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ABSTRACT

A financial crisis is an event of sudden information acquisition about the collateral backing short-term debt in credit markets. When investors see a financial crisis coming, however, they react by more intensively acquiring information about firms in stock markets, revealing those that are weaker, which as a consequence end up cut off from credit. This cleansing effect of stock markets' information on credit markets' composition discourage information acquisition about the collateral of the firms remaining in credit markets, slowing down credit growth and potentially preventing a crisis. Production of information in stock markets, then, acts as a macroprudential tool in the economy.

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1 Introduction

In stock markets agents produce information, which is then impounded in prices, improving the allocation of resources in the economy. Stock prices are information-sensitive. Credit markets, particularly collateralized credit markets, perform better when information about collateral is not produced – when debt is information-insensitive (see Dang et al. (2019)). To preserve this insensitivity, loan quantities sometimes adjust to reduce the incentive to produce information about the collateral value. In a financial crisis, information production about collateral in credit markets cannot be prevented, and quantities adjust to zero (a run).

These two systems, one a price system and one a quantity system, interact dynamically through the cross-incentives to acquire information. We propose a model in which information production in stock markets is about firms' productivities and determines the allocation of credit, while information production – or the lack thereof – in credit markets is about the firms' collateral and determines the volume of credit.

Lack of information production about collateral increases the amount of credit available in credit markets. The volume of credit determines total output in the economy and the average productivity of projects (the more projects are undertaken, the lower is the productivity of the marginal project). This reduction in the average quality of projects in the economy induces information acquisition in stocks markets. When information is produced in stock markets, weak firms (those with relatively lower project quality) are identified and stop participating in credit markets. This *cleansing effect* of stock markets' information on credit markets' composition discourages information acquisition about the collateral of the firms remaining in credit markets, slowing down credit growth and potentially preventing a crisis. Stock markets act as an *automatic macroprudential tool* – it slows down credit and stabilizes the economy.

This novel dynamic interaction between stock and credit markets through information acquisition highlights the delicate balance of their function in macroeconomics. When credit is booming because there is scarce information about collateral, output also booms but the average productivity declines. Both forces make the economy more fragile. On the one hand lenders are more worried about the quality of collateral backing their loans, which is concerning as information production about a high volume of collateral of uncertain quality (the one fueling the credit boom) is a crisis. On the other hand, worse average project quality induces investors in stock markets to investigate firms. Information from stock markets, however, feeds back into the composition in credit markets and reduces the incentives for information acquisition in credit markets, and if strong enough can prevent a crisis altogether.

As the linkage between these two markets operates through the evolution of the average quality of projects, the model incorporates technology shocks in a different way than standard macroeconomic models. Credit booms can be triggered by a positive technology shock, generating a credit boom and giving rise to the aforementioned dynamics. Similarly, negative technological shocks can induce a crisis, regardless of the amount of information produced in stock markets.

The macroprudential role of stock markets is enhanced if the cost of producing information in stock markets is low, and crises less likely if the cost of acquiring information in credit markets is high. This rationalizes the endogenous push in markets towards facilitating information about firms in stock markets (large investment in fast computers and detailed analysis of projects), while hampering information about collateral in credit markets (the design of complex securities that back credit using over-the-counter opaque contracts).

The model generates empirical counterparts of information acquisition in stock markets, which can be proxied by the evolution of the cross-sectional dispersion of stock returns. We also obtain the empirical counterparts for the average quality of projects from a credit perspective, which can be proxied by the average time-series volatility of stocks – a proxy of average fragility. As we want to capture the relation between stock markets and financial crises, we implement an empirical analysis exploiting data for many countries over a relatively long period of time, so we can include enough crisis events. For that purpose, we construct stock market information measures from daily stock price data for 52 countries over the period 1973-2012, amounting to approximately 105 million observations.

With these measures of information, credit and quality of projects, we confront testable implications of our model. In particular, information in stock markets reduces future credit growth and tends to precede and predict financial crises, but less so during high-TFP credit booms.

Related Literature: In this paper we exploit the informational interpretation of financial crises in Gorton and Ordonez (2014) and 2016), and add a stock market with informative prices and endogenous incentives to acquire such information. Then we extend the pure interaction between credit markets and macroeconomic variables to include the role of stock markets and their informative role, uncovering a novel purpose of such information as a leaning force against financial crises. Our work suggests that in the absence of a well-developed stock markets we could have seen more crises developing in several countries.

Our view of stock markets is consistent with a long literature on stock prices being informative and feeding back onto real variables (see, e.g., Dow and Gorton (1997) and Dow et al. (2017)). In this literature, the information content in asset markets direct managers' investments decisions and allows for a better allocation of resources in the economy. In the work here, however, information in stock markets has another, unexplored, positive role in the economy beyond its pure allocative use – it endogenously acts as a macroprudential tool to reduce the likelihood of a financial crisis. While information about firms' collateral can be counterproductive by reducing aggregate credit in the economy, information in stock markets can be beneficial in allocating such credit. Holmström (2015) and Dang et al. (2019) discuss the two systems independently. Here we explore their interaction.

There is a rich literature considering the conceptual link between information production and economic booms and busts, such as Van Nieuwerburgh and Veldkamp (2006), Straub and Ulbricht (2017), Fajgelbaum et al. (2017), Farboodi and Kondor (2019), and Petriconi (2019). Perhaps the closest to our paper is Asriyan et al. (2019), who study a setting in which credit can be backed either by collateral (with perfect information) or by costly screening of projects, with this mix affecting macroeconomic dynamics and the probability and recovery from crises. Our setting considers both information about projects for trading in stock markets and information about collateral in credit markets, and the effect of their interaction for macroeconomic dynamics and the likelihood of crises.

In the model, households lend directly to firms and loans are collateralized (because output is not verifiable) by an asset that we call "land." Indeed, real estate is very important for firm borrowing behavior (see, e.g., Benmelech et al. (2005) and LaPoint (2019)) and for firm investment behavior (see, e.g., Chaney et al. (2012), Campello and

Giambona (2013)). Even though there is no explicit financial intermediation in the model, our preferred interpretation is that the collateral represents assets like mortgage-backed securities, for example, and we think of the loans as short-term, as with sale and repurchase agreements (repo).

Some literature has studied the interaction between stock and credit markets, but it tends to be empirical and to focus on the pricing interactions. Examples include Beck and Levine (2004) and Gilchrist et al. (2009). Our work highlights the informational interactions between these two markets, with opposite informational properties but complementary informational implications. Furthermore, we explore this interaction through its impact on macroeconomics, providing a contribution to most standard macroeconomic models, which focus on the stock pricing implications of macro, while we are focusing on the macro implications of the informational content of stock prices.

The paper proceeds as follows. Section 2 presents the model, first in a general setting, and then with a more detailed, tractable model. Section 3 analyzes the dynamic interactions between stock markets and credit markets. In Section 4 we provide tests of three hypotheses implied by the model. Section 5 concludes.

2 Model

This model highlights the interaction between the incentives to acquire information in stock markets and in credit markets, their interdependence, and effects in business cycles and financial crises. We first provide a general overview (not a complete model) of the main sources of interactions and their dynamic implications. Then we present a full model that can allow us to illustrate those dynamics in a transparent way and to map the model to data counterparts.

2.1 General Overview

Time is discrete and is denoted by $t \in \{0, 1, ...\}$. At the beginning of each period t there is a continuum of firms and households. Each firm i has an investment opportunity (a *project*) which requires external funding K to operate. The firm's project succeeds with probability $q_{it} \sim G_q$ (we call this the *quality of the project*), in which case it generates cash of $F(K)$ such that $F'(K) > 0$ and $F''(K) < 0$. We normalize the project to produce 0 if it fails. The firm also holds an asset, which it can pledge as collateral, of value $C_{it} \sim G_C$ (we call this the *quality of collateral*). The distributions G_q and G_C constitute the underlying fundamentals in the economy.

There are two markets that open at the beginning of period t, and operate sequentially. First, there is a stock market to trade firms (that is, the combination of a project and a pledgeable asset, with their qualities not necessarily correlated and not necessarily known at the beginning of the period). Then, there is a credit market for firms to obtain funding for the project to operate. At the end of period t there is production, all credit contracts are fulfilled and each firm draws a new project and a new pledgeable asset to operate next period. These new realizations can potentially depend on the firm's identity, in which case their expected characteristics depend on past information about the individual firm.

We start by describing credit markets. Given that projects have a decreasing return to scale there is an optimal operation level K^*. As firms do not have any K at the beginning of the period, firms would like to borrow K^* but they may be restricted by their available collateral. Lenders know they will receive the collateral in case of default, which happens with probability $1 - E(q_{it}|P_{it})$ (this is, the expected probability the project defaults, *conditional* on observing the price at which firm i was traded at t in the preceding stock market). Hence, lenders may want to acquire information about the collateral before granting a loan, which is costly in terms of consumption goods. We will denote the value of acquiring information (the difference between the expected lenders' utilities from acquiring information and from not acquiring information about the firm's collateral), as

$$\mathcal{V}_{credit} = f\left(K, E(q_{it}|P_{it}), E(C_{it})\right),$$

a function of the loan size, the expected probability of default and the expected value of collateral. It is intuitive (and we will show later) that the value of information about collateral increases with the loan size (as more collateral is at stake in the loan), increases with the probability of getting the collateral (i.e., decreasing in $E(q_{it}|P_{it})$) and decreases with the expected value of the collateral (this is, decreasing in $E(C_{it})$).

We assume that the borrower asks for a loan of K that either induces information production about the collateral quality or does not, to maximize expected profits conditional on lenders' participation constraints. From the previous discussion it is not obvious that the borrower always applies for the desired loan amount, as it may trigger information acquisition about the collateral value. A small loan that does not trigger information production and is of a certain amount may be preferred to a larger loan that triggers information production but introduces uncertainty about project financing depending on the realized collateral quality. Formally, depending on the distribution G_C it may be the case that $E(F(K|C_{it})) < F(K|E(C_{it}))$, in which case increasing K may reduce expected production if it induces information production about the collateral.

The expectation of the project quality conditional on the observed stock price (this is $E(q_{it}|P_{it})$) depends on how much information is generated in the stock market, which depends on the stock market protocol (i.e., the rules that govern trade in the stock market and hence how the stock price is formed), which we denote $\mathcal{M}$. To be more precise, buyers may acquire information about the quality of the project at a cost in terms of consumption goods, and the extent to which this information gets into the price depends on $\mathcal{M}$. For instance, in the case of a continuum of buyers with dispersed unbiased signals, prices perfectly aggregate information and discourage private information acquisition (the celebrated impossibility result of Grossman and Stiglitz (1980)). The literature has explored market protocols that do not completely dissipate the private gains for information acquisition, such as noise traders (as in Kyle (1985) or Black (1986)), multiple dimensions of the asset characteristics (as in Vives (2014) or Bostanci and Ordonez (2020)) or the use of auctions (as in Milgrom (1981) and Cole et al. (2018)). Later we propose a market protocol that does not dissipate private information gains and allows us to highlight information acquisition choices.

We denote the value of acquiring information (i.e. the difference between the expected buyers' utilities from acquiring information and from not acquiring information about the firm's project), as

$$\mathcal{V}_{stock} = f\left(\mathcal{M}, E(q_{it}), E(C_{it})\right),$$

a function of the market protocol, the expected probability of default, and the expected value of the collateral. It is intuitive (and we will show later) that the value of information about the project increases with the expected value of credit that is expected to be obtained in the credit market, which depends on the expectation of what the stock price may reveal, the expected value of collateral $E(C_{it})$ and on the expected implications for information acquisition in credit markets, which depends on the $E(q_{it})$.

