Aggregate Information Dynamics

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Abstract

Information acquisition in stock markets (about firms' values) and in credit markets (about firms' collateral) interact with each other differently depending on the state of the macro economy. This interaction determines the dynamics of productivity and credit in the economy. While information in stock markets affect productivity through reallocating resources, information in credit markets alters the amount of credit available and can induce financial crises, with sudden declines in credit. Our model generates empirical counterparts of information choices, which we take to the data to confront its testable implications. We document feedback effects between the two markets. No information in credit markets eventually induces information production in stock markets, which slows down credit and output, preceding recessions. Further, information in stock markets is only relocative when not accompanied with crises.

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1 Introduction

Stock markets aggregate dispersed information about the value of firms and improves the allocation of resources in the economy. This result has constituted the backbone of the study of how prices feedback into real variables (see, e.g., Dow and Gorton (1997) and Dow et al. (2017)). Less known is that information about firms' collateral can be counterproductive by reducing aggregate credit in the economy, and in the extreme of sudden incentives to acquire information financial crises can be generated (see, e,g. Dang et al. (2012) and Gorton and Ordoñez (2016)). Information in credit markets is costly in terms of the total volume of credit available, while information in stock markets is beneficial in allocating such credit.

How do incentives to acquire information in these two markets interact? What are the feedback effects? We propose a model in which information in stock markets is about the firm's productivity and determines allocation of credit, while information in credit markets is about the firm's collateral and determines the volume of credit. These two sources of information interact dynamically. Information about collateral affects the amount of credit available in credit markets. The volume of credit determines total output and the productivity of the marginal project, which affects the incentives to acquire information about productivity in stock markets. The amount of information in stock markets affects the incentives to acquire information about collateral in credit markets, closing the circle. Further, these interactions depend on the state of the macroeconomy.

Our analysis uncovers the intricate relations between business cycles, the information content of stock prices and financial crises. More specifically, (i) a credit boom eventually induces information production in stock markets; (ii) information in stock prices slows down the amount of credit granted and output, delaying (and possibly preventing) a financial crisis; and (iii) a financial crisis could have been worse without information in stock markets, but discourages further information in stock markets.

Our model generates empirical counterparts on the amount of information produced in stock and in credit markets. Information in stock markets is measured by the cross-sectional dispersion of stock returns: more information about the productivity of individual firms is priced in and increases the dispersion of returns across firms. Information in credit markets is about the availability of credit in the economy: more information about the collateral of individual firms hinders the use of collateral of relatively low value to obtain credit and reduces aggregate credit in the economy, sometimes drastically – a financial crisis.

These variables, which can be measured in the data, are related to business and financial cycles. Using a rich panel with high frequency information on stock returns and a cross-country sample of financial crises, we test (1) for feedback effects between the stock and credit markets; (2) for whether more information is produced prior to a recession, particularly prior to a recessions characterized by a financial crisis. WE find weak evidence of the feedback effects, for reasons explained below. But, we find strong evidence that more information is produced prior to a financial crisis. Finally, based on the information produced,we show that reallocation of resources only occurs in recessions without a crisis – the "cleansing effect" of recessions depend on whether firms can access credit markets to exploit the information generated in stock markets.

The paper proceeds as follows. Section 2 presents the model, first in a general setting, and then a more detailed model. Section 3 is devoted to the definitions of the aggregate economic episodes and the data is explained and summarized. Section 4 examines how our measures of information and fragility are related to the different types of aggregate economic episodes. Section 5 is about possible reallocation of resources based on information produced in the stock market. Section 6 concludes.

2 Model

We construct a model to highlight the interaction between the incentives to acquire information in stock markets and in credit markets, and their effects in business cycles and financial crises. We first develop a general setting that highlights the sources of interactions and the dynamic implications. Then we make simplifying assumptions to illustrate those dynamics and to map the model to data counterparts.

2.1 General Setting

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 $F''(K) < 0$. The project produces 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). 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 expectation depends 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 operating 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 involved 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 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 and prevent any loan at all. A small loan that does not trigger information may be always obtained while a large loan that triggers information represents facing a lottery depending on the information outcome. That is, 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 about collateral.

The expectation of the project quality conditional on the observed price (this is $E(q_{it}|P_{it})$) depends on how much information is generated in stock markets and that 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 $\mathcal{M}$. In stock markets buyers may acquire information about the quality of the project, also at a cost in terms of consumption goods. The extent to which this information gets into the price and the effect of aggregation on the incentives to acquire information depends on $\mathcal{M}$. For instance, with a continuum of buyers with dispersed unbiased signals prices perfectly aggregate information and discourages 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 the use of auctions (as in Milgrom (1981) and Cole et al. (2018)). Later we propose a novel protocol that does not dissipate private information gains and allows to highlight information acquisition choices.

We will 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, as described above, the expected probability of default before observing the stock price 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 obtain in credit markets, which depends on the expected value of collateral $E(C_{it})$ and on the expectation of what the price may reveal and the implications for information acquisition in credit markets, which depends on the $E(q_{it})$.

This general setting highlights the sources of interaction: information in stock markets is encoded in stock prices and affects information acquisition 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.

2.1.1 Dynamics

The dynamics in this setting rely on the 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 $E(C_{it})$.

2.2 Simplified Setting

We now illustrate the above points by fleshing out a model.

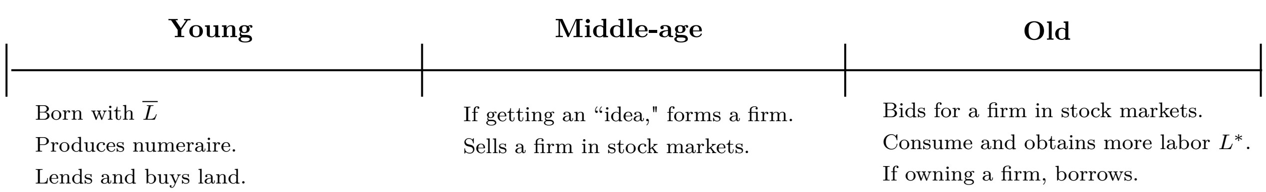
Agents and Goods: To model who buys, who operates and who sells firms, we assume an overlapping generation structure, such that in each period t three overlapping generations coexist – young, middle-aged and old – each generation is of mass 2 of a continuum of agents. There are three goods in the economy – *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 obtain at the beginning of the period and that, when combined with a unit of land constitutes *a firm.* Firms 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 that all firms, regardless of the project quality, operate at 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 an idea for a project. In period $t+1$ the agent becomes middle-aged. Then if he obtained an idea, he can combine it with the unit of land, form a firm and sell it in stock market. In period $t+2$ the agent becomes old and can use the numeraire accumulated to bid for a firm in stock markets. After stock markets close, 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 stock markets close) guarantees that resources are in the wrong hands before production takes place and so firms need to 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

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

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 will never be repaid. The output will 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* and relaxes 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. 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: an 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 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 being obtained and becomes public at the end of the period. Still, the agent can credibly disclose his private information (the certificate) immediately if it is beneficial to do so.

The perception about the quality of collateral then becomes critical for the granting of loans. We further 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*, our 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 project and land) to operate. As there are twice as many buyers as firms we assume a protocol in which two old agents are

[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.

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 stock markets we a bidder can privately acquire information about the firm before submitting the bid. Production of such information costs γ_q in terms of numeraire. In 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. Market for firms (stock markets). A mass one of middle-aged agents have an idea, which combined with a project and collateral creates a firm. Among the firms which are created, those with $p > 0$ 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.

2. Consumption and new labor endowments: Numeraire goods 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 immediate produce $\bar{K}$ units of numeraire goods.

3. 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 and the fraction of collateral that should be transferred to the lender in case of default, x. The loan contract 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 reject the offer.

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

5. Market for land (asset markets): Young agents that 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.

6. 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.

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

Stock Market	**Consumption**	**Credit market**	**Production**	**Asset market**
Match: 1 seller - 2 bidders.	All numeraire consumed.	Match: young - old.	Firm production.	Match: young - old.
Info choice about q.	New labor endowment..	Info choice about C.	Loan contracts settled.	Land traded at pC.
Trade at auction price.	..and numeraire prod.	Loan contract.		Shocks to land type.

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, 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 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 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, which we call 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

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

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 one where firms always borrow just based on the expected value of collateral. In this case, 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,

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

For this contract to be information-insensitive (II), there is the extra constraint of 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. That is, 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,

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

or in terms of the loan size,

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

Borrowers may want to deviate because they can borrow at beneficial contract terms 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,

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

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).

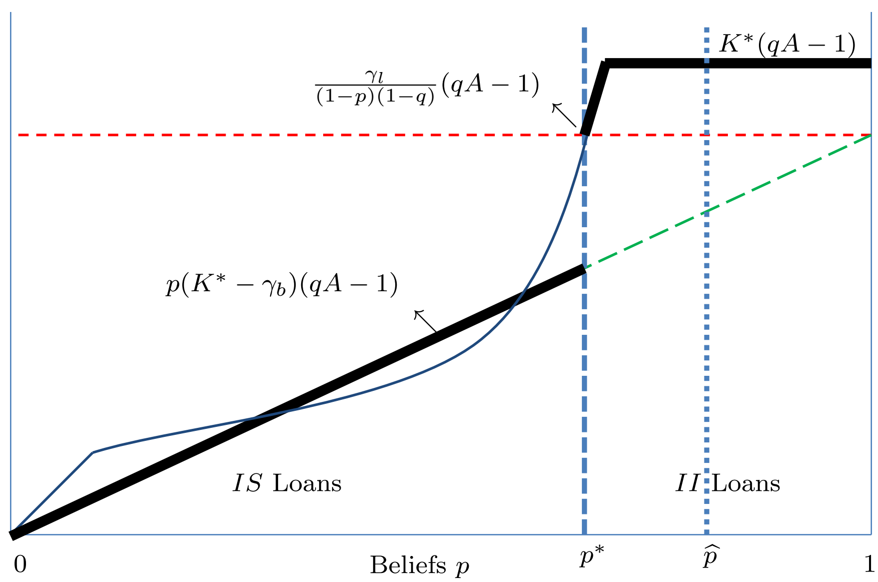
Then

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

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 in the dynamics, 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. Firms that were getting loans prior to this suddenly cannot get loans. Output and consumption go down.

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 on 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 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 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, which are then exploited in credit markets to determine information about collateral. We here explore this intricate relation.

When a potential buyer is randomly assigned to a firm, he knows 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 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 $P_U(p)$ 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 parts will be jointly determined 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 (as the informed would bid $P^U(p)+\epsilon$ for a good firm) and always buys a low quality firm (as the informed 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 we assume he knows), 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

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

The fraction of uninformed investors y affects the price that uninformed investors bid for a firm. When no investor is informed (this is, $y=1$), then $P_U = zV_H + (1-z)V_L$, the ex-ante value of the firm. When all investors are informed (this is, $y=0$), 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, $y=1$) when $\mathcal{V}_{stock} > \gamma_q$, or as $\Pi^U = 0$ when $\Pi^I(y=1) > \gamma_q$. As in this case P_U is the fair value of the firm, $y=1$ when $\overline{\gamma}_q \equiv x(1-x)(V_H - V_L) > \gamma_q$. This implies that when the cost of information 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' quality. At the other extreme, no investor acquires information (this is $y=0$) when $\Pi^I(y=0) < \gamma_q$.

