brazil	12.32	20.74	no crisis	Developing
132	1991	Brazil	7.25	7.31	crisis	Developing
133	1993	Brazil	10.73	58.78	crisis	Developing
134	2004	Brazil	10.32	1.04	no crisis	Developing
135	2006	Brazil	8.93	28.60	no crisis	Developing
136	2007	Brazil	15.19	18.63	no crisis	Developing
137	2008	Brazil	7.14	10.96	no crisis	Developing
138	1975	Chile	-53.43	36.93	crisis	Developing
139	1977	Chile	14.96	24.29	crisis	Developing
140	1978	Chile	21.60	44.62	crisis	Developing
141	1979	Chile	27.21	25.23	crisis	Developing
142	1995	Chile	32.27	3.40	no crisis	Developing
143	1997	Chile	7.89	24.27	no crisis	Developing
144	1999	Chile	-21.11	4.96	no crisis	Developing
145	1968	Colombia	12.96	8.01	no crisis	Developing
146	1970	Colombia	12.98	0.04	no crisis	Developing
147	1980	Colombia	8.55	12.01	crisis	Developing
148	1981	Colombia	10.81	7.74	crisis	Developing
149	1984	Colombia	-7.96	1.61	crisis	Developing
150	1996	Colombia	-13.66	4.93	crisis	Developing
151	1997	Colombia	22.99	3.26	crisis	Developing
152	2004	Colombia	11.39	9.59	no crisis	Developing
153	2005	Colombia	18.28	7.30	no crisis	Developing
154	2006	Colombia	17.53	13.99	no crisis	Developing
155	2007	Colombia	12.30	12.82	no crisis	Developing
156	2008	Colombia	6.47	0.22	no crisis	Developing
157	1964	Costa Rica	-14.56	9.37	no crisis	Developing
158	1965	Costa Rica	29.28	2.22	no crisis	Developing
159	1996	Costa Rica	-12.71	26.63	no crisis	Developing
160	1997	Costa Rica	21.84	8.52	no crisis	Developing

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Table A.7 – *Continued from previous page*