As we discussed, with regards to the incentives to acquire information, both $\mathcal{V}_{credit}$ and $\mathcal{V}_{stock}$ depend on expectations, which in turn depend on information that changes those expectations. This general setting then highlights the sources of interaction: information in stock markets is contained in stock prices and affects information acquisition and the loan size in credit markets, as it affects the likelihood that lenders receive the collateral. At the same time, information in credit markets affects the amount of funds the firm will obtain in credit markets, affecting the incentives to acquire information about the project in stock markets.

The dynamics in this setting rely on potential shocks to projects and collateral that happen at the end of each period. If, for instance, there is an unconditional new realization of both projects and collateral each period, then the solution is given by the previous interaction, and it is the same every period, as the system lacks persistence. Dynamics occur, however, when shocks do not happen to all projects and/or collateral or when the draw of the new realization of the shock depends on the previous project and/or collateral of the firm. Both of these possibilities would add persistence into the system through the evolution of expectations $E(q_{it})$ and $E(C_{it})$, which correspond to the state variables in this setting.

2.2 Detailed Model

We now illustrate the feedback between information in stock and credit markets, and the dynamic implications, with a full detailed model with specific assumptions that allow us some mileage on the analysis and testable implications.

Agents and Goods: To model who buys, who operates, and who sells firms, we assume an overlapping generation structure, such that in each period t three overlapping generations coexist – young, middle-aged and old – each generation is of mass 2 of a continuum of agents. There are three goods in the economy – *numeraire*, *labor*, and *land*. Numeraire, denoted by K, is productive and reproducible – it can be used to produce more numeraire and it is non-storable and so it should be consumed before new production of numeraire. Land, on the other hand, is storable but non-productive and non-reproducible. Each generation is risk neutral and derives utility from consuming numeraire, without discounting.[1] Labor does not generate any disutility.

Technology: The labor endowment of a member of the young generation, $\bar{L}$, produces numeraire one-for-one, this is $\bar{L} = \bar{K}$. Labor in the hands of the old generation can be used to run *a project*. A project is an *idea* that a middle-aged agent may imagine at the beginning of the period and that, when combined with a unit of land constitutes *a firm*. Firms (the idea and the land) can be sold in a stock market by middle-aged agents to old agents who have the labor L^* to implement the idea. We assume there is a limited supply (mass 1) of projects in the economy per period, so in each period at least half of the old generation will not have the chance to use their labor to produce. The reason for this will become clear shortly.

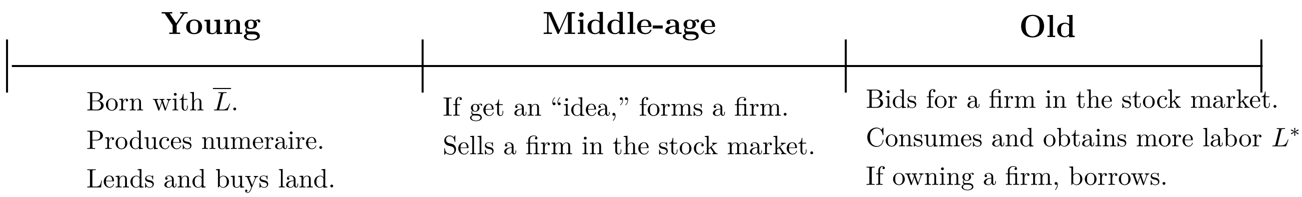
To capture decreasing returns to scale in the most convenient way we assume a piecewise linear production function for the firm: with probability q there is success and $F(K) = A\min\{L, K\}$, otherwise $F(K) = 0$. There are two types of projects available: An exogenous fraction ψ has *high* probability of success, q_H, and the rest have a *low* probability of success, q_L. We assume all projects are efficient, i.e., $q_H A > q_L A > 1$, which implies that it is optimal for all firms, regardless of their project quality, to operate at the optimal scale $K^* = L^*$.

An Agent's Lifetime: The lifetime of an individual agent is as follows: At the start of a period, say t, the individual is born young and obtains a labor endowment $\bar{L}$ that can be transformed immediately into numeraire. The agent can use this numeraire to lend to firms against collateral in credit markets and to buy land in asset markets to create a firm in the next period, if the agent gets to imagine an idea for a project. In period $t+1$ the agent becomes middle-aged. Then if he imagined an idea, he can combine it with the unit of land, form a firm and sell it in a stock market. In period $t+2$ the agent becomes old and can use the numeraire accumulated to bid for a firm in the stock market. After the stock market closes, agents consume what they have because consumption goods are perishable. Then the old agent obtains a labor endowment L^* and can borrow numeraire in credit markets to productively operate the project. Firms produce and loan contracts are settled. At the end of their lives, agents sell land and consume. This time line (in particular that consumption goods perish right after the stock market closes) guarantees that resources are in the wrong hands before production takes place and so firms need to

[1] No discounting and no concern about when to consume makes credit only useful for facilitating production rather than for consumption smoothing.

participate actively in credit markets to operate. We summarize the agent's lifetime in Figure 1.

Figure 1: An agent's lifetime



Land as Collateral: At the time of production, young agents have numeraire while firms have a project and labor but not the numeraire essential to produce. We assume that $\overline{K} > K^*$ and since production is efficient, if output were verifiable it would be possible for young agents to lend the optimal amount of numeraire K^* to firms using state-contingent claims. In what follows, however, we assume *limited liability and a financial friction* – the output of the project is only observable by the borrower and is non-verifiable by the lender. Then firms would never repay their loans and young agents would never be willing to lend since the loan would never be repaid. The output would be hidden. While we assume that firms can hide the numeraire output, we also assume that firms cannot hide land, which makes land useful as *collateral* to relax the financial friction. Firms can credibly promise to transfer a fraction of land to households in the event of not repaying the loan, which relaxes the financing constraint from output non-verifiability.

We say a firm is *active* if it has the chance (based on perceived collateral quality) to obtain a loan in credit markets. We denote by η the *mass of active firms*, which we will show later is endogenous, depending on the loans granted to particular firms. There is an exogenous fraction of good projects in the economy, ψ and we assume that active firms are randomly assigned to a queue to choose their project quality. When a firm has its turn to choose its project quality according to its position in the queue, an active firm naturally picks the project with the highest available quality q of those remaining in the pool. This protocol induces an average productivity of projects among active firms, which we denote by $\widehat{q}(\eta)$, that is given by

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

The average quality of projects in the economy depends on two factors: the exogenous fraction of good projects in the economy, ψ and the endogenous fraction of firms operating projects, η. In other words, the distribution G_q in this simple setting is endogenous: if $\eta \leq \psi$ then G_q is degenerate (the project is q_H with probability 1) and if $\eta > \psi$ it is binomial (the project is q_H with probability $\frac{\psi}{\eta}$ and q_L with probability $1 - \frac{\psi}{\eta}$).

We assume land is non-productive (it is not an input into the project technology) but may have an intrinsic value. If land is *"good"*, it can deliver C units of numeraire, but only once. If land is *"bad"'*, it is worthless. We assume an exogenous fraction $\widehat{p}$ of land is good in every period. In other words, the distribution G_C is binomial (land has value C with probability $\widehat{p}$ and 0 otherwise).

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

The perception about the quality of collateral is critical for the granting of loans. We assume that $C > K^*$ so that land that is known to be good can sustain the optimal loan size, K^*. But 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*, the parameter η, since in contrast to firms that are known to hold bad land, they can actively raise funds to start their projects.[2]

Stock Market Protocol, $\mathcal{M}$: An old agent can buy a firm (a combination of an idea, i.e., a project and land) to operate. As there are twice as many buyers as firms we assume a protocol in which two old agents are randomly assigned to a firm and each submit their individual bids in a sealed envelope. The firm is then sold to the highest bidder. In the stock market bidders can privately acquire information about the firm before submitting their bids. Production of such information costs γ_q in terms of numeraire. In

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

the case of acquiring information we assume the bidder is not only perfectly informed about q but also that he learns whether his competitor has also acquired information. This last part is not relevant to the mechanism but greatly simplifies the exposition.

2.3 Timing and Equilibrium

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

1. Technology: The technology ψ arrives. Of the available projects, fraction ψ are q_H projects.

2. Market for firms (stock markets): A mass one of middle-aged agents have an idea for a project, which together with collateral creates a firm. Among the firms which are created, those with a sufficiently high p will be active and will draw the quality of the project q, according to the process (1). Two old agents (buyers) are randomly assigned to a middle-aged agent who created a firm (seller) and bid for that firm. At the time of bidding the firm is composed of the idea, a project of quality q, and a collateral with known belief p. Each bidder can choose to become informed about q at a cost γ_q before submitting the bid.

3. Consumption and new labor endowments: Numeraire goods will perish at this point so all numeraire will be consumed. After consumption, young and old agents are endowed with $\bar{L}$ and L^* units of labor, respectively. Using their labor, young agents immediately produce $\bar{K}$ units of numeraire goods.

4. Market for loans (credit markets): There is random matching between one young agent (lender) and one old agent (borrower). If the old agent does not own a firm, this market is irrelevant. If the old agent owns a firm, both the lender (l) and borrower (b) know the probability p that the land owned by the borrower is good and observe the price at which the firm was traded at the beginning of the period (then making an inference about the quality q of the firm's project). The borrower makes a take-it-or-leave-it offer for a loan that specifies the size of the loan K, the face value R to be repaid, and the fraction of collateral that should be transferred to the lender in case of default, x. The loan contract (in effect) also specifies whether the lender or borrower acquires information (an information-sensitive loan, denoted IS) or not (an information-insensitive loan, denoted

II), which should be consistent with an agent's choice. The lender either accepts or rejects the offer.

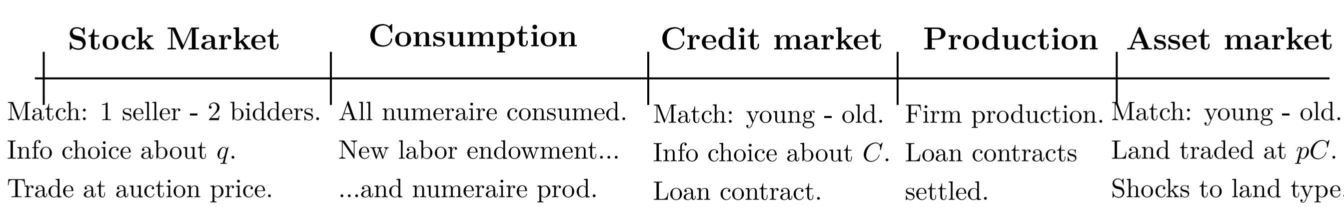
5. Production and loan contract settlements: Production takes place and all information generated about land at the time of the loan (information privately acquired) gets revealed. Loan contracts are settled.

6. Market for land (asset markets): Young agents who did not receive land as collateral because of default randomly match with old agents with land. As old agents are about to die they will sell their land in order to consume. Buyers of land have all the bargaining power and the price of land is its expected value pC.

7. Idiosyncratic shocks to land: After the land market closes, there are mean-reverting idiosyncratic shocks to land types as follows. Either the true quality of each unit of land remains unchanged with probability λ, or there is an idiosyncratic shock that changes its type with probability $(1 - \lambda)$. In this last case, land becomes good with a probability $\widehat{p}$, independent of its current type. Even when the shock is observable, its realization is not. An implication of this is that the distribution of collateral qualities has a three-point support: 0, $\widehat{p}$, 1. This process insures that the distribution of collateral in the economy is not changed over time, but its perception changes. As beliefs change, there is a credit boom as more firms become active.

We summarize the timeline of a single period t in Figure 2. The timing is such that credit and stock markets operate separately in a period and periods are only linked by the evolution of beliefs about land quality.