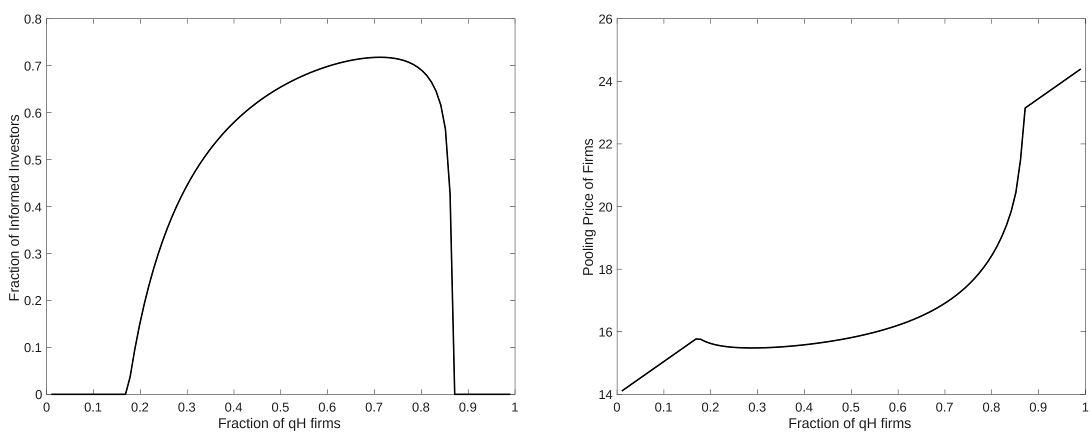
As in this case $P_U = V_L$, $y = 0$ when $\underline{\gamma}_q \equiv \frac{x}{2}(V_H - V_L) < \gamma_q$. This implies that when the cost of information is very large no investor has the incentive to deviate and become informed. This is the case in which stock markets are the least informative as all firms are traded at the same P_U in stock markets.

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 $z = \psi/\eta$). The incentives to acquire information are maximized when there is a relative large uncertainty from the balanced composition of projects in the market. The second panel shows the pooling price, P_U, also as a function of the fraction of active firms with q_H-projects. 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.

Figure 4: Fraction of Informed Investors and Pooling Price



Notice that the solution of y^* determines *the information content in stock markets*. 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 reveal the firm has a q_H-project, a fraction $(1-z)(1-y^*)^2$ of firms trade at price V_L, which reveal the firm has a q_L-project, and a fraction $1-(1-y^*)^2$ of firms are trade 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 stock markets and affect information in credit markets.

2.6 Dynamic interactions of information between credit and stock markets

In this subsection we illustrate the dynamic interactions between information about collateral in credit markets and information about projects in stock markets.

Recall the idiosyncratic shock process for collateral. With probability λ the true quality of the land remains unchanged, and with probability $1-\lambda$ the land type changes. So, in the latter case, land becomes good with probability $\widehat{p}$ independent of its current type. Given this process of idiosyncratic shocks for land, a unit of land is either known to be good ($p=1$), known to be bad ($p=0$) or it is of uncertain quality ($p=\widehat{p}$). This implies that the mass of active firms is given by the mass of all firms that may have good collateral. This is $\eta = m(\widehat{p}) + m(1)$. In this exercise we will assume that $\widehat{p} < p^*(q_L)$ (there is information about collateral in credit markets for firms known to operate with q_L-projects) and that $\widehat{p} > p^*(q_H)$ (there is no information about collateral in credit markets for firms known to operate with q_H-projects). The reason is for this is to focus our analysis to situations in which information available about firms affects their performance in credit markets.

It is informative how collateral types flow into these different bins over time. After idiosyncratic shocks to land but before the stock markets open, the mass of land that corresponds to each belief p are

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

where t refers to the end of period t *before* idiosyncratic shocks, and t' refers to the end of period t *after* the idiosyncratic shocks have been realized. These masses also determine the mass of active firms for the period, $\eta_{t+1} = m(\widehat{p})_{t'}$, which determines $z_{t+1} = \frac{\psi}{\eta_{t+1}}$ and $\widehat{q}_{t+1} = z_{t+1}q_H + (1-z_{t+1})q_L$. Notice that active firms in a period are given by all those firms that in principle could operate (as they have collateral with a chance to obtain credit), as our assumption is that those are the firms that could choose a project before being traded in stock markets.

At the beginning of period $t+1$, after firms are traded in stock markets, the fraction of informed bidders will be determined by η_{t+1}. If $p^*(\widehat{q}_{t+1}) \leq \widehat{p}$ there is no information production in credit markets for firms for which stock markets have not provided information about the quality of projects. Then,

$$\begin{aligned} m(0)_{t+1} &= m(0)_{t'} + (1-z)(1-y)^2(1-\widehat{p})m(\widehat{p})_{t'} \\ m(1)_{t+1} &= m(1)_{t'} + (1-z)(1-y)^2\widehat{p}m(\widehat{p})_{t'} \\ m(\widehat{p})_{t+1} &= (1-(1-z)(1-y)^2)m(\widehat{p})_{t'}. \end{aligned}$$

where $(1-z)(1-y)^2$ are the firms that stock markets have revealed to have q_L-projects, and are then subject to examination in credit markets. Notice that in the case that stock markets are non-informative (this is, $y=1$), then there is no discovery of collateral quality in period $t+1$, just depreciation of information due to the idiosyncratic shocks to land.

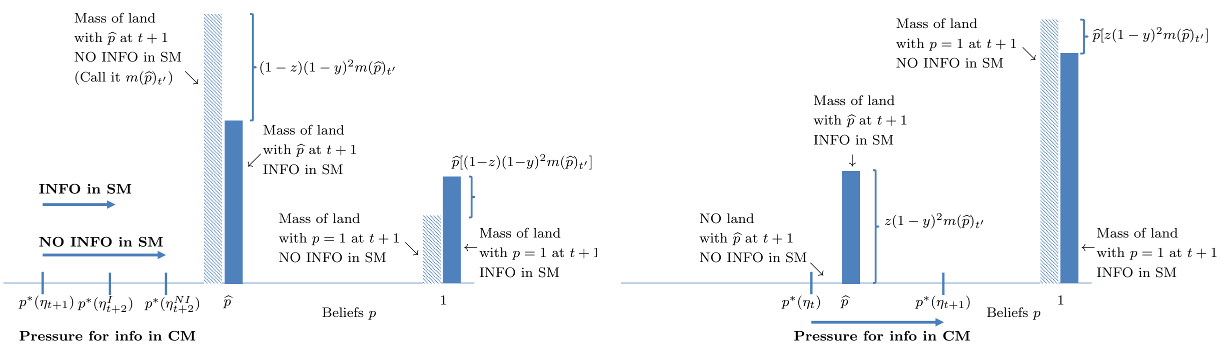
If in contrast, $p^*(\widehat{q}_{t+1}) > \widehat{p}$ there is information production in credit markets for firms for which stock markets have not provided information about the quality of projects. Then,

$$\begin{aligned} m(0)_{t+1} &= m(0)_{t'} + [1-z(1-y)^2](1-\widehat{p})m(\widehat{p})_{t'} \\ m(1)_{t+1} &= m(1)_{t'} + [1-z(1-y)^2]\widehat{p}m(\widehat{p})_{t'} \\ m(\widehat{p})_{t+1} &= z(1-y)^2m(\widehat{p})_{t'}. \end{aligned}$$

where $z(1-y)^2$ are the firms that stock markets revealed to be ones with q_H-projects, and then where the collateral is not subject to examination in credit markets.

We illustrate the interaction between information acquisition in credit and stock markets in Figure 5, in which we show the mass of active firms that obtain credit in a period $t+1$ under different information scenarios. In the panel (a) we focus on a set of parameters under which there is no information produced in credit markets in period $t+1$ (as the threshold $p^*(\eta_{t+1})$ for a firm with project quality $\widehat{q}$ is smaller than $\widehat{p}$). As the credit boom in the economy evolves (an increase in the mass of active firms between t and $t+1$) there is an increase in the incentives to acquire information about projects in stock markets. The light bars in the figure show the mass of firms that obtain credit when there is no information in stock markets, and the solid bars when a fraction y of bidders in stock markets that become informed. There are two effects of information in stock markets. First, *the fraction of firms that obtain credit in* $t+1$ *declines*. This is because a fraction $1-z$ of firms are discovered to be of quality q_L and their collateral is investigated in credit markets (reducing the mass of firms who obtain credit without investigation) and only a fraction $\widehat{p}$ will be found to have good collateral (adding to the mass of firms who obtain credit because of their good collateral). Second, *the pressure for financial crises (massive information in credit markets) in period* $t+2$ *declines.* This is because partial investigation of collateral for firms that are discovered to have low quality projects delays the buildup of active firms and prevents the average quality of projects from dropping too fast.

Figure 5: Interaction of information between credit and stock markets



(a) No Information in Credit Markets

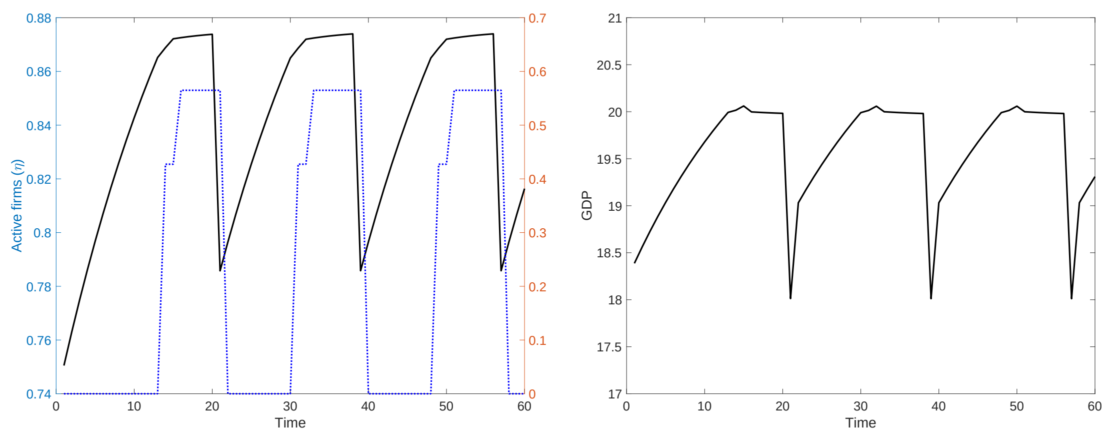
(b) Information in Credit Markets

Panel (b) of Figure 5 considers the set of parameters under which the credit boom in period t raised the mass of active firms to a point of massive information acquisition in credit markets (an informational financial crisis). If the financial crisis is not preceded by information acquisition in stock markets (again, the light bar) then all collateral is investigated and only those firms with good collateral obtain credit. In contrast, if the financial crisis is preceded by information in stock markets, there is a fraction z of the $(1-y)$ firms investigated that reveal their projects to be of quality q_H and whose collateral is not investigated and obtain credit. A fraction $\widehat{p}$ of those firms would have been revealed to have good collateral otherwise. In this case, *information produced in stock markets prior to a crisis prevents a larger collapse of credit in the economy.*

We further illustrate the dynamic interaction between information acquisition in stock markets and in credit markets, and the evolution of the mass of collateral beliefs over time as follows. We assume an economy with perfect information about the quality of collateral in the initial period, and when $\eta = \widehat{p}$ there is no information acquisition about firms (in stock markets) or collateral (in credit markets). These assumptions guarantee that there is a credit boom after the initial period, and correspond to the ones that generated Figure 4.

The first panel of Figure 6 shows that, as the credit boom evolves there is an increase in the fraction of active firms (solid black) and a decline in the fraction of q_H-projects in the economy. At some point there is information acquisition in stock markets (dashed light blue) where almost 60% of investors become informed about the quality of projects. This information in stock markets has the effect of slowing down the credit boom. Even though there is no information about the collateral of firms with uncertain projects, there is information about the collateral of firms for which stock markets have revealed to operate q_L-projects. Once credit booms become large enough, however, there is sudden information production in credit markets, a financial crisis that suddenly reduces the fraction of active firms in the economy. As there are less firms operating, the fraction of q_H-projects increase, which also relaxes the incentives to acquire information in stock markets.

