Rational Overoptimism and Limited Liability

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Abstract

Is excessive risk-taking in credit cycles driven by incentives or biased beliefs? I propose a framework suggesting that the two are actually related and, specifically, that procyclical overoptimism can arise rationally from risk-taking incentives. I show that when firms and banks have a limited liability payoff structure, they have lower incentives to pay attention to the aggregate conditions that generate risk. This leads to systematic underestimation of the accumulation of risk during economic booms and overoptimistic beliefs. As a result, agents lend and borrow excessively, further increasing downside risk. Credit cycles driven by this new "uninformed" risk taking are consistent with existing evidence such as high credit and as low risk premia predicting higher probability of crises and negative returns for banks. My model suggests that regulating incentives can decrease overoptimistic beliefs and thus mitigate boom-and-bust cycles.

Keywords: Overoptimism, expectations, information, limited liability, credit cycles
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1 Introduction

Recent empirical studies has revived the long-held hypothesis that boom-and-bust credit cycles are driven by overoptimistic beliefs (Minsky, 1977; Kindleberger, 1978). In particular, empirical evidence suggests that high credit growth and low risk premia are strong predictors of financial crises (Schularick and Taylor, 2012; Jordà et al., 2013; Krishnamurthy and Muir, 2017; Greenwood et al., 2022). A recent literature ascribes this evidence to overoptimistic beliefs, supported by two additional observations. First, credit booms also predict low or even negative excess returns on bank stocks (Baron and Xiong, 2017), and second, forecasts are systematically too optimistic when credit spreads are low (Bordalo et al., 2018b; Gulen et al., 2019). Behavioral models of extrapolative beliefs have been particularly successful at explaining this systematic bias in belief formation and excessive risk taking (Maxted, 2019; Bordalo et al., 2021; Krishnamurthy and Li, 2021). As a result, these models have moved the focus away from the role of risk-taking incentives, which have been previously studied in relation to the excessive risk-taking that contributed to the recent financial crisis (DeYoung et al., 2013; Boyallian and Ruiz-Verdú, 2018; Armstrong et al., 2022). In this paper, I argue that biased beliefs might actually be the result of risk-taking incentives.

I propose a theory in which overoptimism arises from individuals' rational decision to ignore information about the endogenous buildup of aggregate risk. Additionally, I argue that this lack of attention may be motivated by risk taking incentives. I present these two contributions sequentially. First, I show how the overoptimism driving credit-boom-and-busts stems from inattention to aggregate risk factors. I present a model in which a shock to aggregate productivity leads to an increase in borrowing and production of firms facing a downward sloping demand for their combined output. As higher aggregate production leads to lower selling prices, firms and banks that do not pay attention to their competitors' investment decisions form overly optimistic expectations about their own revenues. As a result, these inattentive firms over-borrow and over-invest, creating excess supply in the market and further driving down prices. As firms' revenues fall short of expectations, their default risk increases. My model implies that even rational agents can be systematically overoptimistic during credit booms (and overpessimistic in busts) due to a lack of attention. Furthermore, because inattentive banks underestimate the probability of borrower default, they misprice risk and experience negative excess returns following credit booms, consistent with existing evidence.

Second, I demonstrate that inattention to risk factors can be the result of risk taking incentives in information choice. Because agents form their beliefs rationally, I can use the model to examine the incentives that leads them to either ignore or pay attention to risk factors. I introduce limited liability in their payoffs and allow them to pay a cost access information about aggregate economic conditions. The convex structure of payoffs insures agents from risk, leading to a lower marginal benefit of information and a corresponding decrease in attention to risk. Uninformed firms underestimate the increase in competition and decline in revenue after booms and are overoptimistic about their company's revenue. As a result, limited liability not only leads to excessive risk taking for given beliefs, but also to neglect of risk and overoptimistic beliefs in during periods of economic expansion. This finding helps to bridge the two narratives about excessive risk taking prior to the financial crisis of 2008-2009: the initial criticisms of managers' moral hazard incentives (e.g. Blinder 2009) and the more recent behavioral overoptimism theory (e.g., Gennaioli and Shleifer 2018). I show that overoptimism is actually a consequence of risk taking incentives, and therefore regulating these incentives can reduce biases in belief formation.

Since beliefs depend on incentives, my model suggests that policy makers can reduce overoptimism in credit booms by regulating incentives to collect information. When agents are informed, they reduce borrowing and investment during credit booms, mitigating economic fluctuations. Providing information through public announcement or direct communication could improve risk assessment, but it may still be costly for agents to process this information (Sims, 2003, 2006). Instead, reducing risk-taking incentives by altering payoffs, for example through regulation of managers' compensation, would not only address their "informed" excess risk taking, but also encourage them to pay attention to aggregate risk factors.