Figure 2: Timeline in period t



We will use the following notation: IS^l indicates an information-sensitive loan contract where the information is produced by the lender; similarly IS^b indicates an information-sensitive loan contract where the information is produced by the borrower; and II indicates an information-insensitive contract, where no party produces information.

Now we can define the equilibrium.

Definition 1. Equilibrium:

- *In the credit market borrowers choose the loan contract type ($i \in \{IS^l, IS^b, II\}$ and K_i, R_i and x_i) to maximize expected profits conditional on the lender accepting the given loan (participation constraint); the borrower repays when the project succeeds and defaults when the project fails (truth-telling constraint); and there are no private incentives to acquire information in the information-insensitive contract (incentive-compatibility constraint).*

- *In the stock market potential buyers choose to acquire information or not before submitting a bid for a firm, conditional on knowing collateral type p of a randomly assigned firm and the mass of active firms that will be participating in credit markets in the next period (η). The stock price for each firm is determined by the highest bid.*

2.4 The Credit Market

The functioning of the credit market and the information acquisition about collateral follows the same logic and analysis as Gorton and Ordoñez (2014) and Gorton and Ordoñez (2016), which we briefly discuss here. We first study the optimal short-term collateralized debt contract for a single firm with a unit of land that is good with probability p and that has a project that is believed to succeed with probability q.

There are two possible loan contracts. The first, information-sensitive debt (IS), specifies information production by either lenders (at a cost γ_C^l) or borrowers (at a cost γ_C^b in units of labor, or $\gamma_C^b p(qA-1)$ in units of expected numeraire), whichever is smaller. Denote $\gamma_C = \min\{\gamma_C^l, \gamma_C^b p(qA-1)\}$, where the second argument reflects the opportunity cost of the amount that cannot be invested in the project because it is used to produce information.

Lenders are willing to lend the optimal amount $K^* < C$ only if they find out that the collateral is good (with probability p). Then from an ex-ante perspective, the participation constraint implies

$$p[qR_{IS} + (1-q)x_{IS}C - K^*] \geq \gamma_C,$$

where R_{IS} is the promised return in case of repayment and x_{IS} the fraction of land of value C that a lender expects to receive if the firm defaults. The truth-telling constraint implies $R_{IS} = x_{IS}C$, otherwise the firm always pays or defaults. This implies

$$R_{IS} = K^* + \frac{\gamma_C}{p} \qquad \text{and} \qquad x_{IS} = \frac{R_{IS}}{C} \leq 1.$$

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

The second possible loan contract is information-insensitive debt, where firms borrow just based on the expected value of collateral. No information is produced. In this case, the lenders' participation constraint binds when

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

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

$$R_{II} = K \qquad \text{and} \qquad x_{II} = \frac{R_{II}}{pC} \leq 1.$$

For this contract to be information-insensitive (II), there are the extra constraints for guaranteeing that neither lenders nor borrowers have incentives to deviate and check the value of collateral privately.

Lenders may want to deviate because they can lend at beneficial contract terms if the collateral is good, and not lend at all if the collateral is bad. They do not want to deviate if the expected gains from acquiring information, evaluated at x_{II} and R_{II}, are lower than the private loss, γ_C^l, from acquiring information,

$$\mathcal{V}^l_{credit} = p[qR_{II} + (1-q)x_{II}C - K] < \gamma_C^l,$$

or in terms of the loan size,

$$K < K^l(p|q, II) \equiv \frac{\gamma_C^l}{(1-p)(1-q)}. \tag{2}$$

So, quantities adjust to maintain information-insensitivity.

Borrowers may want to deviate because they will not lend if the collateral is bad and renegotiate even better terms if the collateral is good. They do not want to deviate if the expected gains from acquiring information, evaluated at x_{II} and R_{II}, are smaller than the losses γ_C^b from acquiring information. Specifically when

$$\mathcal{V}_{credit}^b = [pK^* + (1-p)K](qA-1) - K(qA-1) < p\gamma_C^b(qA-1),$$

or in terms of the loan size,

$$K > K^b(p|q, II) \equiv K^* - \gamma_C^b. \tag{3}$$

Combining conditions (2) and (3), information-insensitive debt is feasible only when the loan is both above the red dotted line in Figure 3 (to avoid information acquisition by borrowers) and below the blue solid line (to avoid information acquisition by lenders). The y-axis is expected profits. In other words, information-insensitive debt (*II Loans*) is feasible only for relatively high beliefs $p > p^*$ about collateral quality, where the threshold p^* is given by the point in which $K^l(p^*) = K^b(p^*)$ from equations (2) and (3). Then

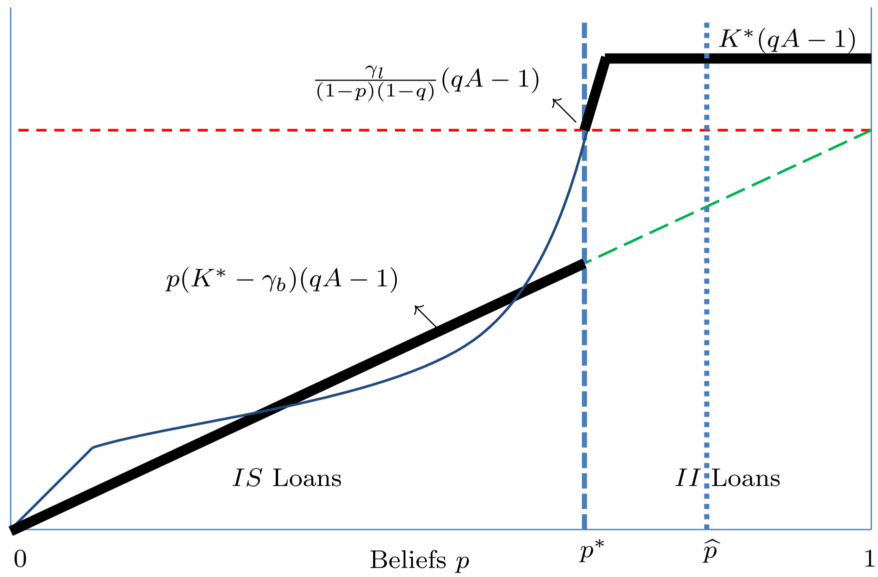
$$p^* = \max\left\{1 - \frac{\gamma_C^l}{(K^* - \gamma_b)(1-q)}, \frac{K^* - \gamma_C^b}{C}\right\}. \tag{4}$$

This threshold, and the expected payoffs of a firm as a function of p, are depicted in Figure 3. Firms with low enough p cannot obtain information-insensitive loans while firms with p close to 1 can. In the figure, firms with land of quality $\widehat{p}$, for instance, can obtain information-insensitive loans but if p^* increases above $\widehat{p}$, that would not be a possibility for those firms anymore. Subsequently, as the credit boom proceeds, p^* will increase as q declines (as H projects are used up), as can be seen in (4), eventually exceeding $\widehat{p}$. This is a crisis because of the discontinuous jump resulting in information production about all collateral. Some firms that were getting loans prior to this suddenly cannot get loans.

Output and consumption go down–a crisis.

It is clear from inspecting equation (4) that the information-insensitive debt region widens with information costs (p^* decreases with γ_b and γ_l) and shrinks with the project's expected probability of success (p^* decreases with q). This is the main link between stock markets and credit markets. When prices in stock markets are informative about q they will create greater heterogeneity about which firms will be examined in credit markets, and as such how much information will be generated in credit markets.

Figure 3: Expected Profits in Equilibrium



2.5 The Stock Market

The stock market is the place where all firms are offered for sale at the end of each period and where two buyers compete for each firm. The information production choices of the two bidders, which depend on beliefs about the collateral of the firm, are relevant for the informativeness of firms' stock prices about q, information which is then used in credit markets to determine the size of the loan and whether information should be produced about collateral quality. Here we explore this intricate relation.

When a potential buyer is randomly assigned to a firm, he has a belief about the quality of the land of that particular firm (p). The buyer also knows the fraction of active firms in credit markets (η) and then the probability of bidding for a firm with a q_H-project, which we define as $z(\eta) \equiv Pr(q_H) = \frac{\psi}{\eta}$. A firm's value is composed of two parts, one is the expected value of its collateral pC and the other is the expected profit generated by the project according to Figure 3. We define $V_H(p)$ as the value of a firm with a q_H-project and $V_L(p)$ as the value of a firm with a q_L-project.

Define y to be the fraction of uninformed buyers in the economy and let $P_U(p)$ to be the *pooling price* (i.e., the bid submitted by an uninformed investor for a firm known to have collateral with belief p). These two variables will be jointly determined in equilibrium by the bidding and the information production decisions of the potential buyers.

The expected gains for an *uninformed potential buyer* are:

$$\Pi^U(p) = z\left[\frac{y}{2}(V_H - P_U)\right] + (1-z)\left[\left(1 - y + \frac{y}{2}\right)(V_L - P_U)\right].$$

In words, an uniformed buyer always bids the pooling price in equilibrium $P_U(p)$. When he faces another uninformed bidder, he buys with a probability 1/2, regardless of the firm's project quality. When the uninformed bidder faces an informed bidder, he never buys a good firm in equilibrium (as the informed bidder would bid $P^U(p) + \epsilon$ for a good firm) and the uninformed bidder always buys a low quality firm (as the informed bidder would bid less than $P_U(p)$).

Similarly, the expected gains for an *informed potential buyer* are:

$$\Pi^I(p) = z\left[\left(y + \frac{1-y}{2}\right)(V_H - P_U)\right].$$

In words, an informed buyer always bids the value of the firm when facing another informed bidder (which for simplicity we assume he knows), a bit above the pooling price when facing an uninformed bidder and the firm is of high quality, and less than the pooling price when facing an uninformed bidder and the firm is of low quality.

This implies that there will not be information acquisition as long as

$$\mathcal{V}_{stock} = \Pi^I(p) - \Pi^U(p) < \gamma_q.$$

Notice that bidding competition across uninformed investors implies that $\Pi^U = 0$, otherwise there are incentives to marginally increase the bid P_U and discretely raise the probability of buying the firm. This implies that P_U should be such that, for a given y, the pooling price P_U balances the gains of buying a good firm and the losses of buying a bad one. Hence

$$P_U = \omega V_H + (1-\omega)V_L \qquad \text{with} \qquad \omega(z,y) = \frac{zy}{zy + (1-z)(2-y)}.$$

The fraction of uninformed investors y affects the price that uninformed investors bid for a firm. When no investor is informed (this is when $y = 1$), then $P_U = zV_H + (1-z)V_L$, the ex-ante value of the firm. When all investors are informed (i.e., when $y = 0$), then $P_U = V_L$, as the only firms that are available for uninformed to buy are those of bad quality.

All potential buyers acquire information (this is, $y = 0$) when $\mathcal{V}_{stock} > \gamma_q$. When $y = 0$, $\omega = 0$ and $P_U = V_L$. This implies that $\Pi^U(y = 0) = 0$ and $\Pi^I(y = 0) = \frac{z}{2}(V_H - V_L) > 0$, and then we can express the condition for all investors being informed as $\overline{\gamma}_q \equiv \frac{2}{2}(V_H - V_L) > \gamma_q$. In words, when the cost of information production is very small all buyers acquire information and all firms are traded either at a price V_H if the firm has a q_H-project or at a price V_L if the firm has a q_L-project. This situation is the most informative one, in which all prices in the stock market are informative about the projects' qualities.