	Year	Country	INV	Credit	Classification	Advanced
161	1998	Costa Rica	22.44	27.06	no crisis	Developing
162	1999	Costa Rica	-17.59	9.57	no crisis	Developing
163	1967	Ecuador	14.75	8.87	no crisis	Developing
164	1975	Ecuador	13.85	14.38	crisis	Developing
165	1976	Ecuador	-7.90	10.95	crisis	Developing
166	1977	Ecuador	18.01	3.02	crisis	Developing
167	1978	Ecuador	8.75	11.60	crisis	Developing
168	1979	Ecuador	-5.52	3.51	crisis	Developing
169	1993	Ecuador	-5.93	55.17	crisis	Developing
170	1994	Ecuador	9.44	34.93	crisis	Developing
171	1996	Ecuador	-10.87	0.55	crisis	Developing
172	2004	Ecuador	9.53	15.01	no crisis	Developing
173	2005	Ecuador	8.22	8.02	no crisis	Developing
174	2007	Ecuador	5.29	4.77	no crisis	Developing
175	2008	Ecuador	12.40	3.62	no crisis	Developing
176	1968	Mexico	12.20	3.37	no crisis	Developing
177	1969	Mexico	-10.65	8.57	no crisis	Developing
178	1990	Mexico	9.52	12.17	crisis	Developing
179	1991	Mexico	7.94	19.90	crisis	Developing
180	1992	Mexico	11.23	33.99	crisis	Developing
181	2005	Mexico	20.16	8.08	no crisis	Developing
182	2006	Mexico	5.73	19.40	no crisis	Developing
183	2009	Mexico	-18.83	9.28	no crisis	Developing
184	1963	Peru	-6.21	4.63	no crisis	Developing
185	1964	Peru	5.05	0.23	no crisis	Developing
186	1965	Peru	8.81	6.02	no crisis	Developing
187	1971	Peru	13.11	8.21	crisis	Developing
188	1972	Peru	-14.33	11.64	crisis	Developing
189	1973	Peru	51.89	4.23	crisis	Developing
190	1974	Peru	34.06	-8.77	crisis	Developing
191	1975	Peru	-7.79	0.93	crisis	Developing
192	1980	Peru	32.68	15.07	crisis	Developing
193	1981	Peru	17.35	20.17	crisis	Developing
194	1982	Peru	-9.46	12.77	crisis	Developing
195	1983	Peru	-40.21	18.12	crisis	Developing
196	1993	Peru	9.43	12.95	crisis	Developing
197	1994	Peru	30.32	14.92	crisis	Developing
198	1995	Peru	17.88	17.06	crisis	Developing
199	1996	Peru	-6.64	30.38	crisis	Developing
200	1962	Uruguay	-12.01	5.23	no crisis	Developing
201	1963	Uruguay	-11.32	1.52	no crisis	Developing
202	1964	Uruguay	-15.24	12.07	no crisis	Developing
203	1970	Uruguay	11.93	37.23	crisis	Developing
204	1971	Uruguay	6.04	12.72	crisis	Developing
205	1972	Uruguay	-16.20	22.58	crisis	Developing
206	1973	Uruguay	-5.11	-43.98	crisis	Developing
207	1998	Uruguay	11.47	56.42	crisis	Developing
208	1999	Uruguay	-10.37	7.59	crisis	Developing
209	2000	Uruguay	-13.31	3.44	crisis	Developing
210	2001	Uruguay	-9.07	19.43	crisis	Developing
211	2002	Uruguay	-35.22	30.94	crisis	Developing
212	1962	Israel	5.73	6.61	crisis	Developing
213	1964	Israel	16.37	20.23	crisis	Developing
214	1966	Israel	-18.20	17.19	crisis	Developing
215	1982	Israel	13.06	10.87	crisis	Developing
216	1983	Israel	8.02	3.65	crisis	Developing
217	1984	Israel	-8.55	14.82	crisis	Developing
218	1995	Israel	6.81	-6.66	no crisis	Advanced
219	1974	Egypt	14.49	25.37	crisis	Developing
220	1975	Egypt	57.07	24.77	crisis	Developing
221	1977	Egypt	7.66	8.05	crisis	Developing
222	1978	Egypt	19.87	-0.78	crisis	Developing
223	1993	Egypt	13.48	6.71	no crisis	Developing
224	1996	Egypt	9.06	11.61	no crisis	Developing
225	1997	Egypt	17.33	8.65	no crisis	Developing
226	1962	India	8.74	5.45	no crisis	Developing
227	1963	India	6.29	1.41	no crisis	Developing
228	1964	India	8.00	-6.27	no crisis	Developing
229	1999	India	17.09	7.37	no crisis	Developing
230	2000	India	-6.43	11.47	no crisis	Developing
231	2002	India	8.98	12.88	no crisis	Developing
232	1966	Korea	70.65	8.70	no crisis	Developing
233	1967	Korea	11.07	50.97	no crisis	Developing
234	1968	Korea	33.00	50.88	no crisis	Developing
235	1978	Korea	28.22	9.39	no crisis	Developing
236	1979	Korea	15.33	8.27	no crisis	Developing
237	1980	Korea	-20.07	14.43	no crisis	Developing
238	1982	Korea	6.99	8.80	no crisis	Developing
239	1996	Korea	9.63	6.54	no crisis	Advanced
240	1997	Korea	-6.73	9.83	no crisis	Advanced
241	1998	Korea	-30.10	9.19	no crisis	Advanced
242	1999	Korea	25.06	8.71	no crisis	Advanced
243	2000	Korea	12.63	7.63	no crisis	Advanced
244	1961	Malaysia	6.56	33.12	no crisis	Developing
245	1962	Malaysia	16.78	6.68	no crisis	Developing
246	1965	Malaysia	7.94	11.12	no crisis	Developing
247	1994	Malaysia	14.84	2.59	crisis	Developing

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Table A.7 – *Continued from previous page*