Model I incorporate limited liability and information choice in a macroeconomic model with endogenous default. The economy consists in a continuum of bank-firm pairs, which

I refer as islands (following Lucas (1972)). In this model, firms borrow from banks to finance investment, while banks receive funding at a constant risk-free rate from international markets. I assume that the payoffs of both firm and bank have limited liability, meaning that the agents managing these companies are partially protected from losses (for example, due to convexity of manager compensation, such as option and bonuses versus stock holdings, or the payoffs of shareholders, such as loan guarantees from the government or public bailout policies).

I introduce two novel elements to an otherwise standard model. First, I assume strategic substitutability between the "islands" in the model. Each firm produces intermediate goods that are sold to an aggregate final good producer with downward sloping demand. Firm's productivity is affected by both local and aggregate shocks, but because of competition in the intermediate goods market, firms benefit more from local shocks than from aggregate shocks. In fact, aggregate shocks increase the production of competitors, lowering firm's selling price and expected revenue, which leads to higher probability of default relative to a local shock of the same magnitude. Second, I introduce incomplete information in the model. Following the Lucas "island" framework, I assume that agents face a cost to access information about aggregate economic conditions. Specifically, I allow bank and firm on each island to pay a cost to observe aggregate shocks and the investment decisions of their competitors.[1] This assumption is consistent with Coibion et al. (2018)'s survey evidence of large dispersion in managers' beliefs about both future and current economic condition.

I compare the implications of the model in two limit cases: full information and dispersed information. First, I show that the full information model is unable to replicate the existing evidence on risk premia during a credit boom even qualitatively. If companies are able to observe aggregate shocks, they take into account the negative effect on revenue resulting from the increase in competition,and therefore reduce their investment and borrowing. As a result, the economy is always safer during a credit boom and risk premia are lower.[2]

[1] I follow the rational inattention literature (Sims, 2003, 2006) in interpreting the information cost as a cognitive cost agents pay in order to processing information which could be freely accessible.

[2] Even if the negative price externality has a dampening effect on the credit boom, the model is qualitatively

The model with dispersed information, on the other hand, is able to replicate the existing evidence on credit cycles. If agents do not pay attention to aggregate conditions, they confuse aggregate and local shocks. This is consistent with empirical evidence showing that firms' expectations about aggregate economic conditions respond to industry-specific shocks even though these shocks have no aggregate effects (Andrade et al., 2022). Similarly, after aggregate shocks, agents in the model incorrectly attribute the higher productivity to a local shock and underestimate the increase in production of competitors. As a result, they borrow and invest excessively, further overheating the economy. Even though perceived risk and risk premia decline, the default rate increases. This mechanism is consistent with the evidence in Hoberg and Phillips (2010), that market participants in competitive industries do not fully internalize the negative externality of competition on revenues. Moreover, the model is consistent with existing macro-financial evidence. First, credit growth predicts a higher average probability of default (Krishnamurthy and Muir, 2017). Second, low risk premia also predict a higher average probability of default (Krishnamurthy and Muir, 2017). Third, bank's excess return during the boom and bust is negative on average (Baron and Xiong, 2017).

Next, I allow agents to pay an attention cost to observe aggregate conditions and show that limited liability in payoff discourages them to collect this information. I show that limited liability makes companies less exposed to risk and therefore lowers their marginal benefit of information, discouraging them from collecting information.[3] As a result, they will be inattentive to the endogenous increase in risk during credit booms. Importantly, I show that the procyclicality of risk is a consequences of this information channel of risk-taking incentives, and not the standard "informed" risk-taking channel. In order to isolate the information channel of limited liability, I shut down information choice and allow agents to observe aggregates. I show that in my baseline calibration limited liability increases unconditional risk taking, but conditional on aggregate shocks the economy is safer. On the other hand, with endogenous information limited liability discourages

similar to a standard model without this additional channel (Strebulaev and Whited, 2011). However, because the economy is safer after a boom in this model, it does not match the existing evidence.

[3] Mackowiak and Wiederholt (2012) also show that limited liability reduces optimal information choice in more stylized setting, while Lindbeck and Weibull (2017) study optimal contracts between principal and manager in rational inattention setting, from which I abstract here.

attention allocation, which results in excessive "uninformed" risk taking in booms and procyclical risk.

Finally, I embed the model in a infinite-periods framework to study its implication for credit cycles and relate it to existing evidence. I find that the model with a realistic calibration is able to reproduce two important sets of moments in the data. First, it reproduces the systematic decrease in spreads and increase in credit growth prior to financial crises. Second, it reproduces the ability of declining spreads and increasing credit to predict financial crises.