At the other extreme, no investor acquires information (this is, $y = 1$) when $\mathcal{V}_{stock} < \gamma_q$. When $y = 1$, $\omega = z$ and $P_U = zV_H + (1-z)V_L$. This implies that $\Pi^U(y = 1) = 0$ and $\Pi^I(y = 1) = z(1-z)(V_H - V_L) > 0$, and then we can express the condition for no investor being informed as $\overline{\gamma}_q \equiv z(1-z)(V_H - V_L) > \gamma_q$. In words, when the cost of information is very large no investor has incentives to deviate and become informed. This is the case in which the stock market is the least informative as all firms are traded at the same price, P_U.

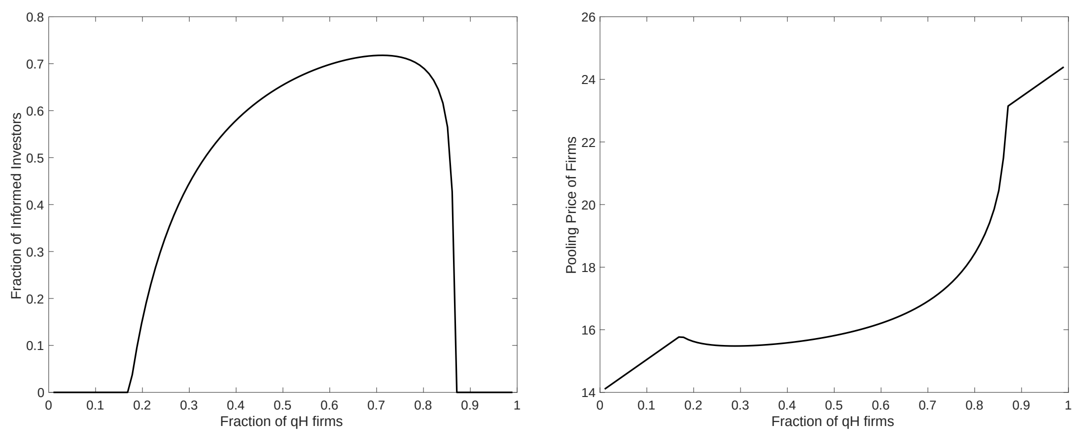
Hence, there is an intermediate range of the cost $\gamma_q \in (\underline{\gamma}_q, \overline{\gamma}_q)$ in which the equilibrium is given by $\Pi^I = \gamma_q$, with an interior y that has to be consistent with equilibrium prices P_U. In this case y^* is the solution to the following equation

$$\frac{zy^*(1-z)(2-y^*)}{zy^* + (1-z)(2-y^*)}(V_H - V_L) = \gamma_q.$$

The first panel of Figure 4 shows a particular numerical illustration of how the fraction of informed investors $(1-y)$ depends on the fraction of active firms with q_H-projects (this is $z=\psi/\eta$). In the figure, the fraction of q_H projects is on the x-axis. The economy will initially be one in which all firms are of type q_H and so the economy will start at the right side of the x-axis where the fraction is one. As there are more and more active firms during the credit boom, eventually more of the projects will be q_L firms. The incentives to acquire information are maximized when there is relatively large uncertainty about the composition of projects in the market, the peak of the inverted-U shape. At the right end of the inverted-U, most firms have q_H projects and at the left end, most firms have q_L projects. Notice that the shape in the figure is just one possible outcome. It may be that there is no decline at the left side, for example, depending on the available mix of high and low projects and the cost of producing information.

The second panel shows the pooling price, P_U, also as a function of the fraction of active firms with q_H-projects. Again, starting from the right on the x-axis, not surprisingly, as the composition of projects in the market worsens, P_U declines. As more informed bidders participate in the market they decline faster because those bidders "cream skim" the market. Note that the two kinks in in the second panel correspond to points where there are no informed investors, because either almost all the projects are q_H (RHS) or q_L (LHS) so it does not pay to produce information.

Figure 4: Fraction of Informed Investors and Pooling Price



Notice that the solution y^* determines *the information content in the stock market.* The distribution of observed prices in the economy determines beliefs about q. A fraction $z(1-y^*)^2$ of firms trade at price V_H, which reveals that the firm has a q_H-project, a fraction $(1-z)(1-y^*)^2$ of firms trade at price V_L, which reveals that the firm has a q_L-project, and a fraction $1-(1-y^*)^2$ of firms are traded at the pooling price P_U, which is uninformative about q. As can be seen, the higher is the fraction of informed bidders (the lower is y^*), the more information about q will be revealed in the stock market and affect information in the credit market.

3 Credit and stock markets - Dynamic interactions

In this section we show how information about collateral in credit markets and information about projects in stock markets interact.

3.1 The Evolution of Beliefs

The idiosyncratic shock process for collateral generates depreciation of its information. With probability λ the true quality of land remains unchanged, and with probability $1-\lambda$ it changes. In this last case, land becomes good with probability $\widehat{p}$ independent of its current type. Given this stochastic process, a unit of land falls into one of three possible categories: it is either known to be good ($p=1$), known to be bad ($p=0$) or of uncertain quality ($p=\widehat{p}$). We denote the mass of land in each category $p \in \{0, \widehat{p}, 1\}$ at the beginning of period t (after idiosyncratic shocks to land but *before* the stock market opens) as $m(p)_t$.

We define the mass of *active firms* as all firms that may have good collateral, then

$$\eta_t = m(\widehat{p})_t + m(1)_t. \tag{5}$$

These are all those firms that could in principle operate (as they have perceived collateral quality with a chance to obtain some credit) and then these firms are traded at a positive price in the stock market.

In what follows we assume that $\widehat{p} < p^*(q_L)$ (there is information production about collateral of unknown quality for firms known to operate with q_L-projects) and that $\widehat{p} > p^*(q_H)$ (there is no information production about collateral of unknown quality for firms known to operate with q_H-projects). These assumptions allow us to focus on an environment in which information about firms' projects affects their performance in credit markets. Otherwise, information about collateral in the credit market does not depend on the availability of information about projects in the stock market.

After the stock market operates in period t, credit markets open and a fraction v_t of land of unknown quality is investigated based on the observed stock prices. This implies that the mass of land in each category after credit markets close (which we denote by t') changes to:

$$\begin{aligned} m(\widehat{p})_{t'} &= (1 - v_t)m(\widehat{p})_t \\ m(1)_{t'} &= m(1)_t + v_t\widehat{p}m(\widehat{p})_t \\ m(0)_{t'} &= m(0)_t + v_t(1 - \widehat{p})m(\widehat{p})_t. \end{aligned}$$

These are the masses of beliefs at the end of period t, and then the masses at the beginning of the next period $t + 1$ further change according to idiosyncratic shocks, and then:

$$\begin{aligned} m(\widehat{p})_{t+1} &= \lambda m(\widehat{p})_{t'} + (1 - \lambda) \\ m(1)_{t+1} &= \lambda m(1)_{t'} \\ m(0)_{t+1} &= \lambda m(0)_{t'}. \end{aligned}$$

Putting these elements together, the mass of active firms in period $t + 1$ is

$$\begin{aligned} \eta_{t+1} &= m(\widehat{p})_{t+1} + m(1)_{t+1} \\ &= \lambda m(\widehat{p})_{t'} + (1 - \lambda) + \lambda m(1)_{t'} \\ &= \lambda(1 - v_t)m(\widehat{p})_t + (1 - \lambda) + \lambda[m(1)_t + v_t\widehat{p}m(\widehat{p})_t] \\ &= \lambda[1 - v_t(1 - \widehat{p})]m(\widehat{p})_t + \lambda m(1)_t + (1 - \lambda). \end{aligned} \tag{6}$$

The first term corresponds to land $\widehat{p}$ that was not examined during last period's credit market, that was examined and was found to be good and that has not suffered an idiosyncratic shock in the transition between t and $t + 1$. The second term correspond to land known to be good (i.e., $p = 1$) that has not suffered an idiosyncratic shock. The last term corresponds to all land that has suffered an idiosyncratic shock.

Combining equations (5) and (6) *a credit boom* is defined as the change in credit in the economy,

$$\begin{aligned}\eta_{t+1}-\eta_t &= (1-\lambda)(1-m(1)_t)-[1-\lambda(1-v_t(1-\widehat{p}))]m(\widehat{p})_t \\ &= (1-\lambda)m(0)_t-\lambda v_t(1-\widehat{p})m(\widehat{p})_t. \end{aligned} \tag{7}$$

The credit boom is given by the old collateral known to be of bad quality that suffered an idiosyncratic shock and started in the pool of unknown collateral, minus the unknown collateral that is investigated and found to be bad collateral.

Now, we can put structure on the fraction of collateral v_t that is investigated in period t. First, the mass of active firms η_t reduces the fraction $z_t=\frac{\psi}{\eta_t}$ of q_H-projects in the economy. This fraction reduces the average quality of projects, $\widehat{q}_t=z_tq_H+(1-z_t)q_L$ and, as depicted in Figure 4, determines information acquisition in the stock market, $(1-y_t)$. Among firms with collateral $\widehat{p}$, a fraction $(1-z_t)(1-y_t)^2$ is identified in the stock market as q_L-firms, a fraction $z_t(1-y_t)^2$ as q_H-firms, and the rest are not explored in the stock market. If $p^*(\widehat{q}_t)\leq\widehat{p}$ there is no information production about the third group, just about the first. If in contrast, $p^*(\widehat{q}_t)>\widehat{p}$ there is also information production about the third group, which we denote *a crisis*. Denoting by $\mathbb{I}_C$ a crisis indicator function with $\mathbb{I}_C=1$ in case of a crisis and 0 otherwise,

$$v_t=(1-z_t)(1-y_t)^2+\mathbb{I}_C\left[1-(1-y_t)^2\right] \tag{8}$$

In short, when $\mathbb{I}_C=0$ and there is no information production about collateral of unknown quality of a firm with unknown project quality, $v_t=(1-z_t)(1-y_t)^2$ (only the collateral of q_L-projects are investigated). In contrast, during a crisis (this is $\mathbb{I}_C=1$) only the collateral of known q_H-projects is not investigated, and then $v_t=1-z_t(1-y_t)^2$.

The fraction of collateral that is examined in credit markets, v_t, is a function of the mass of active firms in the economy, η_t and changes in the following way.

$$\frac{\partial v_t}{\partial \eta_t}=\begin{cases}\frac{\psi(1-y_t)}{\eta_t^2}\left[(1-y_t)+2(1-z_t)\frac{\partial y_t}{\partial z_t}\right] & if \quad \mathbb{I}_C=0 \quad (i.e.,\ \eta_t<\eta^*)\\ \frac{\psi(1-y_t)}{\eta_t^2}\left[(1-y_t)-2z_t\frac{\partial y_t}{\partial z_t}\right] & if \quad \mathbb{I}_C=1 \quad (i.e.,\ \eta_t>\eta^*)\end{cases} \tag{9}$$

where η^* is the mass of active firms for which $p^*(\widehat{q}_t(\eta^*))=\widehat{p}$.

This derivative shows that information in credit markets changes with the volume of credit in the economy (the mass of active firms) through two channels. The first is by triggering a *a financial crisis*, in which v_t increases discontinuously after a certain volume of credit requests. From equation (4), $p^*(\widehat{q}_t)$ decreases with $\widehat{q}_t$ (which increases with η_t), and then the indicator $\mathbb{I}_C$ switches from 0 to 1 when η_t gets large enough.

The second channel is more continuous and comes from changes in *information in stock markets*. When there is no crisis, there is more collateral examination when there is *more* information in the stock market and there are more q_L-projects. When there is a crisis, there is more collateral examination when there is *less* information in the stock market, but more q_L-projects.

Given these relations, the next Lemma characterizes the evolution of credit in the economy.