Figure 6: Active Firms, Information and Output



The second panel of Figure 6 illustrates the evolution of output in this economy, which is an aggregation of production based on the evolution and volume of credit. As the credit boom evolves there is an increase in output. Once information is generated in stock markets, credit slows down and output stagnates. The ensuing financial crisis is characterized by a sudden decline in output followed by a slow recovery as the credit boom develops again.

This analysis highlights the intricate relations between business cycles,the information content of stock prices and financial crises. More specifically, (i) a credit boom eventually induces information production in stock markets; (ii) information in stock prices slows down the amount of credit granted and output, delaying (and possibly preventing) a financial crisis; and (iii) a financial crisis could have been worse without information in stock markets, but discourages further information in stock markets.

3 Stock Market and Credit Market Feedback Effects

Our empirical work is in two parts. In this section we show some simple results that characterize the feedback effects between the two markets during credit booms. We first explain the various information measures, including a stock price-based measure of fragility, and discuss the data. Then we test for feedback effects.

3.1 Definitions of Measures of Information and Fragility

We examine two measures of information, the first is a stock price-based measure of economy-wide fragility and the second is a stock price-based measure of information in the economy.

In the model, more information is produced as more and more firms are active and average productivity is declining over the course of a credit boom. Our empirical counterpart which we construct is the cross-section of firms' average stock returns. In particular we look at the standard deviation of firms' average returns: $CsAvg$. In other words, this variable is a cross-section characterization. This variable is related to the cross-section of firms' stock return volatility: $CsVol$. These two variables are highly correlated, 0.96, so we will restrict attention to $CsAvg$. We label this variable *Information.* $1/Vol$ is also based on stock information and we label it *Fragility*. For both $CsAvg$ and $1/Vol$ we have in mind the idea that underlying these variables are agents in the economy who are producing more or less information in reaction to the unobserved (to us) state of the economy. Based on the private information that these agents produce, they trade and stock prices respond. This interpretation is not crucial. It could be public information, or a combination. In a later section, we will show that thinking of all of these measures as informative is correct because some reallocation of capital occurs in response to these variables in recessions.

The 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 are especially fragile periods. These periods stand out.[3]

Above we also showed that as the H projects are used up more and more firms will default because default is more likely with the L projects. We capture this with the mean $1/Vol$ of each country in each year as a state variable about the *Fragility* of the economy. 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. There was never a panic without the threshold being exceeded; and the threshold was never exceeded without a panic.[4]

These variables are calculated as follows. Using daily stock price data, the monthly return and volatility are calculated for each firm in each country of the sample. Both returns and volatilities are annualized and $CsAvg$ and $1/Vol$ are computed. For each country we find the mean ($1/Vol$) and compute the cross-sectional standard deviation of averages. Then these two monthly series are averaged across firms to create quarterly series. The annual series are formed using the last quarter observation of the quarterly series.

Appendix tables 14 and 15 show the correlations between the Information and Fragility variables and changes in those variables at the quarterly and annual horizons. As mentioned above, $CsAvg$ and $CsVol$ are

[3] 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] See the discussion in Gorton (2012), p. 75-77.

highly correlated, as are changes in these two variables. Notably, the other variables are not highly correlated.

We use the definition of a credit boom from Gorton and Ordoñez (2016) and we use the booms that they identified. They define a credit boom as starting whenever a country experiences three consecutive years of positive credit growth (as a fraction of GDP) that average more than x^s. The boom ends whenever a country experiences at least two years of credit growth (also as a fraction of GDP) not higher than x^e. In our baseline experiments we choose $x^s = 5\%$ and $x^e = 0\%$.

3.2 Data Sources and Preliminary Univariate Results

In the empirical work that follows we need a measure of credit in an economy and some macroeconomic variables. Annual Real GDP is from the Penn World Tables (PWT), TFP is from Kose et al. (2008), domestic credit-to-the-private-sector is from the World Development Indicators, and labor productivity is constructed using the hours-adjusted output-labor ratio from the Total Economy Database (TED). Our measures of economy-wide fragility and the level of information in the economy, are constructed using daily stock price data for the countries in our sample. The source of stock price data is Thomson/Reuters DataStream. The countries and dates of coverage are listed in Tables 30 and 31 of the Appendix. Also see Figure 9 in the Appendix.[5] Later we will use WorldScope data to calculate Q-ratios. Table 1 shows the summary statistics for these variables.

The measure of credit that we use is credit-to-the-private-sector divided by GDP. The ratio essentially detrends credit growth because in a boom credit must grow faster than GDP.

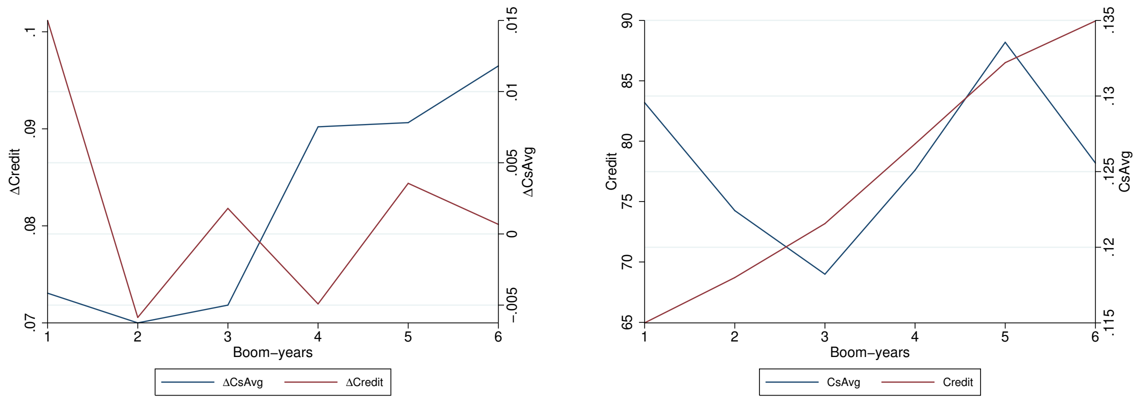
Table 1 presents summary statistics. Figure 7b shows the two variables in changes and levels average over the first six years of credit booms. In changes, the correlation is negative over years three, four, and five. In levels the variables are negative correlated over the first three years of the booms.

Table 1: **Summary statistics (Annual)**. The table reports summary statistics for *real GDP in bn.* \$, TFP, $Credit/rGDP$, *Labor Productivity in hours*, *Recession Measure*, $\Delta rGDP$, ΔTFP, $\Delta Credit/rGDP$, Δ*Labor Productivity*, $1/Vol$, $CsAvg$, $CsVol$, $\Delta(1/Vol)$, $\Delta CsVol$, 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 2010. "Count" label refers to country-years.

	Count	Mean	StDev	Min	Max
real GDP in bn \$	886	734.419	1395.693	5.704	9651.111
TFP	732	594.578	114.943	187.514	823.585
$Credit/rGDP$	886	81.129	46.947	8.766	232.097
Labor Productivity in hours	874	20.744	7.574	6.520	40.215
Recession Measure	886	-0.001	0.028	-0.218	0.061
$\Delta rGDP$	886	0.028	0.031	-0.177	0.113
ΔTFP	732	0.003	0.028	-0.179	0.113
$\Delta Credit/rGDP$	886	0.044	0.168	-0.634	2.881
Δ*Labor Productivity*	873	0.022	0.024	-0.110	0.140
$1/Vol$	820	3.225	1.014	0.921	6.680
$CsVol$	820	0.462	0.393	0.078	3.657
$CsAvg$	820	0.127	0.084	0.023	0.854
$\Delta(1/Vol)$	793	0.017	0.877	-2.867	3.403
$\Delta CsVol$	793	0.009	0.360	-2.141	2.181
$\Delta CsAvg$	793	0.002	0.080	-0.429	0.536

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

Figure 7: **Information variable and Credit during credit booms**. The figure summarizes the evolution of cross-sectional average returns ($CsAvg$) and Credit to private sector ($Credit$) during a credit boom (years 1 through 5). The variables are averaged across all countries in the sample. The data are from 1973 until 2010 (annual frequency).



(a) $\Delta CsAvg$, $\Delta Credit$ (b) $CsAvg$, $Credit$

3.3 Feedback Effects

The model predicts that at some point during a credit boom agents will produce more information in the stock market and, subsequently during the boom, they may produce less, or there may be a financial crisis. Information production over booms, then, can follow different patterns. We can only look for average effects.

Our general approach is to run two types of regressions. One type has the change in our measure of information $\Delta CSAvg$ regressed on the change in credit, $\Delta Credit$, interacted with boom years. Specifically, we interact the change in credit separately with each boom year. The second type of regression looks at the feedback in the other direction. The dependent variable is now $\Delta Credit$ and the right-had side variables include $\Delta CsAvg$ interacted with different boom years.

Looking first at Table 2, columns (1)-(5) show the results separately for each boom year, while column (6) has all of the first five years entered. In the first year of the boom, column (1) an increase in credit is associated with more information being produced. But, this is reversed in the second year, column (2). None of the interaction terms are significant when all the boom years are included.

Table 3, on the other hand, looks at feedback going in the other direction and the columns follow the same pattern as before. More information being produced in the second year of the boom on average dampens credit growth, in Columns (2) and (6).

Overall, the results in these tables are very weak. Partly this may be due to different booms having different patterns of interaction between Information growth and Credit growth. And partly it may be due to having to use annual data. Finally, it is not clear that the measure of Credit, the only available for a broad sample of countries, does not line up exactly with collateralized borrowing. For example, it includes government loans to the private sector.

For these reasons, in the next section, we refine the test to looking at only one direction, the relationship between $\Delta CSAvg$ as the independent variables and an extreme example of credit changing, during a financial crisis.

Table 2: **CsAvg, Credit and Credit booms**. The table summarizes the predictive power of credit and macroeconomic variables on information production. The regression specification is $\Delta CsAvg_{n,t+1} = \alpha_n + \beta \Delta Credit_t + \gamma \Delta Credit_t \times \mathbb{1}_{n,t}(Boom = y) + \delta \mathbb{1}_{n,t}(Boom = y) + \zeta X_{n,t} + \epsilon_{n,t}$, 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 2014. All regression specifications take into account country and decade fixed effects, and standard errors are clustered at the country and year level.