Contribution to the literature This paper contributes to several strands of the literature. First, the theoretical research on financial crises, which can be divided in two categories. The first emphasizes the role of behavioral bias in belief formation and credit market sentiments (Bordalo et al., 2018b; Greenwood et al., 2019; Maxted, 2019; Farhi and Werning, 2020). The most related is Bordalo et al. (2021), who incorporate extrapolative expectations in a firm dynamic model with lending and default. In their model, beliefs overreact to good news, leading to overoptimism in credit booms. In my model, overoptimism results instead from rational underreaction to bad news. As a result, forecast errors exhibits cyclical predictability even in a fully rational setting.

A second line of research emphasizes the role of financial frictions in intermediation as sources of fragility (Gertler and Kiyotaki, 2010; He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014; He and Krishnamurthy, 2019; Jeanne and Korinek, 2019; Bianchi and Mendoza, 2020). This class of models use full information and strategic complementarity in leverage choices to rationalize the overaccumulation of debt during booms, as individuals do not internalize the externality effects of their decision on the whole economy. In other words, investors ride the bubble as long as others ride it. Differently from them, my model features strategic substitutability and incomplete information: if investors knew about the increase in aggregate risk, they would reduce leverage and therefore reduce risk. In other word, they would like to exit the bubble before it burst. The lack of information is what leads them to accumulate risk, resulting in a unexpected boom-and-bust.

My paper is also complementary to a growing literature on the link between information generation in the credit market and credit cycles (Martinez-Miera and Repullo, 2017; Gorton and Ordonez, 2020; Asriyan et al., 2022). In these papers, credit booms are associated with lower production of information about borrowers or collateral, leading to lower investment quality and higher financial fragility. Differently from them, I focus on information about aggregate and not idiosyncratic risk factors. This is what in my model gives rise to systematic overoptimism and losses by lenders during credit booms.

Finally, my paper relates to the literature on strategic games with incomplete information (Woodford, 2001; Coibion and Gorodnichenko, 2012; Maćkowiak and Wiederholt, 2015; Angeletos and Lian, 2017; Benhima, 2019). Similarly to Kohlhas and Walther (2021), agents here pay asymmetric attention to local and aggregate quantities, which leads to "extrapolative beliefs" even in a rational setting. Differently from them, the determinant of the attention allocation is not the difference in shock volatility, but risk taking incentives.

Structure of the paper The remaining sections of the paper are organized as follows. In section 2 I provide some motivational evidence on information frictions in expectations surveys. In section 3 I propose a model of credit booms-and-bust with information frictions. I solve the model backwards. In section 4 I present the solution of the lending and investment choice problem for a given information structure (second stage). In section 5 I present the solution of the information choice problem (first stage). In section 6 I extend the baseline model to a infinite-period setting. Section 7 discusses policy implications and section 8 concludes.

2 Motivational Evidence on Beliefs in Booms

While existing theories of overoptimism assume full information and depart from rational expectation, in this section I present suggestive evidence on the importance of information frictions in business cycles. Specifically, I show that aggregate beliefs under-react to changes in macroeconomic quantities during booms and busts, consistent with models of dispersed information.[4]

[4] A prominent behavioral theory of overoptimism is belief extrapolation, and in particular diagnostic expectations, which causes agents to over-react to recent news (Gennaioli and Shleifer, 2010; Bordalo et al., 2018b, 2021).