Lemma 1. *The mass of active firms follows the following first-order difference equation.*

$$\eta_{t+1} = 1 - \lambda + \lambda[v_t(\eta_t)\widehat{p} + (1 - v_t(\eta_t))\eta_t] \tag{10}$$

and then

$$\frac{\partial \eta_{t+1}}{\partial \eta_t} = \lambda(1 - v_t(\eta_t)) - \lambda(\eta_t - \widehat{p})\frac{\partial v_t}{\partial \eta_t} \tag{11}$$

with $\frac{\partial v_t}{\partial \eta_t}$ *given by equation (9).*

Proof Among collateral with known quality (this is, $1 - m(\widehat{p})_t$), a fraction $\widehat{p}$ is of good quality. Then, $m(1)_t = \widehat{p}(1 - m(\widehat{p})_t)$. Substituting into equation (5), we can express $m(\widehat{p})_t$ as a function of η_t. This is,

$$\eta_t = \widehat{p} + (1 - \widehat{p})m(\widehat{p})_t \qquad \Longrightarrow \qquad m(\widehat{p})_t = \frac{\eta_t - \widehat{p}}{1 - \widehat{p}},$$

and we can rewrite equation (6) as

$$\begin{aligned} \eta_{t+1} &= (1 - \lambda) + \lambda(m(\widehat{p})_t + m(1)_t) - \lambda v_t(1 - \widehat{p})m(\widehat{p})_t \\ &= (1 - \lambda) + \lambda\eta_t - \lambda v_t(1 - \widehat{p})m(\widehat{p})_t \end{aligned}$$

Replacing $m(\widehat{p})_t$ in this equation we obtain the equation (10) in the Lemma. Q.E.D.

3.2 Steady States

We use the equations in the Lemma to characterize the stationary equilibrium in the economy. We start with three benchmark cases: first, we take the case of no information production in the stock market; second, we examine the case of perfect information in the stock market; and third, the case of a constant amount of information in the stock market. Finally, in the next subsection, we use these cases to explore the general case where the amount of information produced in the stock market is endogenous.

Assume first that $\gamma_q = \infty$, then there is never information production in the stock market (i.e., $y_t = 1$ in all t). Here we show the economy can be in a stationary *good boom* equilibrium (in which all firms receive credit), a stationary *no boom* equilibrium (in which a fraction of firms receive credit) and a stationary *cyclical bad boom* equilibrium, with a deterministic sequence of booms and busts.

Proposition 1. *Assuming $\gamma_q = \infty$, $y_t = 1$ for all t. From equation (8), $v_t = \mathbb{I}_C$ in all t. Then*

$$\eta_{t+1} = 1 - \lambda + \lambda[\mathbb{I}_C\widehat{p} + (1 - \mathbb{I}_C)\eta_t]$$

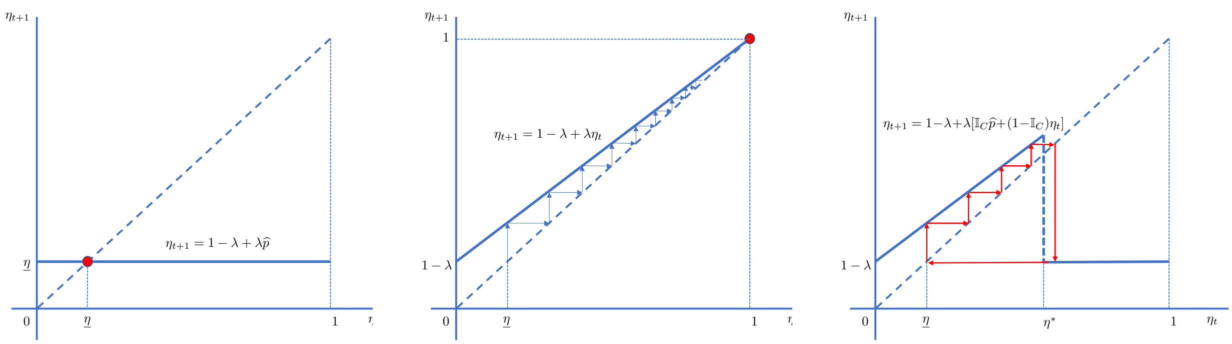
where $\mathbb{I}_C = 1$ for all $\eta_t > \eta^*$ and 0 otherwise, with η^* is given by $p^*(\widehat{q}(\eta^*)) = \widehat{p}$.

Defining $\underline{\eta} \equiv 1 - \lambda + \lambda\widehat{p}$ the lowest possible mass of active firms (the fraction of collateral facing an idiosyncratic shock and good quality collateral not facing an idiosyncratic shock), the stationary equilibria are:

1. *No Boom: If $\eta^* \leq \underline{\eta}$, information is replenished every period and $\eta_{SS} = \underline{\eta}$.*
2. *Good Booms: If $\eta^* \geq 1$, information is never generated and $\eta_{SS} = 1$.*
3. *Cycles of Bad Booms: If $\eta^* \in (\underline{\eta}, 1)$, information is generated only when $\eta_t > \eta^*$.*

The proof comes from the dynamics in equation (10) and (11). When there is no crisis, $\frac{\partial \eta_{t+1}}{\partial \eta_t} = \lambda$ and when there is a crisis $\frac{\partial \eta_{t+1}}{\partial \eta_t} = 0$. We show this next using a phase diagram. The first panel of Figure 5 shows the first case of the proposition, in which the mass of active firms is constant and at the minimum, as information is replenished every period. The second panel shows the second case of the proposition, in which an economy with information transits to a steady state without information about any collateral and all firms being active (a *good boom*). The third panel shows the last case of the proposition, in which the economy cycles between booms that end in crises once there mass of active firms (η^*) is high enough, just to restart the process again from $\underline{\eta}$.

Figure 5: No Booms and Good Booms



(a) No Boom **(b)** Good Booms **(c)** Bad Booms

Now we analyze the opposite extreme, assume $\gamma_q = 0$, then there is always information in the stock market (this is, $y_t = 0$ in all t). Here we show the economy just has one stationary equilibrium with an intermediate level of active firms, and there is never a crisis.

Proposition 2. *Assuming $\gamma_q = 0$, $y_t = 0$ in all t. From equation (8), $v_t = 1 - z_t$ in all t. Then*

$$\eta_{t+1} = 1 - \lambda + \lambda[(1 - z_t)\widehat{p} + z_t\eta_t] \qquad \texttt{with } z_t = \min\left\{\frac{\psi}{\eta_t}, 1\right\}$$

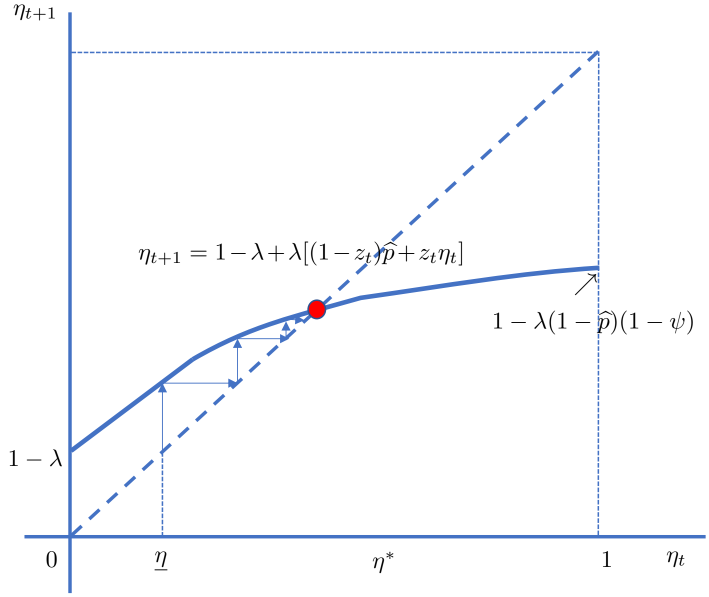
There is a unique steady state in which $\eta_{SS} \in (\underline{\eta}, 1)$.

When there is perfect information in the stock market, collateral of unknown quality is only investigated if it is backing q_L-projects. This is why there are no crises, as there are only two possible thresholds for information acquisition, $p^*(q_L) > \widehat{p}$ and $p^*(q_H) < \widehat{p}$. The credit boom is continuous, strictly increasing at a decreasing rate, as there are more q_L-firms operating in the economy. Formally, from equation (11), $\frac{\partial \eta_{t+1}}{\partial \eta_t} = \frac{\lambda\widehat{p}\psi}{\eta_t^2}$ (positive and decreasing in η). Figure 6 shows this result graphically.

3.3 The Stock Market as Macroprudential Mechanism

The comparison of the two previous extremes suggests that information in the stock market generates a stationary equilibrium that is mediocre (i.e., low consumption because

Figure 6: Full Information in the Stock Market



fewer firms get credit) but prevents fragility. To highlight this result, we now assume the case in which there is constant information production in the stock market (this is, $y_t = y \in (0,1)$) in all t.

Proposition 3. *Information in the stock market prevents crises and, if not, it reduces their magnitude.*

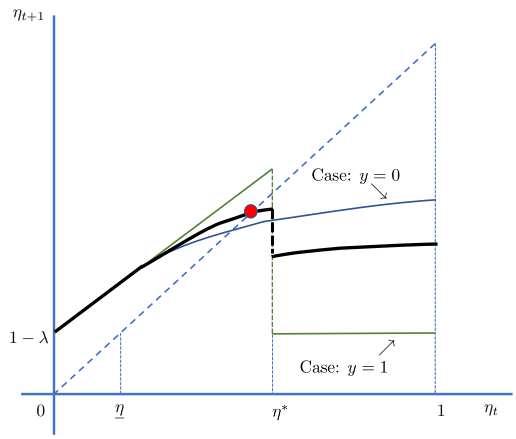
Proof The sufficient condition for this result is that the credit boom grows at a slower rate than without information when there is no crisis, and that the mass of active firms is larger than without information when there is crisis.

Formally, the first condition is $\frac{\partial \eta_{t+1}}{\partial \eta_t}|_{\mathbb{I}_C=0,y_t=y} < \frac{\partial \eta_{t+1}}{\partial \eta_t}|_{\mathbb{I}_C=0,y_t=1}$ from equation (11). This is the case, as $\frac{\partial \eta_{t+1}}{\partial \eta_t}|_{\mathbb{I}_C=0,y_t=y} = \lambda[1-(1-z_t)(1-y)^2] - \lambda(\eta_t - \widehat{p})\frac{\psi}{\eta_t^2} < \lambda$, because $1-(1-z_t)(1-y)^2 < 1$ and $\eta_t > \underline{\eta} > \widehat{p}$.

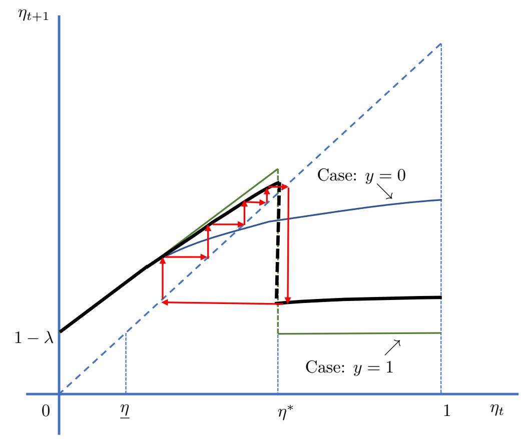
Formally, the second condition is $\eta_{t+1}|_{\mathbb{I}_C=1,y_t=y} > \eta_{t+1}|_{\mathbb{I}_C=1,y_t=1}$ from equation (10). This is the case, as $\eta_{t+1}|_{\mathbb{I}_C=1,y_t=y} = 1-\lambda+\lambda\widehat{p}+\lambda z_t(1-y)^2(\eta_t-\widehat{p}) > \underline{\eta}$, because $\underline{\eta} = 1-\lambda+\lambda\widehat{p}$.