	(1) $y = 1$	(2) $y = 2$	(3) $y = 3$	(4) $y = 4$	(5) $y = 5$	(6) *all*	(7) *booms*
$\Delta Credit_t$	-0.037*	-0.001	-0.005	-0.005	-0.005	-0.049	
	(-2.56)	(-0.22)	(-0.64)	(-0.70)	(-0.62)	(-1.27)	
$\mathbb{1}_t(Boom)$						0.009	0.001
						(1.30)	(0.13)
$\Delta Credit_t \times \mathbb{1}_t(Boom = 1)$	0.046*					0.050	
	(2.58)					(1.27)	
$\mathbb{1}_t(Boom = 1)$	-0.007					-0.012	-0.007
	(-1.07)					(-1.54)	(-0.87)
$\Delta Credit_t \times \mathbb{1}_t(Boom = 2)$		-0.056*				-0.007	
		(-2.10)				(-0.18)	
$\mathbb{1}_t(Boom = 2)$		-0.002				-0.008	-0.004
		(-0.46)				(-1.20)	(-0.35)
$\Delta Credit_t \times \mathbb{1}_t(Boom = 3)$			-0.093			-0.051	
			(-0.68)			(-0.33)	
$\mathbb{1}_t(Boom = 3)$			0.018			0.012	-0.008
			(0.86)			(0.56)	(-0.76)
$\Delta Credit_t \times \mathbb{1}_t(Boom = 4)$				-0.119		-0.064	
				(-0.97)		(-0.50)	
$\mathbb{1}_t(Boom = 4)$				0.025		0.019	0.004
				(0.97)		(0.68)	(0.36)
$\Delta Credit_t \times \mathbb{1}_t(Boom = 5)$					-0.448	-0.437	
					(-1.20)	(-1.13)	
$\mathbb{1}_t(Boom = 5)$					0.040	0.039	0.005
					(1.28)	(1.11)	(0.21)
$\Delta(1/Vol)_t$	-0.007*	-0.007*	-0.007*	-0.007*	-0.007*	-0.007*	
	(-2.50)	(-2.46)	(-2.54)	(-2.53)	(-2.42)	(-2.24)	
$\Delta CsAvg_t$	-0.571***	-0.572***	-0.567***	-0.575***	-0.567***	-0.556***	
	(-3.69)	(-3.74)	(-3.70)	(-3.80)	(-3.86)	(-4.10)	
$CsAvg_{t-1}$	-0.348	-0.346	-0.343	-0.344	-0.348	-0.316	
	(-1.52)	(-1.51)	(-1.50)	(-1.52)	(-1.55)	(-1.48)	
ΔLP_t	-0.163	-0.164	-0.160	-0.175	-0.181	-0.209	
	(-0.66)	(-0.66)	(-0.64)	(-0.69)	(-0.73)	(-0.82)	
$\Delta rGDP_t$	0.052*	0.057**	0.057**	0.056*	0.054*	0.042^{+}	
	(2.29)	(2.73)	(2.72)	(2.45)	(2.49)	(1.75)	
ΔTFP_t	-0.056	-0.052	-0.054	-0.056	-0.031	0.005	
	(-0.41)	(-0.37)	(-0.37)	(-0.41)	(-0.22)	(0.04)	
ΔINV_t	-0.001	-0.005	-0.009	-0.006	-0.009	-0.027	
	(-0.01)	(-0.12)	(-0.21)	(-0.15)	(-0.22)	(-0.59)	
N	565	565	565	565	565	565	929
R^2	0.25	0.25	0.25	0.25	0.25	0.25	0.01
F	2.09	2.27	2.07	1.97	2.30	2.06	0.29
Cluster (country)	YES	YES	YES	YES	YES	YES	YES
Cluster (time)	YES	YES	YES	YES	YES	YES	YES
FE (country)	YES	YES	YES	YES	YES	YES	YES
FE (time)	YES	YES	YES	YES	YES	YES	YES

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

Table 3: **CsAvg, Credit and Credit booms**. The table summarizes the predictive power of information measures and macroeconomic variables on changes in credit. The regression specification is $\Delta Credit_{n,t+1} = \alpha_n + \beta \Delta CsAvg_t + \gamma \Delta CsAvg_t \times \mathbb{1}_{n,t}(Boom = y) + \delta \mathbb{1}_{n,t}(Boom = y) + \zeta X_{n,t} + \epsilon_{n,t}$, 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 2014. All regression specifications take into account country and decade fixed effects, and standard errors are clustered at the country and year level.

	(1) $y=1$	(2) $y=2$	(3) $y=3$	(4) $y=4$	(5) $y=5$	(6) *all*	(7) *booms*
$\Delta CsAvg_t$	-0.152**	-0.117**	-0.137***	-0.134**	-0.157**	-0.108	
	(-3.31)	(-2.99)	(-3.45)	(-2.97)	(-2.88)	(-1.51)	
$\Delta CsAvg_t \times \mathbb{1}_t(Boom=1)$	0.068					0.011	
	(0.31)					(0.04)	
$\mathbb{1}_t(Boom=1)$	0.007					-0.011	-0.007
	(0.39)					(-0.51)	(-0.49)
$\Delta CsAvg_t \times \mathbb{1}_t(Boom=2)$		-0.345***				-0.344***	
		(-8.28)				(-3.78)	
$\mathbb{1}_t(Boom=2)$		-0.007				-0.022	0.002
		(-0.22)				(-0.62)	(0.12)
$\Delta CsAvg_t \times \mathbb{1}_t(Boom=3)$			-0.247			-0.263	
			(-0.55)			(-0.53)	
$\mathbb{1}_t(Boom=3)$			-0.019			-0.033	-0.009
			(-0.80)			(-1.55)	(-0.54)
$\Delta CsAvg_t \times \mathbb{1}_t(Boom=4)$				-0.071		-0.098	
				(-0.83)		(-0.78)	
$\mathbb{1}_t(Boom=4)$				-0.007		-0.022	0.005
				(-0.68)		(-1.53)	(0.29)
$\Delta CsAvg_t \times \mathbb{1}_t(Boom=5)$					0.067	0.012	
					(1.19)	(0.17)	
$\mathbb{1}_t(Boom=5)$					0.004	-0.010	0.003
					(0.28)	(-0.76)	(0.42)
$\mathbb{1}_t(Boom)$						0.022	0.033*
						(0.88)	(2.45)
$\Delta(1/Vol)_t$	0.012	0.012	0.012	0.013	0.012	0.012	
	(1.25)	(1.19)	(1.20)	(1.21)	(1.20)	(1.22)	
$\Delta Credit_t$	-0.107^{+}	-0.104^{+}	-0.102	-0.104	-0.104^{+}	-0.111^{+}	-0.063
	(-1.69)	(-1.74)	(-1.66)	(-1.65)	(-1.68)	(-1.88)	(-1.00)
$\Delta CsAvg_{t-1}$	-0.273***	-0.285***	-0.280***	-0.271***	-0.279***	-0.294***	
	(-3.78)	(-3.60)	(-3.50)	(-3.92)	(-3.90)	(-3.44)	
ΔLP_t	-0.164	-0.177	-0.166	-0.161	-0.172	-0.146	
	(-0.26)	(-0.30)	(-0.27)	(-0.26)	(-0.28)	(-0.24)	
$\Delta rGDP_t$	0.235	0.228	0.231	0.233	0.234	0.207	
	(0.91)	(1.00)	(1.02)	(1.03)	(1.01)	(0.85)	
ΔTFP_t	-0.204	-0.183	-0.218	-0.201	-0.197	-0.173	
	(-0.44)	(-0.45)	(-0.51)	(-0.49)	(-0.50)	(-0.37)	
ΔINV_t	0.222***	0.221***	0.230***	0.223***	0.221***	0.226***	
	(5.49)	(6.17)	(4.85)	(6.79)	(6.36)	(4.99)	
N	566	566	566	566	566	566	990
R^2	0.04	0.05	0.05	0.04	0.04	0.05	0.04
F	7.75	7.68	6.54	6.06	5.92	7.25	4.33
Cluster (country)	YES	YES	YES	YES	YES	YES	YES
Cluster (time)	YES	YES	YES	YES	YES	YES	YES
FE (country)	YES	YES	YES	YES	YES	YES	YES
FE (time)	YES	YES	YES	YES	YES	YES	YES

t-statistics in parentheses

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

4 Financial Crises and Aggregate Economic Activity

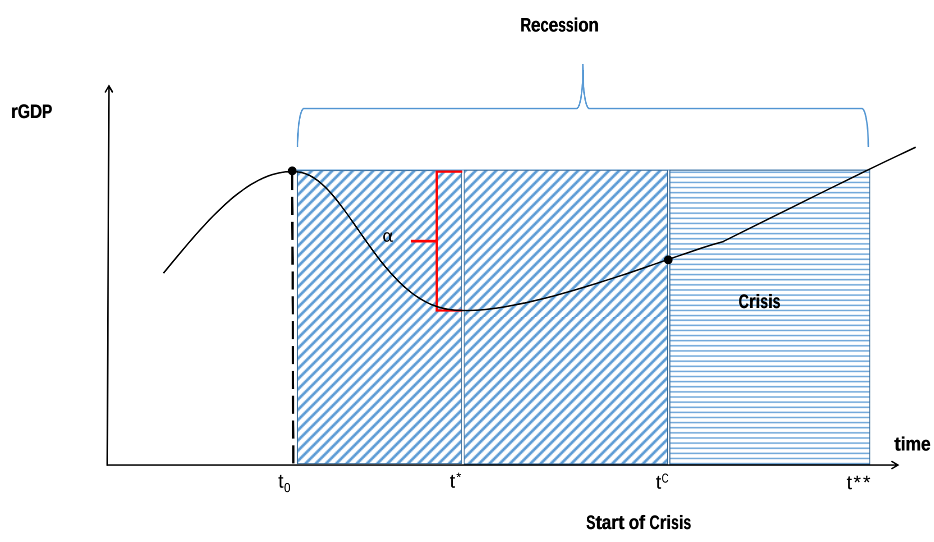
In this section we focus on only one direction, namely, does information produced in the stock market more intensive as the economy nears a recession and, in particular, a recession with a financial crisis. A financial crisis is an event in which the reduction in quantities of short-term debt go down precipitately. So financial crises offer a clear case of credit quantities changing.

In order the study the relations between the amount of information produced in the stock market and aggregate economic activity, we must first define aggregate macro states, like recessions.

4.1 Definitions

In defining aggregate states, we do not want to impose a great deal of preconceived structure on the data such as detrending or defining peaks and troughs because there is no theoretical justification for this.[6] Instead, we will define recessions and growth periods differently, as follows. At date t^* we look backwards four years and determine if the level of real GDP (rGDP) today is below that level by a threshold of $\alpha \leq -0.005$. If it is, then we say that a *recession* has started from the previous peak and it continues until this previous peak is again attained. In Figure 8, looking back from today, date t^*, to date t_0 real GDP at date t^* is below the peak at t_0 by α, and so we say that a recession has started at t_0. The recession continues until the level of real GDP is at least the level it was at at date t_0. This definition is based on the level of GDP. As Burns and Mitchell (1946) put it: "Aggregate [economic] activity can be given a definite meaning and made conceptually measurable by identifying it with gross national product" (p. 72).

Figure 8: **Definition of recessions**. A recession period is identified when the minimum quarterly real GDP change over a period of n quarters (t^*-t_0) is less than a specified threshold (α). The recession begins at the highest GDP level (t^0) prior to the drop and continues until the previous peak is again attained (t^{**}). A financial crisis can occur at any point over the course of a recession (t^C).



In the figure, a financial crisis starts at date t^C during the recession and continues until date t^{**} which is the end of both the crisis and the recession. A crisis may come anywhere during a recession and in a few

[6]H-P filtering uses and arbitrary smoothing parameter and the peaks and troughs approach requires that a peak follow a trough and so on.

cases the crisis is not associated with a recession. In what follows we will look at predictive regressions to try to explain the starting date of recessions (date t^*) and the starting dates of crises (date t^C). We also look at *growth* periods. A period of *growth* is said to occur when, by the same backward looking procedure we find that rGDP has increased by 0.01. So, there are four states that macroeconomy may be in: growth, recession, recession with crisis, or normal, where "normal" is the complement of the first three states.

Note that the structure imposed on real GDP is only the choice of the thresholds. We do not detrend, which imposes much more structure. And we do not require that a peak follow a trough and a trough follow a peak. Lastly, we impose the same threshold on all countries. Under our definitions, there can be a pattern of aggregate activity such as the following: recession, normal, recession, growth, normal, recession with a crisis, normal. This pattern would not be possible using a peaks and troughs structure.

Recessions fall into two types: recessions with a crisis and recessions with no crisis. We make this classification by first defining recessions and then checking Valencia and Laeven (2012) who provide crisis dates worldwide since 1970. Based on the data discussed below we identify these different types of aggregate economic activity shown in Table 4.

Table 4: **Duration of economic events**. The table summarizes the total number and duration of the following economic events: recession, recession with a crisis, recession without a crisis, growth, and normal times. The economic episodes are computed using quarterly real GDP data from the OECD iLibrary over a period of thirty years from 1973 until 2010.