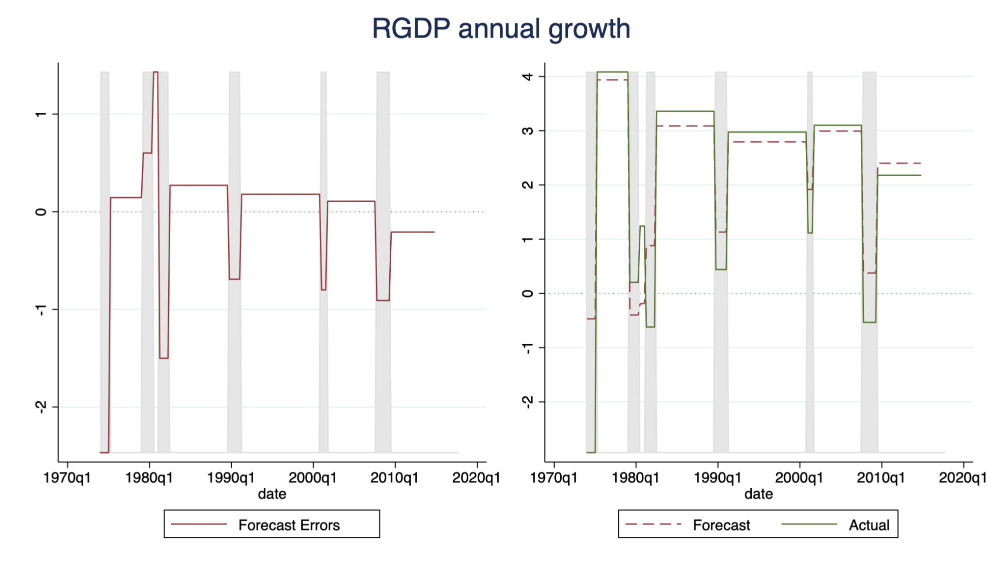

Figure 1: Forecast errors on Real GDP growth

Notes: Left panel: the red line plots the forecast errors on annualized real GDP growth averaged between shaded area. Forecast errors are defined as $fe_t = x_t - f_t(x_t)$, where x_t is the average annualized growth of real GDP in the current and the next three quarters, and $f_t(x_t)$ the average (consensus) forecast in quarter t about annualized growth of real GDP in the current and the next three quarters. The shaded area indicates the NBER recession dates. Right panel: the dashed red line plots the average forecast on annualized real GDP growth $f_t(x_t)$, while the solid green line the actual real GDP growth x_t. All expectation data are from the Survey of Professional Forecasters, collected by the Federal reserve's Bank of Philadelphia

First, I examine the business cycle fluctuations in forecast errors for real GDP growth by comparing average errors during booms and recessions. Forecast errors are defined as the difference between actual and average expected GDP growth in current and next three quarters, with data on forecasts taken from the Survey of Professional Forecasters. A positive forecast error indicates that the consensus forecast underestimates the actual GDP growth. Figure 1 shows that during booms, forecasters underestimate real output, while during recessions they overestimate it. This suggests that at the aggregate level, expectations exhibit underreaction to changes in macroeconomic quantities.

I also present suggestive evidence for belief under-reaction during the most recent credit boom-and-bust episode. Financial crises are less frequent than business cycle recession, and given the limited time span of expectations data the only meaningful credit boom-and-bust I can consider is the recent financial crisis of 2007-2008. Figure 2 plots annualized housing starts growth and forecasts, averaged across the current and the next

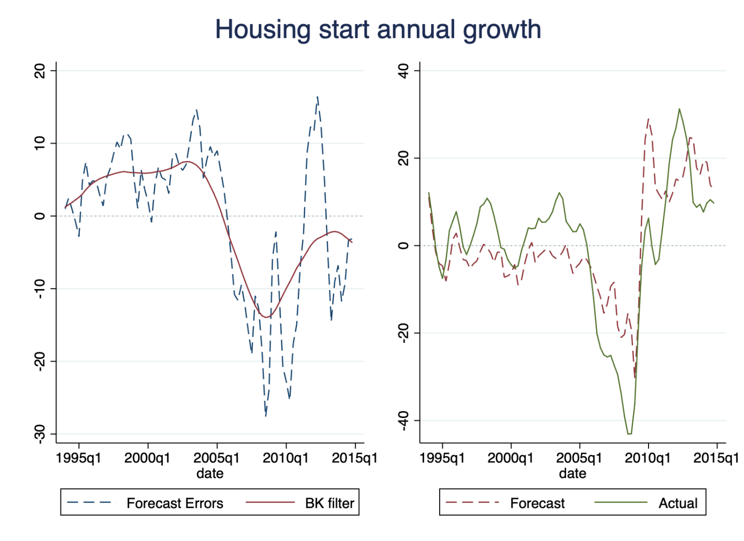

Figure 2: Forecast errors on Housing Start

Notes: The blue line plots the forecast errors on annualized housing start growth from the Survey of Professional Forecasters, collected by the Federal reserve's Bank of Philadelphia. Forecast errors are defined as $fe_t = x_t - f_t(x_t)$, where x_t is the average annualized growth of housing starts in the current and the next three quarters, and $f_t(x_t)$ the average (consensus) forecast in quarter t about annualized growth of housing starts in the current and the next three quarters. The red line plot the Baxter-King filtered trend, where I filtered out periods lower than 32.

three quarters. The pattern is similar to the previous figure and suggests that forecasters underestimated housing starts growth during the boom. In my model, I show how underestimation of an increase in supply leads to overestimation of the equilibrium market price, which may provide insight to the apparent overoptimism that fueled the housing bubble in the years preceding the crisis.

In addition to the evidence presented here, a growing literature uses surveys of professional forecasters to document the importance of information frictions compared the full information hypothesis (Coibion and Gorodnichenko, 2012, 2015; Gemmi and Valchev, 2022).[5] The evidence of aggregate stickiness in belief updating supports models of dispersed information, where agents have access to different information and are always in disagreement about the fundamentals. Additionally, the professional forecaster expectations data used here likely underestimate the amount of information friction faced by firms.