Q.E.D.

Figure 7: Some Information in the Stock Market



(a) High Info (Low y)



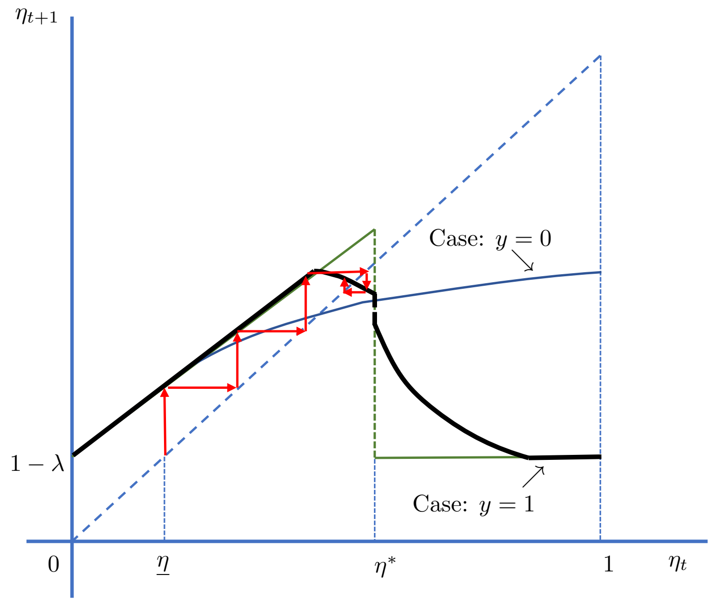
(b) Low Info (High y)

Figure 7 is based on the parametric combination that generates bad booms in the absence of information in the stock market (third panel of Figure 5). The first panel displays the case with relatively high information in the stock market (that is, relatively low y). This information slows down the credit boom so much that the economy comes to a steady state without triggering a crisis. The second panel displays the case with relatively low information in the stock market (that is, relatively high y). This information slows down the credit boom, but not so much to prevent a crisis. However, the information acquired in the stock market allows q_H-projects to avoid collateral examination and decreases the magnitude of the crisis relative to the situation without information in the stock market. In other words, information in stock markets may prevent crises, and if not, reduces the volatility of the deterministic cycles.

Finally, in general, information in stock markets changes as credit booms and the mass of active firms evolve. The first panel of Figure 4 shows how y_t changes with z_t and then with η_t. That information in the stock market reacts to credit changes the nature of the stationary equilibrium. If stocks markets attract information acquisition before crises develop, then not only does information production in the stock market prevent a crisis but it may also generate *non-crisis cycles*. Figure 8 shows this possibility. As can be seen the evolution of η_t bends as information acquisition in the stock market changes. If at some point information starts being acquired in the stock market, the difference equation transitions gradually from the case without information ($y = 1$) to the case of full information ($y = 0$). Once the credit moves back to a situation with low information acquisition in the stock market, the difference equation transitions back to the case $y = 1$.

The shape of the difference equation will critically depend on the shape of the first panel of Figure 4. In the depicted case, the economy cycles before suffering a crisis. The cycle still displays less volatility that the one involving crises.

Figure 8: No-Crises Cycles



4 Testing Aggregate Information Dynamics

In this section, we test a number of implications of the model. First, we explain the empirical measures that we use in our analysis. Motivated by our setting, we use stock market price data to construct an empirical proxy of information produced in the economy and a measure of economy-wide fragility that captures the probability of default in credit markets. We then discuss our dataset. Finally, we turn to the hypotheses tests.

4.1 Measures of Information and Fragility

Corresponding to the model we examine two measures that capture information encoded in stock markets and a stock-based measure of fragility or default probability in credit markets.

The first is a stock price-based measure of information in the economy. If information is produced in stock markets, firms are distinguished by the quality of their project, which gets embedded in firms' stock prices. Our empirical counterpart is a cross-section characterization, more specifically the cross-section of firms' average stock returns. In particular we look at the standard deviation of firms' average returns: $CsAvg$.[3] We label this variable *Information*.

The second measure also comes from the model and corresponds to default probability in credit markets, which has implications for the likelihood of information acquisition about collateral, and then credit. It is is a stock price-based measure of economy-wide fragility. When ψ is low, eventually there are more q_L firms in the economy and these firms are more likely to default because $q_L < q_H$. We measure fragility (the extent of low-quality projects operating in the economy) with the inverse of the time-series volatility of a stock, which we denote by $1/Vol$ and label as *Fragility*.[4]

This definition of fragility is from Atkeson et al. (2013). Based on Leland's (Leland (1994)) and Merton's (Merton (1974)) structural models these authors develop two concepts of default: Distance-to-Insolvency and Distance-to-Default. They then show that the variable one over the firm's equity volatility ($1/Vol$) is bounded between these two measures. Intuitively, when a firm's equity volatility is high, the firm is more likely to default (for given leverage). The fragility of an economy moves over time and spikes significantly during a crisis. Based on $1/Vol$, Atkeson et al. (2013) study the U.S. over 1926-2012 and show that 1932-1933, 1937 and 2008 stand out as especially fragile periods.[5]

[3] This variable is related to the cross-section of firms' stock return volatility: $CsVol$, and are highly correlated, 0.96. Hence, we will restrict attention to $CsAvg$ in the remaining of the paper.

[4] Fragility is essentially a measure of economy-wide bankruptcy risk. There is a history of research that shows that firms are increasingly prone to bankruptcy leading up to a recession. Burns and Mitchell (1946) show that the liabilities of failed non-financial firms is a leading indicator of recession. Also see Zarnowitz and Lerner (1961). As mentioned above, Gorton (1988) shows that when the unexpected component of this variable spikes there was a banking panic during the U.S. National Banking Era, 1863-1914. There was never a panic without the threshold being exceeded; and the threshold was never exceeded without a panic. See the discussion in Gorton (2012), p. 75-77.

[5] Vassalou and Xing (2004) use the Merton (1974) model measure of default risk to show that default risk is a systematic risk and that the Fama-French asset pricing factors partially reflect default risk.

4.2 Data

The measures of *Information* and *Fragility* are constructed using daily stock price data from Thomson/Reuters DataStream. We use daily stock price data from 52 countries over 1973-2012, which amounts to approximately 105 million observations.[6] Online Appendix Figure 9 shows the evolution of the number of countries included in the sample and Tables 6 and 7 summarize our quarterly and annual data respectively. Online Appendix Tables 4 and 5 show the countries and the time period covered for each country. The panel is unbalanced. We follow Valencia and Laeven (2012) for the dating of financial crises.

We proceed as follows. To measure $CsAvg$ in each country we compute the cross-sectional standard deviation of average of firms' monthly stock returns in the stock market of that country. For $1/Vol$, we compute the average of firms' monthly stock return volatilities in each country. For stability of these figures, we take these two monthly series and average them across months to create quarterly series. The annual series that we study next are formed using the last quarter observation of the quarterly series.

4.3 Three Tests

In this subsection we test three hypotheses that follow from the model.

1) *Information* and *Fragility* predict financial crises: As the credit boom goes on, the economy is becoming increasingly fragile. This is because the marginal project is of lower quality and higher fragility that the average (in the model, more q_L projects are under taken and they are more likely to default than q_H projects). As this occurs, information is increasingly produced in the stock market, leading up to the crisis. Table 1 below addresses this hypothesis. The left-hand side variable is a dummy variable indicating that there was a crisis in a specific country that year when equal to 1, as per Valencia and Laeven (2012). We provide results from Linear Probability and LOGIT specifications (controlled by GDP, credit and productivity, as well as clustering). We confirm the hypothesis, as an increase in *Information* (this is, an increase in $CsAvg$ and an increase in Fragility (this is, a decline in $1/Vol$), both tend to precede and predict

[6] We drop stock price data when there are less than 100 listed stocks.

financial crises.[7]

Table 1: Information Measures, Macroeconomic Variables, and Financial Crises. The table summarizes the predictive power of information measures ($1/Vol$, $CsAvg$, $\Delta(1/Vol)$, $\Delta CsAvg$) and macroeconomic variables ($\Delta rGDP$, $\Delta Credit$, ΔTFP, Δ*Labor Productivity*) on the occurrence of financial crises. The linear probability model regression specification is: $\mathbb{1}_{n,t}(Crisis) = \alpha_n + \beta' X_{n,t-1} + \epsilon_{n,t}$ and the logit regression specification is: $\mathbb{1}_{n,t}(Crisis) = \alpha_n + \beta' X_{n,t-1} + \epsilon_{n,t}$, where $X_{n,t-1} = (1/Vol_{n,t-1}, CsAvg_{n,t-1}, \Delta Vol_{n,t-1}, \Delta CsAvg_{n,t-1}, \Delta rGDP_{n,t-1}, \Delta Credit_{n,t-1}, \Delta TFP_{n,t-1}, \Delta LP_{n,t-1})'$. The data are annually and span a period from 1973 until 2012. All regression specifications take into account country fixed effects and standard errors are clustered both at a country and time level.

	(1) LPM	(2) LOGIT
$1/Vol_{t-2}$	-0.052	-0.796^{+}
	(-1.48)	(-1.65)
$CsAvg_{t-2}$	0.743^{+}	7.555*
	(1.80)	(2.18)
$\Delta(1/Vol)_{t-1}$	-0.087**	-1.337***
	(-2.82)	(-6.21)
$\Delta CsAvg_{t-1}$	0.551^{+}	4.983^{+}
	(1.84)	(1.87)
$\Delta rGDP_{t-1}$	-4.052***	-45.629***
	(-4.35)	(-3.65)
$\Delta Credit_{t-1}$	-0.000	-0.275
	(-0.02)	(-0.59)
ΔTFP_{t-1}	0.780	14.046
	(0.99)	(1.45)
ΔLP_{t-1}	0.789	7.469
	(0.87)	(0.76)
Constant	0.267^{+}	0.208
	(1.66)	(0.13)
N	674	575
R^2	0.22	.
F	3.79	.
Cluster (Time)	YES	YES
Cluster (Country)	YES	YES
FE (Country)	YES	YES

t-statistics in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

2) *Information* and *Fragility* do not predict financial crises when preceding credit boom happens jointly with high productivity growth: The theoretical analysis showed that the technological (or TFP) level, ψ is important to drive credit booms and to determine the dynamic interaction between stock and credit markets. More

[7]Table 8 in the internet Appendix confirms the result using quarterly data, but without the macro variables which are only available annually. Also, Table 9 in the internet Appendix shows that the predictive power of the *Information* measure extends up to four quarters prior to the crisis, whereas that of the *Fragility* measure extends up to eight quarters (two years) prior to a crisis.

specifically, when TFP is high, the probability of default in the $\widehat{q}(\eta)$ is lower for all η and the condition $p^*(\widehat{q}(\eta^*)) = \widehat{p}$ at which a crisis happens implies η^* is larger and that crises are less likely, regardless of information in stock markets.

We follow the definition of Gorton and Ordoñez (2016), who show that good booms (those that do not end in a crisis) are indeed characterized by high productivity growth during the boom, i.e., high ψ. Bad booms (those that do end in a crisis) have a growth path that starts to decline leading up the crisis, low ψ. Similar to Gorton and Ordoñez (2016), we define a credit boom as follows. The beginning of a credit boom is marked by three consecutive years of credit growth greater or equal to 3% and the end by two consecutive years of negative credit growth. Empirically, we distinguish between high-TFP and low-TFP credit booms by dividing the booms around the mean growth in TFP across all the identified booms. Since low and high-TFP are indeed interpreted as low and high Fragility, we dispense from Fragility in the regression. Table 2 shows that indeed *Information* predicts financial crises during low-TFP booms, but not in high-TFP booms.