	Count	Mean	StDev	Min	Max
Normal Times	133	2.49	1.83	1.00	9.00
Growth	106	1.61	1.17	1.00	8.00
Recessions	109	2.78	1.26	1.00	7.00
Recessions with Crises	25	2.96	0.84	1.00	5.00
Recessions with No Crises	96	2.39	1.15	1.00	5.00

The column labeled "count" in Table 4 shows the number of each type of episode across the countries of our sample. As expected, episodes of "normal times" predominate. There are 106 growth episodes and 109 recessions, among which 25 are associated with crises and 96 include instances of no crises.[7]. After the column labeled Count are statistics on the average duration in years of each event type. The average duration of a recession with a crisis episode is longer than that of a recession with no crisis. Growth episodes are the briefest.

Table 5: **Transition matrix (Three states)**. The table summarizes the transition probabilities for normal, growth, and recession states of the economy. The data are quarterly from 1973Q1 until 2013Q4.

	normal	growth	rcss	Total
normal	82.36	27.59	12.16	50.52
growth	10.58	70.32	1.32	19.77
rcss	7.06	2.09	86.52	29.71
Total	100.00	100.00	100.00	100.00
	(2041)	(812)	(1209)	(4062)

[7] There are recession episodes which include both crises and no crises episodes

Table 6: **Transition matrix (All states)**. The table summarizes the transition probabilities for normal, growth, recession with crisis, recession without crisis, and crisis without recession states of the economy. The data are quarterly from 1973Q1 until 2013Q4.

	normal	growth	rcssC	rcssNC	nrcssC	Total
normal	82.09	27.48	0.30	15.39	7.29	48.52
growth	10.77	70.51	0.00	1.60	1.04	19.40
rcssC	0.15	0.00	90.36	0.68	22.92	8.15
rcssNC	6.17	1.88	5.72	82.21	0.00	21.57
nrcssC	0.82	0.13	3.61	0.11	68.75	2.36
Total	100.00	100.00	100.00	100.00	100.00	100.00
	(1960)	(797)	(332)	(877)	(96)	(4062)

4.2 Univariate Results

We now turn to the first set of results which concern univariate comparisons of variables before the beginning of different types of aggregate events. Table 7a shows a univariate comparison of key variables *four quarters prior* to the beginning of a recession with a crisis episode versus the beginning of a recession with no crisis episode. Leading to a recession with a crisis, growth in real GDP ($\Delta rGDP$) is lower and, not surprisingly, α is negative. Prior to recessions with crises, we observe a higher level of fragility ($1/Vol$ is smaller). The significant difference in fragility is natural. As an economy heads towards a crisis, the distance to default of the average firm decreases. Leading to a recession with a crisis, $CsAvg$ and $CsVol$, i.e., the standard deviation of average returns and the standard deviation of firm level volatility, are significantly higher. This is an indication of a higher dispersion of volatility and returns among companies, which we interpret as an increase in the information produced by agents in the economy. None of the other measures are significantly different.

Table 7b reports the results of a univariate comparison of the same variables four quarters *prior* to the beginning of a recession versus the beginning of a growth period. The only variables which are statistically different between the two events are Fragility and $CsAvg$ with the first being lower and the second higher prior to a growth episode. This suggests that the short lived (average duration of 1.55 years) growth stage is associated with higher levels of fragility and more production of information.

Table 7: **Difference in mean values - 4 quarters prior (all countries)**. The table summarizes mean values for $\Delta rGDP$, α, $1/Vol$, $CsAvg$, $\Delta(1/Vol)$, $\Delta CsAvg$ 4 quarters prior to instances of: (i) recessions with crises vs. recessions with no crises, and (ii) recessions vs. growth. The third column reports the difference in means and the t-statistic of the difference. The data are quarterly and span a period from 1973 until 2010.

(a) Recessions with Crises vs. Recessions with No Crises

	No-Crisis	Crisis	Mean Diff.
$\Delta rGDP$	0.031	-0.011	0.042***
			(12.83)
α	0.003	-0.030	0.033***
			(23.04)
$1/Vol$	3.311	2.547	0.763***
			(12.11)
$CsVol$	0.423	0.606	-0.183***
			(-7.95)
$CsAvg$	0.120	0.163	-0.043***
			(-8.58)
$\Delta(1/Vol)$	0.007	-0.077	0.084*
			(2.41)
$\Delta CsVol$	-0.000	0.030	-0.030
			(-1.51)
$\Delta CsAvg$	-0.000	0.007	-0.007
			(-1.58)
N	124	26	98

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

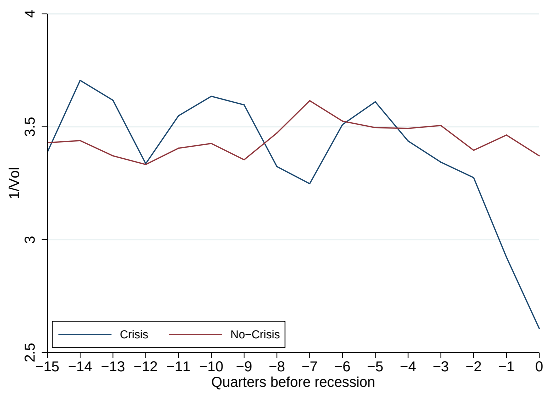
(b) Recessions vs. Growth

	Recession	Growth	Mean Diff.
$\Delta rGDP$	0.023	0.044	-0.021***
			(-9.60)
α	-0.002	0.007	-0.009***
			(-8.85)
$1/Vol$	3.275	3.188	0.088*
			(2.02)
$CsVol$	0.437	0.445	-0.007
			(-0.46)
$CsAvg$	0.122	0.129	-0.006^{+}
			(-1.82)
$\Delta(1/Vol)$	-0.005	0.014	-0.019
			(-0.79)
$\Delta CsVol$	0.004	0.003	0.001
			(0.06)
$\Delta CsAvg$	0.001	0.001	0.000
			(0.01)
N	156	233	-77

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

Table 7 suggests that information measures have predictive content. Figure 9 corroborates that finding. It shows plots of the two information measures averaged over recessions with a crisis and recessions without a crisis, starting 15 quarters *before* the start of the average recession with a crisis and the average recession without a crisis. It is apparent that these measures of information and fragility vary depending on whether the coming recession will involve a financial crisis or not. We observe that fragility is higher and more information is produced prior to the beginning of a recession with crisis episode.[8] In what follows we explore the results in the figures econometrically.

Figure 9: **Information variables prior to a recession with and without a crisis**. The figure summarizes the evolution of average distance-to-insolvency ($1/Vol$) and cross-sectional average returns ($CsAvg$) over 15 quarters prior to the beginning of: (a) a recession with a crisis, and (b) a recession without a crisis. The variables are averaged across all countries in the sample. The data are quarterly from 1973 until 2010.



(a) 1/Volatility

(b) Cross-sectional Average Return

We also conduct univariate comparisons of variables *during* the course of different types of aggregate events. Table 17a in the Appendix shows a univariate comparison of key variables *during* recessions versus periods of no recession (the complement of recession). By definition of a recession, growth in real GDP ($\Delta rGDP$) is lower and so α is negative. Recessions display a higher level of fragility, i.e., $1/Vol$ is smaller in recessions than in non-recession periods. None of the other measures are significantly different.

Table 8a shows the comparison of recessions with a crisis to recessions with no crisis. Recessions with a crisis are significantly deeper in terms of the level of the real GDP decline. Fragility is significantly higher ($1/Vol$ is smaller) as are both $CsAvg$ and $CsVol$, i.e., the standard deviation of returns and the standard deviation of volatility. These two measures are higher, that is there is more dispersion of volatility and returns among companies. None of the other measures are significantly different. In Table 8a we get a glimpse of recessions with crises being different.

[8]Recall that the economy is more fragile when Vol increases, and so $1/Vol$ decreases.

Table 8: **Difference in mean values (all countries)**. The table summarizes mean values for $\Delta rGDP$, α, $1/Vol$, $CsAvg$, $\Delta(1/Vol)$, $\Delta CsAvg$ for instances of: (i) recessions with crises vs. recessions with no crises, and (ii) recessions vs. growth. The third column reports the difference in means and the t-statistic of the difference. The data are quarterly and span a period from 1973 until 2010.

(a) Recessions with Crises vs. Recessions with No Crises

	No-Crisis	Crisis	Mean Diff.
$\Delta rGDP$	-0.007	-0.012	0.005
			(0.99)
α	-0.023	-0.046	0.023***
			(9.72)
$1/Vol$	3.166	2.425	0.741***
			(11.42)
$CsVol$	0.383	0.675	-0.292***
			(-9.70)
$CsAvg$	0.113	0.179	-0.066***
			(-9.88)
$\Delta(1/Vol)$	0.014	0.028	-0.014
			(-0.34)
$\Delta CsVol$	0.007	0.035	-0.028
			(-1.20)
$\Delta CsAvg$	0.001	0.007	-0.005
			(-1.04)
N	632	260	372

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

(b) Recessions vs. Growth

	Recession	Growth	Mean Diff.
$\Delta rGDP$	-0.009	0.073	-0.082***
			(-31.59)
α	-0.030	0.018	-0.048***
			(-36.59)
$1/Vol$	2.950	3.242	-0.293***
			(-6.20)
$CsVol$	0.468	0.426	0.042*
			(2.17)
$CsAvg$	0.132	0.123	0.009*
			(1.98)
$\Delta(1/Vol)$	0.018	-0.024	0.042
			(1.49)
$\Delta CsVol$	0.015	0.009	0.006
			(0.35)
$\Delta CsAvg$	0.003	0.002	0
			(0.10)
N	892	698	194

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

4.3 Information and Crises

In this subsection we further pursue the issue of the predictive power of the information measures for different types of aggregate economic activity. Specifically, we look at predictive regressions of the occurrence of specific economic events (all recessions, recessions with crises, recessions with no crises, growth) on lagged observations of the proposed information measures. Our conjecture is that our measures, being based on stock prices, are forward-looking, have some ability to do this. Figure 9 suggests that this is the case.

We look at each type of aggregate episode using a linear probability model and a Logit model. In all regression specifications, we take into account country fixed effects and perform double clustering over the dimensions of time and country. The dependent variable is an indicator for the years in which the episode takes place; the right-hand side variables are one and two year lags of the fragility and information measures. We start with recessions in Tables 9a and 9b. Table 9a shows that the occurrence of more fragile firms is an indication of a recession, consistent with Burns and Mitchell (1946) and Gorton (1988) as discussed above. No other variable predicts recessions.

Table 9b looks at predicting instances of recessions with financial crises. The results show a very different picture. Now, *all* the right-hand side variables are significant. Note that the signs on the fragility measure and the change in fragility are negative, meaning that a high level of fragility (low $1/Vol$) and an increase in fragility ($\Delta(1/Vol)$) are associated with the coming recession being one that is more likely to have a crisis. This negative correlation is stronger compared to that of Table 9a for both linear and Logit specifications. The information variables ($CsVol$ and $\Delta CsVol$) both exhibit a positive correlation with the occurrence of a recession with a crisis. An increase in information production points to a higher likelihood of a recession with a crisis.[9]

On the other hand, a decrease in the information produced in the economy, predicts a recession without a crisis. Appendix Table 18a focuses on the predictive power of information measures on recessions without

[9]The predictive power of information measures is apparent up to two years before the event (See Table 20 in the Appendix).