[5] Bordalo et al. (2018a) provide evidence supporting behavioral overreaction in individual-level forecasts of financial and macroeconomic variables in surveys of professional forecasters. However, they still find dispersed information and belief stickiness at the consensus level. Moreover, Gemmi and Valchev (2022) present evidence on individual survey forecast that are inconsistent with the diagnostic expectation framework.

Consistent with this, Coibion et al. (2018) study firm-level expectations and find higher information frictions: managers' expectations display much more disagreement than professional forecasters, and this disagreement applies to both future and current economic conditions. They also find that belief updating is consistent with the Bayesian framework, and their attention allocation to aggregates depends on incentives.

In summary, the evidence on aggregate expectations is consistent with information frictions that hinder the dissemination of information or the incorporation of new information into agent's beliefs (Sims, 2003; Woodford, 2001). In the following section, I present a model that is consistent with the data and show that overoptimism arises from incomplete information about aggregate quantities.

3 Model of inattentive credit booms

The economy consists of a continuum of islands $j \in [0, 1]$, each of them populated by a firm-bank pair.[6] Banks in each island obtain funds at a risk-free rate from international markets and lend to firms at a premium above the funding rate to cover repayment risk. Firms borrow from banks to finance investment and production of intermediate goods, which they sell to a single aggregate final good producer. If revenues exceed outstanding debt, the firm repays the bank and keep the net profit, otherwise it defaults.

Timeline The model is divided into three stages. In the first stage, before receiving any information, each bank-firm pair decides whether they want to observe aggregate shocks in the next stage. In the second stage, they observe information and negotiate loans and loan rates. In the final stage, shocks are realized and firms either repay or default. Rather than describing business cycles, the model is intended to depict the phases of a financial bubble, with the second stage representing the building up of the bubble and the third stage its burst.

Final good producer The economy features a representative final good producer who purchase a bundle of intermediate goods $M = \left[\int^{j} M_j^{\xi} dj\right]^{\frac{1}{\xi}}$ with elasticity of substitution

[6] The island assumption reflects the importance of banking relationship and the cost faced by borrowers in switching lender (Chodorow-Reich, 2014). I assume that the sorting of lenders and borrowers across island takes place before markets open and information is observed, at a time when there is no heterogeneity in firms' and banks' characteristics.

$\frac{1}{1-\xi}$, in order to produce final good with production function $Y = M^{\nu}$. Thus, the demand function for intermediate goods M_j in stage 3 is:

$$p_j = \nu M^{\nu-\xi} M_j^{\xi-1} \tag{1}$$

The demand for intermediate good M_j may increase or decrease with aggregate production M depending on the degree of decreasing return to scale in final good production and the elasticity of substitution between goods. If $\nu < \xi$, there is a negative production externality: an increase in aggregate supply of intermediates M leads to a decrease in price p_j and therefore lower revenues for intermediate producer j. On the other hand, if $\nu < \xi$, there is a positive production externality: an increase in aggregate supply of intermediates M leads to an increase in price p_j and therefore higher revenues for intermediate producer j.

Firms In the second stage, firms in island j borrows b_j from the bank to purchase capital inputs and cover the capital adjustment cost. For simplicity, I assume firms start with zero net worth and therefore borrowing equal $b_j = k_j + \phi\frac{k_j^2}{2}$. In the third stage, firms combine labor l_j, pre-installed capital k_j and productivity A_j with production function $M_j = A_j^{\zeta} k_j{}^{\tilde{\alpha}} l_j^{1-\tilde{\alpha}}$, where $\tilde{\alpha} \in (0,1)$ represents the capital share. Firms hire labor in the third stage after observing the shocks realization and pay workers before repaying their debt to the bank. Define the operating profit of the firm as $\pi_j = p_j M_j - w l_j$. One can maximize labor out of the problem and substitute for the demand function (1) to obtain net operating profit as function of only capital, technology and aggregate supply of intermediates

$$\pi(A_j, k_j, M) = \Lambda(M) A_j k_j^{\alpha} \tag{2}$$

where $\alpha = \frac{\tilde{\alpha}\xi}{1-(1-\tilde{\alpha})\xi}$, $\Lambda(M) = \nu^{\frac{1}{1-(1-\alpha)\xi}} M^{\frac{\nu-\xi}{1-(1-\alpha)\xi}}$ with

$$M = \left\{ \left[\frac{w}{(1-\alpha)\xi\nu} \right]^{\frac{(1-\alpha)}{(1-\alpha)\xi-1}} \left[\int^{N} A_j k_j^{\alpha} dj \right]^{\frac{1}{\xi}} \right\}^{\frac{1-(1-\alpha)\xi}{1-(1-\alpha)\nu}} \tag{3}$$

Here I have normalized the parameter ζ so that the profit function is linear in technology and the real wage w so that the constant multiplying $\Lambda(M)$ in the profit function equals 1.