Table 2: Information Production during Low and High Productivity Credit Booms.The table summarizes the predictive power of $\Delta CsAvg$ interacted with dummy variables indicating years into the credit boom on future $\Delta Credit$. The regression specification is: $\mathbb{1}_{n,t}(Crisis) = \alpha_n + \beta \Delta CsAvg_{n,t-1} + \gamma CsAvg_{t-2} + \delta' X_{n,t-1} + \epsilon_{n,t}$, where $X_{n,t-1} = (\Delta rGDP_{n,t-1}, \Delta TFP_{n,t-1}, \Delta LP_{n,t-1}, \Delta INV_{n,t-1})'$. The data are annual and span a period from 1973 until 2012. All regression specifications take into account country fixed effects and standard errors are clustered both at a country and time level.

	(1) *All Booms*	(2) *Low TFP*	(3) *High TFP*
$\Delta CsAvg_{t-1}$	0.691*	0.741*	0.367
	(2.13)	(2.22)	(0.56)
$CsAvg_{t-2}$	0.829*	0.811*	0.583
	(2.54)	(2.36)	(0.61)
ΔLP_t	-1.404	-2.578	0.074
	(-0.89)	(-1.16)	(0.04)
ΔGDP_{t-1}	-0.648+	-1.245	-0.265
	(-1.74)	(-1.33)	(-1.19)
ΔTFP_{t-1}	0.647	0.684	0.490
	(0.91)	(1.31)	(0.39)
ΔINV_{t-1}	-0.771*	-0.649	-0.799+
	(-2.51)	(-1.22)	(-1.96)
N	382	235	147
R^2	0.34	0.33	0.31
F	4.19	5.87	0.87
Cluster (Boom)	YES	YES	YES
Cluster (time)	YES	YES	YES
FE (Boom)	YES	YES	YES

t-statistics in parentheses
$^+$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3: Information production in stock markets negatively predicts future

credit during credit booms. As highlighted when comparing the two panels in Figure 7, information in stock markets delays credit growth during a credit boom (the first panel shows a faster decline in the growth rate of credit than the second). In words, more information production in stock markets reduce the amount of future credit because a larger fraction of weak firms are revealed as such, their collateral is examined and they are cut out of the credit market when found out with bad collateral.

To test this hypothesis and to track the role of information in different phases of the credit boom, we interact the change in the measure of *Information*, $\Delta CsAvg$ with the year of the credit boom, e.g., first year, second year, and so on. Table 3 shows the results. For boom years one, two, and three the coefficients on the interaction terms are negative and significant, implying that indeed, when there is more information generated in stock markets during a credit boom there is a decline in subsequent credit growth.

Table 3: Future Credit in Relation to Information Production During Credit Booms. The table summarizes the predictive power of $\Delta CsAvg$ interacted with dummy variables indicating years into the credit boom on future $\Delta Credit$. The regression specification is: $\Delta Credit_{t+1} = \alpha_n + \beta' \sum_{k=1}^{5} \Delta CsAvg_{k,t-1} \times \mathbb{1}_{n,t}(Boom\text{-}year = k) + \gamma' X_{n,t-1} + \epsilon_{n,t}$, where $X_{n,t} = (\Delta Credit_{t-1}, \Delta(1/Vol)_t, \Delta CsAvg_t, \Delta rGDP_{n,t}, \Delta Credit_{n,t}, \Delta TFP_{n,t}, \Delta LP_{n,t})$. The data are annually and span a period from 1973 until 2012. All regression specifications take into account country and year fixed effects, and standard errors are clustered at the country and year level.

	(1)	(2)	(3)
$\Delta CsAvg_t$	-0.128^{+}	-0.177	
	(-1.72)	(-0.97)	
$\mathbb{1}_t(Boom)$	0.034	0.037	0.033^{+}
	(1.63)	(1.29)	(1.77)
$\Delta CsAvg_t \times \mathbb{1}_t(Boom=1)$	-0.021	-0.150	
	(-0.07)	(-0.36)	
$\mathbb{1}_t(Boom=1)$	0.057*	0.054^{+}	0.059**
	(2.49)	(1.79)	(2.82)
$\Delta CsAvg_t \times \mathbb{1}_t(Boom=2)$	-0.006	-0.012	
	(-0.03)	(-0.04)	
$\mathbb{1}_t(Boom=2)$	0.046***	0.032	0.048***
	(3.39)	(1.28)	(3.35)
$\Delta CsAvg_t \times \mathbb{1}_t(Boom=3)$	-0.281*	-0.280^{+}	
	(-2.42)	(-1.93)	
$\mathbb{1}_t(Boom=3)$	0.003	-0.022	0.003
	(0.20)	(-1.10)	(0.21)
$\Delta CsAvg_t \times \mathbb{1}_t(Boom=4)$	0.214	0.136	
	(1.30)	(0.28)	
$\mathbb{1}_t(Boom=4)$	-0.014	-0.014	-0.010
	(-1.17)	(-1.55)	(-0.86)
$\Delta CsAvg_t \times \mathbb{1}_t(Boom=5)$	-0.069	0.030	
	(-1.22)	(0.12)	
$\mathbb{1}_t(Boom=5)$	0.005	0.001	0.006
	(0.25)	(0.04)	(0.27)
$\Delta Credit_t$	-0.101	-0.137*	-0.085
	(-1.62)	(-2.24)	(-1.39)
$\Delta CsAvg_{t-1}$	-0.187*	-0.367^{+}	
	(-2.47)	(-1.90)	
ΔLP_t		-0.003	
		(-0.01)	
$\Delta rGDP_t$		0.186	
		(0.87)	
ΔTFP_t		-0.168	
		(-0.38)	
ΔINV_t		0.174	
		(1.30)	
N	891	583	930
R^2	0.13	0.13	0.12
F	3.69	2.35	4.36
Cluster (country)	YES	YES	YES
Cluster (time)	YES	YES	YES
FE (country)	YES	YES	YES
FE (time)	YES	YES	YES

t-statistics in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5 Conclusion

A financial crisis occurs when information-insensitive debt becomes sensitive, affecting all collateral that, because it was information insensitive, all looks alike. This is more likely to happen after long credit booms, as the quality of projects undertaken decreases with the boom. As the boom evolves the average quality of projects decline (as marginal projects are of lower quality) and comes a (Minsky) moment when it is suddenly profitable to produce information about all firms' collateral. In a financial crisis information production about all firms' collateral cannot be prevented and the quantity of credit goes to zero.

In this paper we add information about projects in stock markets to these dynamics of information about collateral in credit markets. As credit booms evolve and average projects' quality decline, not only there are more incentives to acquire information about collateral in credit markets but also about firms in stock markets. Once weaker firms are discovered and stop participating in credit markets, lenders are discouraged to acquire information about the collateral of participating firms, potentially preventing a crisis.

In few words, stock markets play an unexplored positive macroprudential role in the economy. Stock markets become an automatic stabilizer of credit markets. This cleansing effect of stock markets? information on credit markets? composition discourage information acquisition about the collateral of the firms remaining in credit markets, slowing down credit growth and potentially preventing a crisis. Without stock markets we may observe more crises.

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6 Appendix

Figure 9: Number of countries. The figure summarizes the evolution of the number of countries in the equity data sample. The data are quarterly from Thomson/Reuters (DataStream) and span a period from 1973 until 2012.

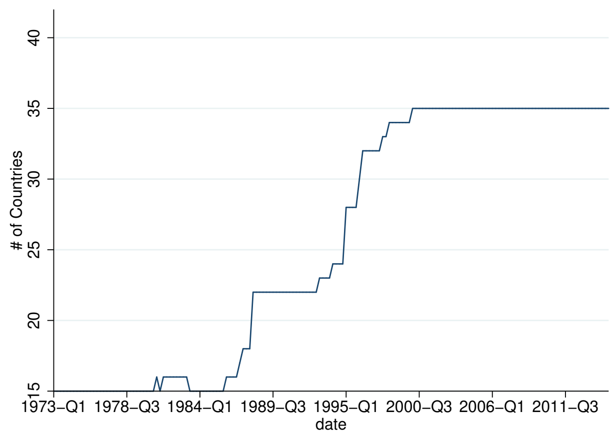

Table 4: Equity data - part 1. The table summarizes the number of firms for a given country and year for which return data is available. The frequency of the data is daily. Data is from Thomson/Reuters DataStream.

Country	1973	1974	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993
Argentina																13	14	16	18	28	78
Australia	73	74	77	79	82	82	82	84	86	80	90	99	100	112	127	250	336	330	370	407	484
Austria	15	13	10	9	12	9	15	11	12	16	15	14	27	24	30	27	49	67	69	78	85
Belgium	34	40	39	40	36	37	39	39	40	41	41	44	48	80	92	86	88	89	85	88	93
Brazil																		10	16	24	40
Bulgaria																					
Chile																	83	101	109	120	138
Colombia																				34	32
Croatia																					
Czech Republic																					94
Denmark	22	29	14	9	16	15	16	19	18	35	39	39	44	45	43	137	151	156	181	191	209
Ecuador																					
Egypt																					
Estonia																					
Finland																32	46	56	54	63	68
France	65	70	83	85	87	86	90	94	98	99	98	104	106	113	130	191	466	559	558	550	590
Germany	109	111	107	99	112	111	100	110	118	121	123	120	135	148	157	325	375	414	440	416	470
Greece																77	78	110	132	147	160
Hungary																			13	10	26
India																10	10	867	985	1110	1341
Ireland	30	26	31	32	34	37	30	31	35	28	33	24	31	38	48	50	59	49	49	44	53
Israel														163	181	180	189	196	181	244	450
Italy	62	63	64	61	60	60	62	62	66	64	65	61	67	192	222	242	273	297	305	308	320
Japan	738	732	751	767	772	781	789	792	804	831	859	890	890	902	1031	1603	1935	2172	2371	2409	2545
Kenya																			22	27	32
Latvia																					
Lithuania																					
Luxembourg																				26	31
Malaysia											15	26	22	182	203	197	229	260	296	350	403
Mexico																55	39	52	85	118	172
Morocco																					14
Netherlands	97	103	102	100	98	98	103	102	103	110	106	103	119	132	151	145	156	154	151	159	162
New Zealand														6	15	43	49	50	61	75	91
Nigeria																					
Norway								15	25	26	37	40	50	53	54	61	76	87	91	100	122
Pakistan																				119	145
Peru																			15	40	64
Philippines																	65	77	78	83	126
Poland																				13	16
Portugal																80	90	103	107	99	103
Romania																					
Russia																					
Slovakia																					
Slovenia																					
South Korea												269	259	320	362	477	579	619	642	656	667
Spain															45	50	81	94	103	106	113
Sweden										32	40	45	51	59	66	105	147	157	165	188	215
Thailand															84	120	163	197	263	297	345
Turkey																48	64	93	120	128	149
Ukraine																					
United Kingdom	1372	1238	1210	1215	1249	1195	1226	1365	1279	1309	1330	1300	1379	1342	1441	1348	1277	1135	1006	1104	1110
United States	706	712	759	761	743	756	767	843	863	900	983	1028	1146	1314	1451	1474	1514	1565	1697	1863	2121

Table 5: Equity data - part 2. The table summarizes the number of firms for a given country and year for which return data is available. The frequency of the data is daily. Data is from Thomson/Reuters DataStream.