Table 9: **Information measures and economic events**. The table summarizes the predictive power of information measures ($1/Vol$, $CsAvg$, $\Delta(1/Vol)$, $\Delta CsAvg$) on the occurrence of economic events (recession and recession with crisis). The regression specification is: $\mathbb{1}_{n,t}(Economic\ Event) = \alpha_n + \beta' X_{n,t-1} + \epsilon_{n,t}$ for linear probability models, and $Pr(\mathbb{1}_{n,t}(Economic\ Event) = 1|X_{n,t-1}) = \Phi(\alpha_n + \beta' X_{n,t-1})$ for LOGIT models, where $Economic\ Event = (recession, recession\ with\ crisis)$ and $X_{n,t-1} = (1/Vol_{n,t-1}, CsAvg_{n,t-1}, \Delta Vol_{n,t-1}, \Delta CsAvg_{n,t-1})'$. The data are quarterly and span a period from 1973 until 2010. All regression specifications take into account country fixed effects and standard errors are clustered both at a country and time level.

(a) $\mathbb{1}_{n,t}(Recession \cap NoCrisis)$

	(1) Linear	(2) Logit
$1/Vol_{t-2}$	-0.061**	-0.520**
	(-2.80)	(-2.98)
$CsAvg_{t-2}$	-0.737***	-7.711**
	(-4.05)	(-2.68)
$\Delta(1/Vol)_{t-1}$	-0.040*	-0.329**
	(-2.34)	(-2.71)
$\Delta CsAvg_{t-1}$	-0.341***	-3.417**
	(-3.86)	(-2.71)
Constant	0.585***	0.680
	(8.37)	(0.85)
N	3377	3215
R^2	0.07	.
F	18.43	.
Cluster (Time)	YES	YES
Cluster (Country)	YES	YES
FE (Country)	YES	YES

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

(b) $\mathbb{1}_{n,t}(Recession \cap Crisis)$

	(1) Linear	(2) Logit
$1/Vol_{t-2}$	-0.098***	-2.215***
	(-3.81)	(-7.04)
$CsAvg_{t-2}$	0.524*	5.345*
	(2.42)	(2.23)
$\Delta(1/Vol)_{t-1}$	-0.052*	-1.254**
	(-2.26)	(-2.91)
$\Delta CsAvg_{t-1}$	0.350**	3.613**
	(2.84)	(2.75)
Constant	0.222**	2.521**
	(2.75)	(2.80)
N	3377	2662
R^2	0.17	.
F	9.46	.
Cluster (Time)	YES	YES
Cluster (Country)	YES	YES
FE (Country)	YES	YES

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

financial crises. The sign of the coefficient of both $CsVol$ and $\Delta CsVol$ is negative indicating that less information produced in the economy predicts a recession without a crisis.[10] Combining this finding with that of Table 9b, we note that an increase in information production is associated with future instances of recessions with crises, while a decrease in information production with recessions without crises, suggesting that agents produce information prior to a recession depending on the aggregate state of the economy (severity of the recession).

Table 10 makes clear that recessions with crises are significantly different compared to recessions without crises. Column (2), shows the predictive power of information measures for recessions with a crisis. The information measure $CsVol_{t-2}$ is significantly positive, suggesting that a higher level of information production is associated with a coming recession associated with a crisis. $\Delta(1/Vol)$ is significantly negative, what is fragility is increasing. And $\Delta CsVol$ is significantly positive, suggesting that more information is being produced. Column (3) shows the results for predicting instances of recessions with no crisis. Note that $CsVol_{t-2}$ is significant as is $\Delta CsVol$, but they have the *opposite* signs compared to predicting recessions *with crises*. Going into a recession that is expected to not have a crisis, less information is produced. Finally, the lagged change in TFP is significantly negative leading into recessions and significantly positive going into a growth period.

[10] This finding holds up to five years before the event, whereas the measure of fragility has no predictive ability for recessions without a crisis (Table 21).

Table 10: **Information measures, macroeconomic variables and economic events (LOGIT model)**. 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, $\Delta Labor\ Productivity$) on the occurrence of economic events (recession, recession with crisis, recession without crisis, no recession with crisis, and growth - columns 1 through 5). The regression specification is: $Pr(\mathbb{1}_{n,t}(Economic\ Event) = 1|X_{n,t-1}) = \Phi(\alpha_n + \beta' X_{n,t-1})$, where $Economic\ Event = (recession, recession\ with\ crisis, recession\ without\ crisis, growth)$ and $X_{n,t-1} = (1/Vol_{n,t-1}, CsAvg_{n,t-1}, \Delta Vol_{n,t-1}, \Delta CsAvg_{n,t-1}, \Delta rGDP_{n,t-1}, \Delta Credit_{n,t-1}, \Delta TFP_{n,t-1}, \Delta LP_{n,t-1})'$. The data are annually and span a period from 1973 until 2010. All regression specifications take into account country fixed effects and standard errors are clustered both at a country and time level.

	(1) Recession	(2) Recession∩Crisis	(3) Recession∩No-Crisis	(4) No-Recession∩Crisis	(5) Growth
$1/Vol_{t-2}$	-0.511	-0.868	-0.367	-0.017	0.042
	(-1.60)	(-1.25)	(-1.22)	(-0.03)	(0.14)
$CsVol_{t-2}$	-5.602	12.335*	-15.876**	-8.615	-0.344
	(-1.63)	(2.07)	(-3.18)	(-0.46)	(-0.14)
$\Delta(1/Vol)_{t-1}$	-0.851**	-1.484***	-0.492*	-0.251	0.364
	(-3.02)	(-4.89)	(-2.36)	(-0.53)	(1.01)
$\Delta CsVol_{t-1}$	-1.231	6.334^{+}	-7.799**	-6.650	0.850
	(-0.57)	(1.94)	(-3.12)	(-0.62)	(0.42)
$\Delta rGDP_{t-1}$	-47.896***	-60.051***	-19.198^{+}	9.239	17.956**
	(-4.87)	(-4.30)	(-1.69)	(0.32)	(2.93)
$\Delta Credit_{t-1}$	0.030	0.178	-0.044	-3.174**	0.059
	(0.07)	(0.66)	(-0.09)	(-3.13)	(0.13)
ΔTFP_{t-1}	2.161	11.066	1.314	8.859	4.673
	(0.35)	(1.37)	(0.23)	(0.41)	(1.01)
ΔLP_{t-1}	12.593	14.538	3.358	-22.590	-2.955
	(1.30)	(0.93)	(0.28)	(-0.59)	(-0.65)
Constant	2.176^{+}	-1.235	2.198^{+}	-1.572	-2.712*
	(1.95)	(-0.57)	(1.73)	(-0.36)	(-2.27)
N	638	540	638	148	617
Cluster (Time)	YES	YES	YES	YES	YES
Cluster (Country)	YES	YES	YES	YES	YES
FE (Country)	YES	YES	YES	YES	YES

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

5 Feedback Effects: Reallocation of Capital

In this section we investigate whether our measures of information and fragility are linked to reallocation of capital within the economy during recessions and recessions with crises. There is a large literature on whether or not there are "cleansing effects" of recessions, which means that capital and labor are moved - reallocated - from low productivity to high productivity firms, so that recessions are times of accelerated productivity gains. Such reallocation is relatively less costly to do during recessions. This literature started with Schumpeter (1939). Subsequent research shows that job reallocation increased in manufacturing during recessions from the late 1940s through the 1990s; see, e.g., **?**. Also, research suggests that the recession in the early 1980s was a time of "cleansing". See Davis and Haltiwanger (1992) and Davis and Haltiwanger (1999).[11] Reallocation involves some firms exiting, but also capital (and labor) moving between firms or sectors as well. Except for exit, reallocation may be difficult because in a financial crisis the banking system is damaged. During a crisis, it may be hard for high productivity firms to get access to credit, which means that these firms may not benefit from their technological advantage. The extant empirical work suggests that this is a

[11] Also see, Caballero and Hammour (1994), and Caballero and Hammour (1996).

problem. This is what **?** found, consistent with the micro evidence of, e.g., Ivashina and Scharfstein (2010), Chodorow-Reich (2013), Greenstone et al. (2014) and Lee and Mezzanotti (2015).

If our measures of information and fragility fluctuate as a result of information produced in the economy, then we conjecture that they are related to reallocation of capital. We characterize the productivity of the firms in our sample by their Tobin's Q.[12] Reallocation would correspond to disinvestment in low Q firms and investment in high Q firms, causing firms' Qs to converge to one. If this is occurring, then firms' Q-ratios should change; the dispersion of Q should decline. However, in a financial crisis the banking system, by definition, is not functioning well.

5.1 Data Sources and Preliminary Univariate Results

Combining the WorldScope data on firms' equity book values with our market values we compute firms' Q's. Tobin's Q is computed as the ratio of *market capitalization* + *liabilities* divided by the book value of *equity* + *liabilities*. We also compute several measures of the cross-sectional dispersion of Q-ratios at a country level. The first measure, the standard deviation of the change in Q measures the magnitude on change in Q, while the second measures the dispersion of the Q-ration. Third, since our right-hand side variables are not at the firm level, we sort firms into quintiles based on their Tobin's Q's. The third Q-dispersion measure is is the difference between the 75th percentile and the 25th percentile divided by the median of the Q-ratio. Table 11 summarizes the data.

Table 11: **Summary statistics - country-level dispersion measures**. The table reports summary statistics for the standard deviation of changes in Q-ratios ($\sigma(\Delta Q\text{-}ratio)$), the standard deviation of Q-ratios ($\sigma(Q\text{-}ratio)$), and a of dispersion in Q-ratio in Q-ratios ($(Q75\% - Q25\%)/Q50\%$). The data are from Thomson/Reuters (WorldScope), and span a period from 1980 until 2010. "Count" label refers to country-years.

	Count	Mean	StDev	Min	Max
$\sigma(\Delta Q$-ratio$)$	710	1.05	0.74	0.02	2.99
$\sigma(Q$-ratio$)$	727	2.21	1.71	0.00	8.35
$(Q75\% - Q25\%)/Q50\%$	727	1.02	0.32	0.00	2.52
$Q\text{-}ratio$	727	0.55	1.32	0.00	22.46

Table 12 compares Q-ratios, and measures of reallocation *during* periods of no recession and recession periods, and no crisis and crisis periods. The Q-ratio is significantly lower during recessions as is the dispersion of Q's, by all the measures. This is consistent with reallocation occurring during recessions compared to non-recession periods (growth and normal periods). Compared to times of no-recession, in times of recessions the "cleansing effect" leads to a lower dispersion of Q's, lower than that of no-recessions indicating some reallocation taking place. Notable, in panel (b), while agents do produce information there is no reallocation in recessions with a crisis compared to a recession with no crisis. It seems that the non-functioning financial system makes it hard for them to reallocate resources, consistent with **?**. Also, comparing the no crisis recessions to those with crises, the change in $CAPEX$ and *R&D* divided by total assets is significantly negative (not shown), suggesting a disinvestment taking place during recessions with a crisis. But, overall the aggregate dispersion measures show that dispersion is higher in recessions with crises compared to recessions without crises. Again, this is consistent with the banking system functioning during recessions without crises, but not during crises.

[12]With respect to productivity Dwyer (2001) merges plant-level fundamental data with firm-level financial variables found that firms that are more productive have higher Tobin's Q's. However, we do not have plant level data or firm level employment for firms in all of the countries of our sample.

Table 12: **Difference in means values - country-level dispersion measures**. The table reports mean values for the standard deviation of changes in Q-ratios ($\sigma(\Delta Q\text{-}ratio)$), the standard deviation of Q-ratios ($\sigma(Q\text{-}ratio)$), a measure of dispersion in Q-ratios in Q-ratios ($(Q75\% - Q25\%)/Q50\%$) for instances of: (i) recessions vs. no-recessions, and (ii) recessions with crises vs. recessions with no crises. The third column reports the difference in means and the t-statistic of the difference. The data are from Thomson/Reuters (WorldScope), and span a period from 1980 until 2010.