Firms payoff in stage 3 are as follows:

$$d_{firm,j} = \begin{cases} (1-\tau)[\pi(A_j,k_j,M) - (1+r_j)b_j] & \text{if } \pi(A_j,k_j,M) \geq (1+r_j)b_j \\ -c_d k_j, & \text{if } \pi(A_j,k_j,M) < (1+r_j)b_j \end{cases} \tag{4}$$

If profits are larger than the outstanding debt $(1+r_j)b_j$, the firm repays the bank and use the remaining amount, minus a tax rate τ, as dividends. If the profits are not sufficient to repay the outstanding debt, the firm pays a default cost c_d proportional to the installed capital, which can be thought as a liquidation or reorganization cost following bankruptcy procedure.[7]

Banks Banks in each island j have deep-pockets and are risk-neutral. In the second stage, they borrow at a risk-free rate r^f from the international market in order to finance risky loans to firms b_j, at loan rate r_j. They maximize their expected profits in the third stage, which equal

$$d_{bank,j} = \begin{cases} [(1+r_j) - (1+r^f)]b_j & \text{if } \pi(A_j,k_j,M) \geq (1+r_j)b_j \\ -(1+r_j)b_j & \text{if } \pi(A_j,k_j,M) < (1+r_j)b_j \end{cases} \tag{5}$$

where risk free rate r^f is exogenous and equilibrium loan rate r_j is determined in stage 2. Firm's revenue is lost when the firm defaults, therefore default represents a net loss for the economy.[8]

Exogenous shocks The logarithm of local technology A_j in each island j is the sum of two independent components: an i.i.d. local island component ϵ_j and an aggregate

[7] I consider here a form of "reorganization" bankruptcy, as in Chapter 11 of US bankruptcy code, under which the firm is allow to keep operating after a period of reorganization. These procedures may include reputation costs, asset fire sales, loss of customer or supplier relationships, legal and accounting fees, and management changes, which I assume to depend on the size of the firm (Branch, 2002; Bris et al., 2006).

[8] While I assume a zero recovery rate for simplicity, a positive recovery rate would not change qualitatively the implications of the model.

component θ:

$$ln(A_j) = \epsilon_j + \theta \tag{6}$$

Agents in each island have common prior $\epsilon_j \sim N(0, \sigma_\epsilon^2)$ and $\theta \sim N(0, \sigma_\theta^2)$. The local shock average out in the aggregate, $\int^j \epsilon_j dj = 0$ Both shocks realize in stage 3 and determine aggregate and local production.

3.1 Limited Liability

I assume firms and banks' payoff have limited liability, protecting them from downside risk. Specifically, I assume they are insured against a fraction ψ of their losses: higher ψ implies a more convex payoff structure and therefore higher risk taking incentives. The payoff structures of bank and firm becomes then

$$w_{firm,j} = \begin{cases} (1-\tau)[\pi(A_j, k_j, M) - (1+r_j)b_j] & \text{if } \pi(A_j, k_j, M) \geq (1+r_j)b_j \\ -(1-\psi)c_d k_j, & \text{if } \pi(A_j, k_j, M) < (1+r_j)b_j \end{cases} \tag{7}$$

$$w_{bank,j} = \begin{cases} [(1+r_j) - (1+r^f)]b_j & \text{if } \pi(A_j, k_j, M) \geq (1+r_j)b_j \\ -(1-\psi)(1+r_j)b_j & \text{if } \pi(A_j, k_j, M) < (1+r_j)b_j \end{cases} \tag{8}$$

I consider a general limited liability constraint specification which embeds different real world cases. First, it can represent the convexity of managerial compensation, e.g., bonuses and option holdings versus shares. In particular, option compensation is one of the most studied sources of moral hazard incentives (Edmans et al., 2017).[9] Moreover, after the 2008-2009 financial crisis, compensation policies were cited as a likely culprit for the excessive risk-taking that led to the crisis (e.g. Bebchuk et al. (2010)). Second, one can interpret the limited liability of the firm as resulting from moral hazard between

[9] Stock option compensation in US companies has increased considerably during the 1980s, and especially in the 1990s, becoming the largest component of executive pay. Options increased from only 19% of manager's pay in 1992 to 49% by 2000, and start declining from mid-2000 and in 2014 they represent 16% of the pay (Edmans et al., 2017).

borrower and lender, such as lower default costs or government bailouts. Third, one can interpret the bank's limited liability as the share of funds coming from insured deposits versus equity (Dell'Ariccia et al., 2014), or the share of loan value covered by government guarantees, an important part of the COVID -19 support packages offered by European governments to firms (OECD, 2020).