Country	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Argentina	74	75	79	70	61	66	57	49	69	74	67	66	72	72	68	67	74	66	67	63	64
Australia	556	598	869	905	910	979	1084	1101	1113	1173	1303	1411	1536	1718	1610	1635	1680	1655	1616	1588	1597
Austria	77	86	77	79	87	94	99	99	79	83	74	81	89	98	99	93	94	79	78	73	80
Belgium	109	107	141	167	187	193	180	183	177	168	173	186	189	199	195	212	187	182	157	143	143
Brazil	47	40	56	59	72	107	93	91	91	121	126	114	147	216	213	213	215	231	215	217	213
Bulgaria					29	27	31	33	41	38	31	30	38	44	48	51	49	55	53	54	55
Chile	139	143	129	145	140	132	122	119	110	114	118	119	122	113	116	123	120	123	116	109	108
Colombia	52	43	48	49	36	25	30	36	32	33	40	49	37	43	30	41	42	34	31	33	29
Croatia			27	42	32	48	43	49	53	67	97	138	151	175	143	138	119	111	105	95	97
Czech Republic	135	224	234	157	148	123	93	87	41	44	65	44	28	30	30	22	26	27	26	21	27
Denmark	198	208	214	218	210	216	209	172	153	162	168	166	184	204	207	199	190	180	164	161	151
Ecuador	8	6	11	7	9	8	2	2	6	5	7	8	4	4	10	11	6	10	8	7	8
Egypt			58	60	67	101	93	92	108	125	116	110	117	123	130	135	129	128	134	140	150
Estonia			10	16	19	21	20	19	17	18	24	25	32	36	39	33	30	29	29	28	28
Finland	105	110	128	138	150	166	169	164	158	153	148	141	149	146	142	134	136	131	130	129	137
France	638	655	793	880	892	891	937	924	870	828	799	805	853	871	820	811	756	707	666	669	695
Germany	466	474	538	596	786	1127	1383	1462	1418	1407	1457	1566	1798	1944	1958	1814	1828	1600	1538	1372	1384
Greece	206	222	230	242	263	292	336	336	338	335	340	320	300	290	280	269	245	231	206	191	178
Hungary	38	43	51	58	69	77	85	76	71	74	76	70	74	67	66	71	74	79	79	74	76
India	1911	2763	2568	2213	1943	2418	1938	1744	1810	1978	2059	2469	2567	2877	2885	3031	3209	3288	3408	3250	3534
Ireland	43	39	42	49	50	51	58	56	51	51	51	53	59	62	62	52	48	47	44	42	43
Israel	538	545	560	544	519	620	549	542	476	465	486	529	559	609	556	565	551	523	487	463	436
Italy	325	312	331	351	356	406	452	464	551	489	521	552	565	577	569	554	555	534	507	530	545
Japan	2731	2948	3041	3179	3205	3326	3446	3577	3634	3617	3703	3802	3896	3928	3872	3716	3610	3546	3467	3507	3539
Kenya	40	30	31	34	35	33	26	34	30	39	36	35	43	46	46	45	45	47	52	50	54
Latvia					16	16	15	13	17	24	19	23	19	20	17	17	39	41	44	32	37
Lithuania					41	35	38	31	35	39	40	42	40	39	38	38	37	61	54	53	55
Luxembourg	38	38	47	48	50	45	40	48	48	47	53	50	54	62	70	67	70	63	64	79	58
Malaysia	462	519	613	698	707	717	738	744	752	855	913	956	1006	961	890	910	917	905	870	880	896
Mexico	145	137	144	141	140	141	113	120	91	93	100	99	107	92	91	106	107	97	114	121	117
Morocco	19	26	21	31	45	44	42	48	46	47	48	56	64	72	79	71	75	76	75	69	70
Netherlands	156	173	192	197	221	227	211	188	173	165	151	147	154	153	146	137	125	126	115	108	108
New Zealand	103	101	107	111	110	103	115	110	103	122	146	139	138	132	116	115	112	107	115	128	132
Nigeria							18	44	39	39	46	31	32	39	27	25	29	24	23	25	31
Norway	155	170	197	230	239	223	218	224	230	219	240	296	334	409	415	412	416	407	401	422	440
Pakistan	164	158	169	194	196	285	245	222	292	289	301	279	253	255	152	235	231	207	222	225	225
Peru	85	86	81	82	64	65	61	56	67	70	83	89	91	96	85	107	92	74	64	63	65
Philippines	152	183	202	203	194	200	170	165	135	170	178	184	197	203	180	212	210	229	234	230	235
Poland	35	47	66	121	176	193	196	216	200	190	214	244	274	338	361	412	534	709	797	850	855
Portugal	110	102	105	100	96	95	78	67	64	59	60	57	55	55	54	51	54	51	50	51	52
Romania			37	133	179	174	152	116	217	222	266	253	254	426	312	261	256	236	209	207	208
Russia		14	15	52	28	33	47	73	32	43	52	91	140	197	221	250	277	277	270	235	215
Slovakia						23	16	17	15	19	19	10	11	3	5	4	6	6	8	8	9
Slovenia			18	38	51	78	86	107	72	60	51	36	25	18	17	12	10	12	13	12	11
South Korea	694	711	903	1009	956	1142	1300	1411	1534	1569	1574	1624	1684	1766	1808	1784	1792	1793	1753	1798	1847
Spain	111	107	122	135	164	162	164	157	150	139	124	132	139	146	145	136	144	140	134	133	142
Sweden	247	266	290	339	381	417	433	409	390	367	381	405	446	502	507	499	504	501	477	494	533
Thailand	387	407	422	381	342	315	292	316	326	382	402	435	483	467	491	488	508	521	539	562	633
Turkey	171	197	221	250	268	262	288	279	284	282	293	296	309	311	307	307	329	352	381	400	394
Ukraine													68	89	82	61	53	46	39	36	37
United Kingdom	939	1016	1170	1165	1180	1209	1274	1295	1313	1322	1478	1684	1758	1754	1615	1502	1480	1386	1297	1328	1366
United States	2359	2615	2871	2924	2787	2675	2525	2472	2531	2593	2721	2854	2976	3202	3263	3330	3466	3598	3738	4005	4352

Table 6: Summary Statistics (Quarterly). The table reports summary statistics for $\Delta rGDP$, α, $1/Vol$, $CsVol$, $\Delta(1/Vol)$, $\Delta CsVol$. The data are from the OECD iLibrary and Thomson/Reuters (DataStream), and span a period from 1973 until 2012. "Count" label refers to country-quarters.

	count	mean	sd	min	max
$1/Vol$	3963	3.226	0.977	0.888	6.796
$CsAvg$	3963	0.134	0.095	0.023	1.138
$\Delta(1/Vol)$	3952	0.002	0.533	-2.721	3.316
$\Delta CsAvg$	3952	0	0.077	-0.654	0.640
No. of Countries	169	25.633	8.809	15	42

Table 7: Summary Statistics (Annual). The table reports summary statistics for *real GDP in bn.* \$, TFP, *Credit/rGDP*, *Labor Productivity in hours*, $\Delta rGDP$, ΔTFP, $\Delta Credit/rGDP$, Δ*Labor Productivity*, $1/Vol$, $CsAvg$, $\Delta(1/Vol)$, and $\Delta CsAvg$. The data are from the Penn World Tables (PWT), WIPO statistics database, World Development Indicators, Total Economy Database (TED), and Thomson/Reuters (DataStream), and span a period from 1973 until 2012. "Count" label refers to country-years.

	Count	Mean	StDev	Min	Max
real GDP in bn \$	2787	383.466	939.771	3.096	10228.909
TFP	1895	451.679	175.543	104.050	823.585
Credit/rGDP	2730	57.454	46.122	1.385	232.097
Labor Productivity in hours	1903	15.171	8.738	1.586	41.145
$\Delta rGDP$	2726	0.035	0.042	-0.321	0.308
ΔTFP	1857	0.007	0.038	-0.180	0.236
$\Delta Credit/rGDP$	2674	0.036	0.168	-0.863	2.881
Δ*Labor Productivity*	1858	0.026	0.033	-0.179	0.196
$1/Vol$	998	3.191	0.999	0.921	6.680
$CsAvg$	998	0.135	0.092	0.023	0.854
$\Delta(1/Vol)$	959	0.007	0.850	-2.867	3.403
$\Delta CsAvg$	959	0.002	0.080	-0.429	0.536

Table 8: Information Measures and Financial Crises - Quarterly Observations. The table summarizes the predictive power of information measures ($1/Vol$, $CsAvg$, $\Delta(1/Vol)$, $\Delta CsAvg$) on the occurrence of financial crises. The regression specification is: $\mathbb{1}_{n,t}(Crisis) = \alpha_n + \beta' X_{n,t-1} + \epsilon_{n,t}$ for linear probability models and $Pr(\mathbb{1}_{n,t}(Crisis) = 1|X_{n,t-1}) = \Phi(\alpha_n + \beta' X_{n,t-1})$ for LOGIT models, where $X_{n,t-1} = (1/Vol_{n,t-1}, CsAvg_{n,t-1}, \Delta Vol_{n,t-1}, \Delta CsAvg_{n,t-1})'$. The data are quarterly and span a period from 1973 until 2012. All regression specifications take into account country fixed effects and standard errors are clustered both at a country and time level.

	(1) Linear	(2) Logit
$1/Vol_{t-2}$	-0.098***	-1.761***
	(-3.88)	(-6.54)
$CsAvg_{t-2}$	0.491+	4.104*
	(1.95)	(2.22)
$\Delta(1/Vol)_{t-1}$	-0.059**	-1.068***
	(-2.89)	(-3.88)
$\Delta CsAvg_{t-1}$	0.327*	2.792**
	(2.33)	(2.71)
Constant	0.180	2.465**
	(1.52)	(3.01)
N	3920	3220
R^2	0.16	.
F	14.64	.
Cluster (Time)	YES	YES
Cluster (Country)	YES	YES
FE (Country)	YES	YES

t-statistics in parentheses
$^+$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Information Measures and Financial Crises - lagged regressions (LOGIT). The table summarizes the predictive power of information measures ($1/Vol$, $CsAvg$, $\Delta(1/Vol)$, $\Delta CsAvg$) on the occurrence of recession with crises events. The regression specification is: $Pr(\mathbb{1}_{n,t}(Crisis) = 1|X_{t-q}) = \Phi(\alpha_n + \beta' X_{t-q})$, where $X_{n,t-q} = (1/Vol_{n,t-q}, CsAvg_{n,t-q}, \Delta Vol_{n,t-q}, \Delta CsAvg_{n,t-q})'$. The data are quarterly and span a period from 1973 until 2012. All regression specifications take into account country fixed effects and standard errors are clustered both at a country and time level.

	(1) q=0	(2) q=1	(3) q=2	(4) q=3	(5) q=4	(6) q=8
$1/Vol_{t-q-1}$	-1.808***	-1.761***	-1.578***	-1.346***	-1.105***	-0.500+
	(-6.58)	(-6.54)	(-5.77)	(-4.76)	(-4.03)	(-1.95)
$CsAvg_{t-q-1}$	4.976**	4.104*	3.173+	2.436	2.026	1.243
	(2.65)	(2.22)	(1.74)	(1.45)	(1.25)	(0.82)
$\Delta(1/Vol)_{t-q}$	-0.955**	-1.068***	-1.179***	-0.969**	-1.015***	-0.491+
	(-3.20)	(-3.88)	(-4.45)	(-3.18)	(-3.53)	(-1.94)
$\Delta CsAvg_{t-q}$	3.011**	2.792**	2.525**	1.818+	1.578+	0.711
	(3.00)	(2.71)	(2.68)	(1.72)	(1.79)	(0.88)
N	3201	3220	3196	3116	3093	3001
Cluster (Time)	YES	YES	YES	YES	YES	YES
Cluster (Country)	YES	YES	YES	YES	YES	YES
FE (Country)	YES	YES	YES	YES	YES	YES

t-statistics in parentheses
$^+$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$