(a) recessions vs. no recessions

	No-Recession	Recession	Mean Diff.
$\sigma(\Delta Q$-ratio)	1.107	0.946	0.161**
			(2.82)
$\sigma(Q$-ratio)	2.353	1.918	0.435***
			(7.56)
$(Q75\% - Q25\%)/Q50\%$	1.040	1.009	0.030**
			(2.80)
$Q\text{-}ratio$	1.996	1.580	0.416***
			(4.22)

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

(b) recessions with crises vs. recessions with no crises

	No-Crisis	Crisis	Mean Diff.
$\sigma(\Delta Q$-ratio)	0.876	1.119	-0.244*
			(-2.57)
$\sigma(Q$-ratio)	1.791	2.243	-0.452***
			(-4.68)
$(Q75\% - Q25\%)/Q50\%$	0.981	1.082	-0.100***
			(-5.64)
$Q\text{-}ratio$	1.591	1.551	0.040
			(0.24)

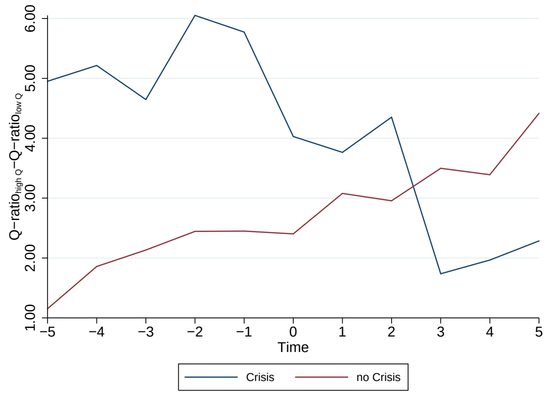
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In Figure 10 we further investigate the relation between the cross-sectional dispersion of Q-ratio and $CAPEX$. The figure displays the spread (difference) of average Q-ratio and $CAPEX$ among firms in the fifth and first quintile for a period of ten years centered on the start of the crisis and no crisis events. The spread in Q-ratio drops significantly prior to the beginning of a financial crisis (Figure 10a), and as predicted by Q-theory the spread in $CAPEX$ drops in turn after the beginning of a crisis (Figure 10b). The observed lag in the reallocation is in line with an improving financial system, which gradually becomes more able to facilitate the reallocation of resources across firms as crises end (note that crises last, on average, for three years), thus leading to a tightening of the spread in $CAPEX$ between the first and fifth quintile.

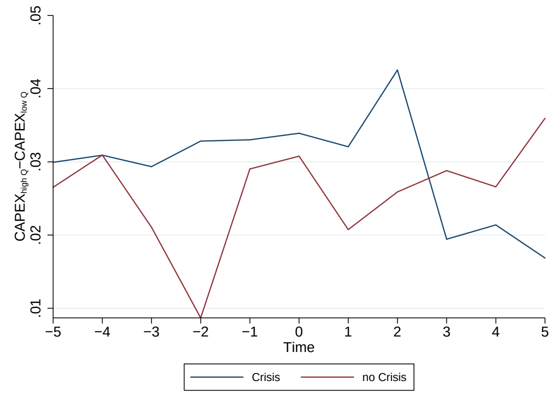
The observed behavior of the spread of Q-ratio and $CAPEX$ in Figure 10 provides a first justification of our proposed mechanism through which the production of information can have a feedback effect to investment. Information production prior to a crisis is reflected in the significant increase and subsequent decrease of the Q-ratio spread which is followed by a decrease in the $CAPEX$ spread. Our measure of information production is directly related to the valuation of firms in the stock market and the dispersion of such valuations. Thus, it becomes clear that this measure is directly linked to Q-ratio.

Motivated by Figure 10, we examine the predictive power of the information measures on reallocation of capital within a country. Table 13 shows the results for two measures of reallocation. The first is measure of dispersion in Q-ratios ($(Q75\% - Q25\%)/Q50\%$) and the second is a the standard deviation of changes in Q-ratios ($\sigma(\Delta Q\text{-}ratio)$). Looking at the first measure (columns (5) and (6)) we observe a negative correlation between the change in our information measure ($CsAvg$) and our measure of dispersion of Q's, and a positive correlation between the change in aggregate fragility ($1/Vol$) and our measure of dispersion of Q's. In words, as the cross-section of average returns rises in the year before the crisis and in the two years before the crisis, the dispersion in Q is expected to fall. That is, capital will be reallocated. The other measure ($\sigma(\Delta Q)$) is a

Figure 10: Figure (a) summarizes the difference in the level of Q-ratios in the first (low Q-ratio) and fifth (high Q-ratio) quintile for a period of 10 years around the beginning of a recession associated with a crisis and a recession without a crisis. Figure (b) summarizes the difference in the level of the average investment between firms.



(a) $Q\text{-}ratio_{Q5} - Q\text{-}ratio_{Q1}$



(b) $CAPEX_{Q5} - CAPEX_{Q1}$

measure of the speed of reallocation. With respect to the speed, during financial crises an increase in our information measure ($CsAvg$) is associated with a decreasing future speed of reallocation, indicating that reallocation has already taken place and the economy is slowing down.

Table 13: **Information measures and measures of dispersion of Q-ratios**. The table summarizes the predictive power of $1/Vol$, $\Delta(1/Vol)$, cross-sectional averages ($CsAvg$), change in cross-sectional averages ($\Delta CsAvg$), their interaction with a dummy indicating a crisis, and macro-variables ($\Delta rGDP$, $\Delta Credit$, ΔTFP, ΔLP) on measures of Q-ratio dispersion ($(Q75\% - Q25\%)/Q50\%$ and $\sigma(\Delta Q\text{-}ratio)$). The regression specification is: $Dispersion_{n,t} = \alpha_n + \beta' X_{n,t-1} + \gamma' X_{n,t-1}\mathbb{1}(Crisis)_{n,t} + \delta Macro\ Variables_{n,t-1} + \epsilon_{n,t}$, where $X_{n,t-1} = (CsAvg_{n,t-2}, \Delta CsAvg_{n,t-1}, 1/Vol_{n,t-2}, \Delta(1/Vol)_{t-1})'$. Data are from WorldScope and span a period from 1980 until 2010. All specifications include country fixed effects. Robust *t-statistics* adjusted for country-level clustering are reported in parentheses.

	(1) $(Q_{75}-Q_{25})/Q_{50}$	(2) $(Q_{75}-Q_{25})/Q_{50}$	(3) $(Q_{90}-Q_{50})/Q_{30}$	(4) $(Q_{90}-Q_{50})/Q_{30}$	(5) $(Q_{50}-Q_{10})/Q_{30}$	(6) $(Q_{50}-Q_{10})/Q_{30}$
$\Delta CsAvg_{t-1}$	0.287	-0.264^{+}	-4.177	-9.582	0.260*	0.003
	(1.57)	(-1.91)	(-0.82)	(-1.07)	(2.11)	(0.03)
$\Delta CsAvg_{t-1} \times \mathbb{1}_t(Crisis)$	-0.697**	-0.160	3.609	12.315	-0.256	0.006
	(-2.99)	(-0.57)	(0.86)	(1.03)	(-1.47)	(0.03)
$\Delta(1/Vol)_{t-1}$	-0.069***	-0.037	-0.137*	-0.504	-0.029*	-0.027
	(-4.62)	(-1.58)	(-2.26)	(-1.02)	(-2.41)	(-1.48)
$\Delta(1/Vol)_{t-1} \times \mathbb{1}_t(Crisis)$	0.063^{+}	0.053^{+}	-0.163	-0.751	0.031	0.018
	(1.84)	(1.93)	(-0.95)	(-0.90)	(1.52)	(0.83)
$CsAvg_{t-2}$	0.497	-0.381	-10.423	-20.890	0.444^{+}	0.033
	(1.44)	(-1.21)	(-0.89)	(-1.06)	(1.93)	(0.18)
$CsAvg_{t-2} \times \mathbb{1}_t(Crisis)$	-1.017*	-0.481	8.473	30.814	-0.623*	-0.233
	(-2.25)	(-1.09)	(1.02)	(1.01)	(-2.67)	(-0.95)
$1/Vol_{t-2}$	-0.078**	-0.018	-0.193	-0.286	-0.031	-0.016
	(-3.09)	(-0.51)	(-1.36)	(-0.79)	(-1.62)	(-0.69)
$1/Vol_{t-2} \times \mathbb{1}_t(Crisis)$	0.060*	0.020	-0.310	-1.207	0.047*	0.017
	(2.46)	(0.94)	(-0.99)	(-1.02)	(2.65)	(0.95)
Constant	1.229***	1.293***	4.639*	3.362***	0.857***	0.912***
	(13.00)	(9.59)	(2.56)	(4.50)	(11.57)	(9.97)
N	602	602	602	602	602	602
R^2	0.38	0.61	0.76	0.77	0.51	0.61
Cluster (Country)	YES	YES	YES	YES	YES	YES
FE (Time)	NO	YES	NO	YES	NO	YES
FE (Country)	YES	YES	YES	YES	YES	YES

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

6 Conclusion

The stock market and the money markets are completely different systems. There is price discovery in stock markets, but money market instruments are opaque because, by design, the price is meant to be constant. No one finds it profitable to produce private information about the collateral backing repo, for example. In money markets, quantities respond because prices cannot move. These two systems interact in important ways that vary over the business cycle. Stock prices reveal information about firms, conditional on the amount of credit that the firm is expected to obtain in the credit market. And credit markets allocate the quantity of credit granted based on observations of the firms' stock prices. More information is produced, and firms become more fragile, leading up to a financial crisis—when quantities go to zero. Our empirical work focused on the interaction between the informativeness of stock prices leading up to a financial crisis. Agents produce more information leading up to a financial crisis.

We agnostically defined movements in aggregate economic activity –the "business cycle" – and studied these movements with respect to empirical measures of the amount of information in the economy and the fragility of the economy. Do these variables move with aggregate economic activity? Consistent with the model, we find that more information is produced before and during recessions with crises, and that recessions with no crises are associated with production of less information. We further explore the effect of information production on reallocation of resources in the economy. We find that it indeed leads to reallocation of resources since the dispersion of Tobin's Q-ratios decreases following an increase in information production.

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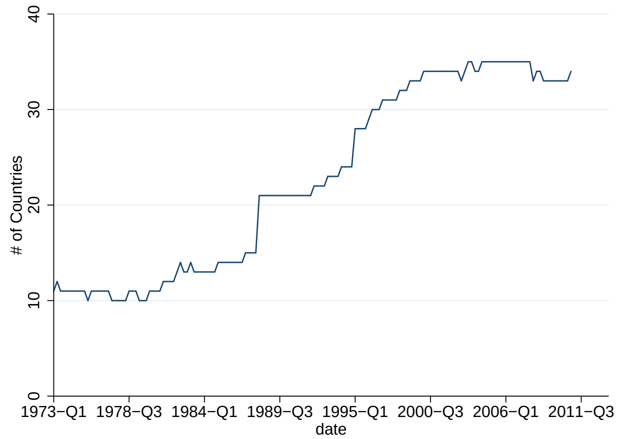
Appendices

A Figures

Figure 11: **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 1973Q1 until 2011Q3.



B Tables

Table 14: **Correlations - Information Measures (Quarterly)**. The table summarizes correlations for $1/Vol$, $CsVol$, and $CsAvg$ (Panel A), and $\Delta(1/Vol)$, $\Delta CsVol$, and $\Delta CsAvg$ (Panel B). The variables are computed on a country level using data from Thomson/Reuters (DataStream), and span a period from 1973 until 2010.