	Year	Country	INV	Credit	Classification	Advanced
248	1995	Malaysia	17.31	13.91	crisis	Developing
249	1997	Malaysia	8.38	11.83	crisis	Developing
250	1998	Malaysia	-44.52	0.08	crisis	Developing
251	1961	Pakistan	55.91	9.43	crisis	Developing
252	1962	Pakistan	7.18	25.60	crisis	Developing
253	1963	Pakistan	13.11	15.95	crisis	Developing
254	1964	Pakistan	7.89	24.11	crisis	Developing
255	1965	Pakistan	18.63	4.69	crisis	Developing
256	1961	Philippines	12.90	28.93	no crisis	Developing
257	1963	Philippines	14.08	12.49	no crisis	Developing
258	1964	Philippines	7.46	9.41	no crisis	Developing
259	1973	Philippines	8.35	5.44	crisis	Developing
260	1974	Philippines	17.40	8.73	crisis	Developing
261	1975	Philippines	19.49	0.17	crisis	Developing
262	1976	Philippines	14.45	1.80	crisis	Developing
263	1987	Philippines	16.81	7.53	crisis	Developing
264	1988	Philippines	12.04	0.92	crisis	Developing
265	1989	Philippines	17.66	7.67	crisis	Developing
266	1990	Philippines	13.10	10.98	crisis	Developing
267	1991	Philippines	-19.13	-7.41	crisis	Developing
268	1967	Thailand	6.34	10.05	crisis	Developing
269	1968	Thailand	7.99	5.88	crisis	Developing
270	1969	Thailand	16.17	6.61	crisis	Developing
271	1971	Thailand	-5.67	6.44	crisis	Developing

Table A.8: rGDP Outliers

	Year	Country	rGDP	Credit	Classification	Advanced
1	1973	UK	6.91	18.01	no crisis	Advanced
2	1964	Austria	5.20	5.23	no crisis	Advanced
3	1964	Belgium	6.41	-0.68	no crisis	Advanced
4	1986	Denmark	5.45	25.04	no crisis	Advanced
5	1969	France	6.45	0.92	no crisis	Advanced
6	1962	Netherlands	5.04	12.56	no crisis	Advanced
7	1964	Netherlands	6.12	-0.69	no crisis	Advanced
8	1963	Sweden	5.02	6.44	no crisis	Advanced
9	1961	Japan	11.08	1.03	no crisis	Advanced
10	1962	Japan	7.81	30.63	no crisis	Advanced
11	1963	Japan	7.53	9.92	no crisis	Advanced
12	1964	Japan	10.35	-3.57	no crisis	Advanced
13	1970	Japan	9.55	41.04	no crisis	Advanced
14	1972	Japan	7.07	7.88	no crisis	Advanced
15	1988	Japan	6.23	5.21	crisis	Advanced
16	1968	Greece	6.53	5.72	crisis	Advanced
17	1969	Greece	9.44	3.17	crisis	Advanced
18	1970	Greece	7.52	6.74	crisis	Advanced
19	1971	Greece	7.33	9.06	crisis	Advanced
20	1977	Ireland	6.32	4.10	no crisis	Advanced
21	1978	Ireland	6.65	11.71	no crisis	Advanced
22	1994	Ireland	5.60	3.86	no crisis	Advanced
23	1995	Ireland	9.35	55.50	no crisis	Advanced
24	1996	Ireland	7.92	6.37	no crisis	Advanced
25	1997	Ireland	9.78	12.41	no crisis	Advanced
26	1998	Ireland	6.15	6.16	no crisis	Advanced
27	1963	Portugal	5.45	5.96	no crisis	Advanced
28	1965	Portugal	7.37	4.49	no crisis	Advanced
29	1967	Portugal	6.75	-2.05	no crisis	Advanced
30	1961	Spain	11.77	3.74	crisis	Advanced
31	1962	Spain	9.68	9.28	crisis	Advanced
32	1963	Spain	9.10	3.15	crisis	Advanced
33	1965	Spain	5.94	8.77	crisis	Advanced
34	1987	Spain	5.50	4.72	no crisis	Advanced
35	1966	Turkey	8.44	4.57	no crisis	Developing
36	1996	Turkey	6.20	23.49	crisis	Developing
37	1997	Turkey	6.22	15.21	crisis	Developing
38	2004	Turkey	7.76	18.78	no crisis	Developing
39	2005	Turkey	6.58	28.77	no crisis	Developing
40	2006	Turkey	5.06	16.60	no crisis	Developing
41	1964	Australia	5.25	4.30	no crisis	Advanced
42	1968	Australia	6.06	3.91	no crisis	Advanced
43	1973	New Zealand	5.99	25.65	no crisis	Advanced
44	1969	Argentina	7.80	15.24	no crisis	Developing
45	1977	Argentina	5.71	35.54	crisis	Developing
46	1981	Argentina	-6.75	32.12	crisis	Developing
47	1997	Argentina	5.82	8.65	crisis	Developing
48	2005	Argentina	7.72	9.38	no crisis	Developing
49	2006	Argentina	6.82	9.98	no crisis	Developing
50	2007	Argentina	6.47	8.45	no crisis	Developing
51	1968	Brazil	8.33	15.50	no crisis	Developing
52	1970	Brazil	8.46	16.49	no crisis	Developing