3.2 Stage 2: lending and borrowing

I describe the two stages backwards, starting with the second stage. Before the shocks realize and production takes place, banks and firms on each island decide on the quantity of credit b_j and the interest rate r_j based on their expectation about profits in stage 3. They allocate the island's surplus through Nash bargaining with the firm holding all bargaining power, which, consistent with the literature, implies a zero expected profit condition for the lender (e.g. Strebulaev and Whited (2011)).

Information structure The bank and firm on island j share the same information.[10] Before deciding on borrowing and lending, they receive up to two signals. First, they observe a free noisy signal about local productivity:

$$z_j = ln(A_j) + \eta_j \tag{9}$$

with $\eta_j \sim N(0, \sigma_\eta^2)$ and local technology described in 6.

Second, they may or may not perfectly observe aggregate productivity. Following the Lucas island setting, I assume agents in each islands do not freely observe aggregate quantities and prices. However, in stage 1 the bank and the firm in island j can decide whether to pay a information cost to perfectly observe the aggregate shock θ. Let Ω_j be the (common) stage-2 information set of agents in island j: if they pay the cost in stage 1, $\Omega_j = \{z_j, \theta\}$, otherwise $\Omega_j = \{z_j\}$. One can think of this as a cognitive cost of not only collecting, but also processing information and compute the optimal individual best response (Sims, 2003, 2006).

[10] Any private information between agents in the same island would be perfectly revealed by local prices.

Lending and borrowing decision The bank's expected excess return equals

$$\begin{aligned} E[w_{bank,j}|\Omega_j] =& b_j[1-p(default_j|\Omega_j)](1+r_j)b_j \\ & -[(1-\psi)+\psi[1-p(default_j|\Omega_j)]](1+r^f)b_j \end{aligned} \tag{10}$$

the expected firm payoff conditioning on second stage information set is

$$\begin{aligned} E[w_{firm,j}|\Omega_j] =& (1-\tau)\int_0^{\infty}\int_{ln\left(\frac{b_j}{\Lambda(M)k(b_j)^{\alpha}}\right)}^{\infty} \Lambda(M)A_j k_j^{\alpha} f(ln(A_j),M|\Omega_j)dA_j dM \\ & -\left[1-p\left(default_j|\Omega_j\right)\right](1+r_j(b_j))b_j - \left[p\left(default_j|\Omega_j\right)\right](1-\psi)c_d k_j \end{aligned} \tag{11}$$

with the posterior default risk being defined by

$$p(default_j|\Omega_j) = \int_0^{\infty}\int_{-\infty}^{ln\left(\frac{b_j}{\Lambda(M)k(b_j)^{\alpha}}\right)} f(ln(A_j),M|\Omega_j)dA_j dM \tag{12}$$

where Ω_j is the information set of island j, $f(ln(A_j),M|\Omega_j)$ is the joint posterior density function of $ln(A_j)$ and M_j, and capital purchased is a monotonic function of borrowing $k(b_j) = \phi^{-1}(\sqrt{1+2b_j\phi}-1)$. Finally, $\Lambda(M) = \nu^{\frac{1}{1-(1-\alpha)\xi}} M^{\frac{\nu-\xi}{1-(1-\alpha)\xi}}$ is the revenue shifter due to the effect of aggregate production on intermediate good price, where M is defined in 3.

Definition 1 (Stage 2 equilibrium) *Given local shock realization $\{\epsilon,\eta\}_{j\in[0,1]}$, aggregate shock realization $\{\theta\}$ and agents information set $\Omega_{j\in[0,1]}$, the market equilibrium in stage 2 is defined as a set of local loan prices $r_{j\in[0,1]}$ and local loan quantities $b_{j\in[0,1]}$ such that*

- *Bank j's expected profits 10 equal zero.*
- *Firm j internalizes loan supply function $r_j(b_j)$ and maximizes expected profits 11.*

Online Appendix A describes in detail the bargaining process underlying the stage-2 equilibrium. The loan rate is implicitly determined by the bank's zero expected profit condition.

$$\frac{1+r_j}{1+r^f} = \frac{(1-\psi)+\psi[1-p(default_j|\Omega_j)]}{[1-p(default_j|\Omega_j)]} \tag{13}$$

The loan rate is proportional to the perceived probability of default, implying that the risk premium on the loan is proportional only to the perceived risk, with no variation in the price of risk.[11]

The firm internalizes the bank's credit supply $r_j(b_j)$ and chooses the optimal borrowing b_j to maximize the expected payoff

$$k_j = argmaxE[w_{firm,j}(r_j(b_j), M_j, ln(A_j))|\Omega_j] \tag{14}$$

Strategic motives The impact of aggregate production of intermediate M on firm j's revenue is described by the term

$$\Lambda(M) = \nu^{\frac{1}{1-(1-\alpha)\xi}} M^{\frac{\nu-\xi}{1-(1-\alpha)\xi}} \tag{15}$$