	$1/Vol$	$CsVol$	$CsAvg$
$1/Vol$	1.000		
$CsVol$	-0.304***	1.000	
$CsAvg$	-0.388***	0.965***	1.000

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

	$\Delta(1/Vol)$	$\Delta CsVol$	$\Delta CsAvg$
$\Delta(1/Vol)$	1.000		
$\Delta CsVol$	-0.094***	1.000	
$\Delta CsAvg$	-0.131***	0.952***	1.000

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

Table 15: **Correlations - Information Measures (Annual)**. The table summarizes correlations for $1/Vol$, $CsVol$, and $CsAvg$ (Panel A), and $\Delta(1/Vol)$, $\Delta CsVol$, and $\Delta CsAvg$ (Panel B). The variables are computed on a country level using data from Thomson/Reuters (DataStream), and span a period from 1973 until 2010.

	$1/Vol$	$CsVol$	$CsAvg$
$1/Vol$	1.000		
$CsVol$	-0.341***	1.000	
$CsAvg$	-0.416***	0.961***	1.000

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

	$\Delta(1/Vol)$	$\Delta CsVol$	$\Delta CsAvg$
$\Delta(1/Vol)$	1.000		
$\Delta CsVol$	-0.217***	1.000	
$\Delta CsAvg$	-0.253***	0.953***	1.000

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

Table 16: **Correlations - Macroeconomic Variables and Information Measures (Annual data)**. The table summarizes correlations for $1/Vol$, $CsVol$, $CsAvg$, $\Delta(1/Vol)$, $\Delta CsVol$, $\Delta CsAvg$, $\Delta Credit$, ΔTFP, ΔLP, $\Delta Granted$. 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 2010.

	$1/Vol$	$CsVol$	$CsAvg$	$\Delta(1/Vol)$	$\Delta CsVol$	$\Delta CsAvg$	$\Delta rGDP$	$\Delta Credit$	ΔTFP	ΔLP
$1/Vol$	1.000									
$CsVol$	-0.294***	1.000								
$CsAvg$	-0.364***	0.957***	1.000							
$\Delta(1/Vol)$	0.444***	-0.059	-0.076^{+}	1.000						
$\Delta CsVol$	-0.120**	0.498***	0.485***	-0.202***	1.000					
$\Delta CsAvg$	-0.124**	0.482***	0.523***	-0.228***	0.940***	1.000				
$\Delta rGDP$	0.095*	-0.104**	-0.104**	-0.118**	-0.065^{+}	-0.057	1.000			
$\Delta Credit$	0.032	-0.012	-0.012	-0.041	0.011	0.021	0.096*	1.000		
ΔTFP	0.087*	-0.050	-0.066^{+}	-0.061	-0.080*	-0.070^{+}	0.730***	0.070^{+}	1.000	
ΔLP	0.140***	-0.182***	-0.189***	-0.000	-0.112**	-0.106**	0.508***	0.033	0.505***	1.000

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

Table 17: **Difference in mean values (all countries)**. The table summarizes mean values for $\Delta rGDP$, α, $1/Vol$, $CsAvg$, $\Delta(1/Vol)$, $\Delta CsAvg$ for instances of: (i) recessions vs. no-recessions and (ii) growth vs. normal. The third column reports the difference in means and the t-statistic of the difference. The data are quarterly and span a period from 1973 until 2010.

(a) recessions vs. no-recessions

	No-Recession	Recession	Mean Diff.
$\Delta rGDP$	0.042	-0.009	0.050^{***}
			(27.46)
α	0.010	-0.030	0.039^{***}
			(51.97)
$1/Vol$	3.369	2.950	0.419^{***}
			(10.96)
$CsVol$	0.434	0.468	-0.034^{*}
			(-2.33)
$CsAvg$	0.122	0.132	-0.010^{**}
			(-3.21)
$\Delta(1/Vol)$	-0.002	0.018	-0.020
			(-0.93)
$\Delta CsVol$	-0	0.015	-0.015
			(-1.19)
$\Delta CsAvg$	-0	0.003	-0.003
			(-1.03)
N	2391	892	1499

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

(b) growth vs. normal

	Normal	Growth	Mean Diff.
$\Delta rGDP$	0.029	0.073	-0.044^{***}
			(-29.17)
α	0.006	0.018	-0.012^{***}
			(-36.15)
$1/Vol$	3.420	3.242	0.178^{***}
			(4.02)
$CsVol$	0.437	0.426	0.011
			(0.70)
$CsAvg$	0.121	0.123	-0.002
			(-0.67)
$\Delta(1/Vol)$	0.007	-0.024	0.031
			(1.28)
$\Delta CsVol$	-0.004	0.009	-0.013
			(-0.90)
$\Delta CsAvg$	-0.001	0.002	-0.004
			(-1.11)
N	1693	698	995

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

Table 18: **Information measures and economic events**. The table summarizes the predictive power of information measures ($1/Vol$, $CsAvg$, $\Delta(1/Vol)$, $\Delta CsAvg$) on the occurrence of economic events (recession without crisis, and growth). The regression specification is: $\mathbb{1}_{n,t}(Economic\ Event) = \alpha_n + \beta' X_{n,t-1} + \epsilon_{n,t}$ for linear probability models, and $Pr(\mathbb{1}_{n,t}(Economic\ Event) = 1|X_{n,t-1}) = \Phi(\alpha_n + \beta' X_{n,t-1})$ for LOGIT models, where $Economic\ Event = (recession\ without\ crisis, growth)$ and $X_{n,t-1} = (1/Vol_{n,t-1}, CsAvg_{n,t-1}, \Delta Vol_{n,t-1}, \Delta CsAvg_{n,t-1})'$. The data are quarterly and span a period from 1973 until 2010. All regression specifications take into account country fixed effects and standard errors are clustered both at a country and time level.

(a) recessions with no crises

	(1) Linear	(2) Logit
$1/Vol_{t-2}$	-0.061^{**}	-0.520^{**}
	(-2.80)	(-2.98)
$CsAvg_{t-2}$	-0.737^{***}	-7.711^{**}
	(-4.05)	(-2.68)
$\Delta(1/Vol)_{t-1}$	-0.040^{*}	-0.329^{**}
	(-2.34)	(-2.71)
$\Delta CsAvg_{t-1}$	-0.341^{***}	-3.417^{**}
	(-3.86)	(-2.71)
Constant	0.585^{***}	0.680
	(8.37)	(0.85)
N	3377	3215
R^2	0.07	.
F	18.43	.
Cluster (Time)	YES	YES
Cluster (Country)	YES	YES
FE (Country)	YES	YES

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

(b) growth instances

	(1) Linear	(2) Logit
$1/Vol_{t-2}$	0.045^{**}	0.343^{**}
	(2.74)	(2.95)
$CsAvg_{t-2}$	-0.311^{*}	-3.843^{**}
	(-2.05)	(-2.83)
$\Delta(1/Vol)_{t-1}$	0.020	0.143
	(1.14)	(1.14)
$\Delta CsAvg_{t-1}$	-0.242^{*}	-2.618^{**}
	(-2.49)	(-3.08)
Constant	0.398^{***}	-2.576^{***}
	(5.62)	(-5.56)
N	3969	3969
R^2	0.11	.
F	11.63	.
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 19: **Information measures and recessions - 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 events. The regression specification is: $Pr(\mathbb{1}_{n,t}(Recession) = 1|X_{t-q}) = \Phi(\alpha_n + \beta' X_{t-q})$, 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 2010. 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
$1/Vol_{t-q-1}$	-0.821***	-0.852***	-0.843***	-0.784***	-0.667***	-0.234
	(-4.53)	(-4.74)	(-4.89)	(-4.84)	(-4.31)	(-1.57)
$CsAvg_{t-q-1}$	0.356	-0.031	-0.495	-0.757	-0.701	-0.790
	(0.45)	(-0.04)	(-0.53)	(-0.75)	(-0.69)	(-0.74)
$\Delta(1/Vol)_{t-q}$	-0.318^{+}	-0.476**	-0.465**	-0.573**	-0.597***	-0.233
	(-1.91)	(-2.68)	(-2.59)	(-3.22)	(-3.55)	(-1.42)
$\Delta CsAvg_{t-q}$	0.470	0.377	0.317	-0.144	-0.072	-0.124
	(0.95)	(0.76)	(0.61)	(-0.24)	(-0.13)	(-0.24)
N	3807	3775	3743	3754	3722	3594
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
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 20: **Information measures and recessions with 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: $Pr(\mathbb{1}_{n,t}(Recession \cap Crisis) = 1|X_{t-q}) = \Phi(\alpha_n + \beta' X_{t-q})$, 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 2010. 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
$1/Vol_{t-q-1}$	-2.123***	-2.215***	-2.036***	-1.721***	-1.459***	-0.393
	(-6.25)	(-7.04)	(-6.65)	(-5.40)	(-4.20)	(-1.34)
$CsAvg_{t-q-1}$	7.053**	5.345*	4.319^{+}	4.205*	4.171*	3.482
	(2.69)	(2.23)	(1.93)	(2.02)	(1.98)	(1.44)
$\Delta(1/Vol)_{t-q}$	-0.973*	-1.254**	-1.454***	-1.200**	-1.141**	-0.623^{+}
	(-2.33)	(-2.91)	(-3.65)	(-3.17)	(-2.95)	(-1.68)
$\Delta CsAvg_{t-q}$	4.461**	3.613**	2.743*	1.804	2.524*	2.534*
	(2.78)	(2.75)	(1.98)	(1.41)	(2.46)	(2.11)
N	2683	2662	2641	2663	2642	2558
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
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 21: **Information measures and recessions with no 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 no crises events. The regression specification is: $Pr(\mathbb{1}_{n,t}(Recession \cap no\ Crisis) = 1|X_{t-q}) = \Phi(\alpha_n + \beta' X_{t-q})$, 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 2010. 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
$1/Vol_{t-q-1}$	-0.508**	-0.470**	-0.535**	-0.516***	-0.390**	0.099
	(-3.13)	(-2.91)	(-3.09)	(-3.34)	(-2.95)	(0.61)
$CsAvg_{t-q-1}$	-6.967**	-6.509**	-8.976**	-9.950**	-9.414**	-6.733*
	(-2.76)	(-2.61)	(-2.90)	(-3.18)	(-3.09)	(-2.21)
$\Delta(1/Vol)_{t-q}$	-0.205^{+}	-0.352**	-0.272^{+}	-0.424**	-0.444**	0.004
	(-1.76)	(-2.72)	(-1.76)	(-2.98)	(-3.27)	(0.03)
$\Delta CsAvg_{t-q}$	-2.951*	-2.498^{+}	-3.419*	-4.728**	-4.915**	-2.475
	(-2.13)	(-1.82)	(-2.20)	(-2.91)	(-2.88)	(-1.56)
N	3244	3208	3186	3157	3128	3012
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
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 22: **Information measures and growth events - 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 no crises events. The regression specification is: $Pr(\mathbb{1}_{n,t}(Growth) = 1|X_{t-q}) = \Phi(\alpha_n + \beta' X_{t-q})$, 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 2010. 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
$1/Vol_{t-q-1}$	0.274*	0.343**	0.357**	0.323*	0.280*	0.146
	(2.19)	(2.95)	(2.78)	(2.32)	(2.07)	(1.18)
$CsAvg_{t-q-1}$	-4.454***	-3.843**	-2.474^{+}	-2.071	-2.542*	-2.171^{+}
	(-3.36)	(-2.83)	(-1.83)	(-1.62)	(-1.97)	(-1.92)
$\Delta(1/Vol)_{t-q}$	-0.045	0.143	0.251*	0.190	0.189	0.026
	(-0.34)	(1.14)	(2.01)	(1.45)	(1.33)	(0.21)
$\Delta CsAvg_{t-q}$	-1.906*	-2.618**	-1.907*	-0.708	-1.078	-1.361*
	(-2.27)	(-3.08)	(-2.15)	(-0.95)	(-1.34)	(-2.19)
N	4003	3969	3935	3901	3867	3731
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
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 23: **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 24: **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