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Table A.8 – *Continued from previous page*

	Year	Country	rGDP	Credit	Classification	Advanced
53	1971	Brazil	9.44	20.74	no crisis	Developing
54	2007	Brazil	5.04	18.63	no crisis	Developing
55	1975	Chile	-16.32	36.93	crisis	Developing
56	1977	Chile	8.42	24.29	crisis	Developing
57	1978	Chile	7.16	44.62	crisis	Developing
58	1979	Chile	7.91	25.23	crisis	Developing
59	1995	Chile	9.89	3.40	no crisis	Developing
60	1996	Chile	6.54	8.84	no crisis	Developing
61	1997	Chile	5.67	24.27	no crisis	Developing
62	1997	Colombia	18.42	3.26	crisis	Developing
63	2006	Colombia	6.09	13.99	no crisis	Developing
64	2007	Colombia	6.43	12.82	no crisis	Developing
65	1965	Costa Rica	7.36	2.22	no crisis	Developing
66	1967	Ecuador	5.30	8.87	no crisis	Developing
67	1975	Ecuador	5.43	14.38	crisis	Developing
68	1977	Ecuador	6.70	3.02	crisis	Developing
69	2004	Ecuador	5.32	15.01	no crisis	Developing
70	2008	Ecuador	5.51	3.62	no crisis	Developing
71	1968	Mexico	5.49	3.37	no crisis	Developing
72	2005	Mexico	12.00	8.08	no crisis	Developing
73	2009	Mexico	-8.76	9.28	no crisis	Developing
74	1962	Peru	6.68	2.37	no crisis	Developing
75	1974	Peru	7.01	-8.77	crisis	Developing
76	1983	Peru	-15.21	18.12	crisis	Developing
77	1994	Peru	11.29	14.92	crisis	Developing
78	1995	Peru	6.61	17.06	crisis	Developing
79	1998	Uruguay	5.09	56.42	crisis	Developing
80	2002	Uruguay	-14.49	30.94	crisis	Developing
81	1962	Israel	5.79	6.61	crisis	Developing
82	1963	Israel	5.29	1.43	crisis	Developing
83	1964	Israel	5.39	20.23	crisis	Developing
84	1976	Egypt	17.72	0.96	crisis	Developing
85	1978	Egypt	9.50	-0.78	crisis	Developing
86	1999	India	9.66	7.37	no crisis	Developing
87	1966	Korea	10.55	8.70	no crisis	Developing
88	1968	Korea	9.33	50.88	no crisis	Developing
89	1969	Korea	11.39	25.11	no crisis	Developing
90	1978	Korea	10.43	9.39	no crisis	Developing
91	1979	Korea	7.74	8.27	no crisis	Developing
92	1980	Korea	-5.95	14.43	no crisis	Developing
93	1982	Korea	5.77	8.80	no crisis	Developing
94	1996	Korea	6.66	6.54	no crisis	Advanced
95	1998	Korea	-10.73	9.19	no crisis	Advanced
96	1999	Korea	11.86	8.71	no crisis	Advanced
97	2000	Korea	7.96	7.63	no crisis	Advanced
98	1994	Malaysia	8.20	2.59	crisis	Developing
99	1995	Malaysia	8.74	13.91	crisis	Developing
100	1996	Malaysia	7.11	13.84	crisis	Developing
101	1998	Malaysia	-10.79	0.08	crisis	Developing
102	1961	Pakistan	5.97	9.43	crisis	Developing
103	1963	Pakistan	7.31	15.95	crisis	Developing
104	1964	Pakistan	5.35	24.11	crisis	Developing
105	1965	Pakistan	8.64	4.69	crisis	Developing
106	1973	Philippines	6.66	5.44	crisis	Developing
107	1975	Philippines	5.56	0.17	crisis	Developing
108	1976	Philippines	7.22	1.80	crisis	Developing
109	1970	Thailand	8.61	14.49	crisis	Developing
110	1971	Thailand	5.94	6.44	crisis	Developing