Depending on the sign of $\nu - \xi$, the model can exhibit strategic substitutability or complementarity between islands in lending and borrowing decisions. First, suppose that $\nu < \xi$: the shifter $\Lambda(M)$ is decreasing in aggregate intermediate output M and there is *strategic substitutability*. For a given level of local output M_j, a higher aggregate output M implies a lower price p_j and lower revenue for firm j. As a result, the optimal borrowing b_j and loan rate r_j are decreasing in aggregate output M. Second, suppose that $\nu > \xi$: the shifter $\Lambda(M)$ is increasing in aggregate intermediate output M and there is *strategic complementarity*. For a given level of local output M_j, a higher aggregate output M leads to a higher price p_j and higher revenue for firm j. As a result, the optimal borrowing b_j and loan rate r_j are increasing in aggregate output M. I formalize this relation in the sction 4.1.

3.3 Stage 1: Information choice

Before observing any signal, each island decides whether to pay an information cost c to perfectly observe aggregate shock θ stage 2, which provides information about the aggregate output M. Similarly to the equilibrium ion stage 2, I assume banks and firms share information and decide cooperatively through Nash bargaining with the firm holding all

[11] This result follows from the assumption that the firm retains all bargaining power, which implies a zero expected profits condition for the bank. A nonzero bargaining power for the bank does not change the mechanism of the model, but it does change the determination of the risk premium, which could decline for a higher quantity of risk if the price of risk also declines. See Online Appendix A for an alternative calibration of the model in which the bank has a nonzero bargaining power.

bargaining power.[12] As a result, island j's information problem is

$$max_{n_j \in \{0,1\}} \quad E[E[w_{firm,j}(b_j, r_j)|\Omega_j(n_j)] - n_j c] \tag{16}$$

where the binary indicator takes value $n = 1$ if they decide to pay the cost c and $n = 0$ otherwise. The first expectation term is conditional on the information set in stage 1, which consists only of priors, while the second expectation operator is conditioning on stage-2 information set Ω_j. If they pay the cost, they will be able to observe aggregates in the next stage: $\Omega_j(1) = \{z_j, \theta\}$. If they do not pay the cost, they will be not able to observe aggregates: $\Omega_j(0) = \{z_j\}$. In other words, island j decides to pay the attention cost if

$$E[w^*_{firm,j}(\theta \in \Omega_j, \lambda) - c] \geq E[w^*_{firm,j}(\theta \notin \Omega_j, \lambda)] \tag{17}$$

where w^*_{firm} is the firm's payoff given stage-2 equilibrium r_j from equation 13 and b_j from equation 14. The equilibrium price and quantities, and therefore the payoff, are functions of stage-2 information set Ω_j, which is the object of this stage choice problem. Expectation in stage 1 are instead conditional only on common priors, as agents have no access to any signal at this stage.

As argued in the previous section, optimal local prices and quantities in stage 2 depens on aggregate decision through the price externality $\Lambda(M)$. Thus, the optimal information choice of island j depend on the share of the other islands that decide to b informed, $\lambda \in [0, 1]$. In particular, $\lambda = 1$ if all islands decide to pay the cost to observes aggregate shocks and $\lambda = 0$ if none decides so. In equilibrium, λ^* is such that all island are indifferent between paying or not paying the cost.[13]

Definition 2 (Stage 1 equilibrium) *Given prior beliefs about local shock realization* $\{\epsilon, \eta\}_{j \in [0,1]}$

[12] Any private information between agents on the same island would be perfectly revealed by local prices. Therefore, any individual decision about whether to observe private information would have to take this information spillover into account, leading to strategic considerations between agents even on the same island. To avoid this, I use a Nash bargaining setting in which the decision is made cooperatively with the same bargaining power as in stage-2 bargaining. As a result, the firm receives the surplus and pays the information cost. I allow for a different allocation of surplus and cost in Online Appendix D.

[13] While I consider the extensive margin of information choice, i.e. observing or not aggregates, the outcome is qualitative similar to modeling information choice on the intensive margin, i.e. deciding the accuracy of a signal about aggregates as in the rational inattention literature (for a review, Mackowiak et al. (2018)).

and aggregate shock realization $\{\theta\}$, the market equilibrium in stage 1 is defined by a share $\lambda \in [0,1]$ of islands such that all islands $j \in [0,1]$ are indifferent between paying and not paying the information cost, i.e. equation 17 holds with equality $\forall j \in [0,1]$.

4 Credit booms with information frictions

4.1 Analytical results

To illustrate the mechanism of the model, I consider a first-order approximation of the second stage model around the risky steady state (Coeurdacier et al., 2011).[14] At the steady state, all islands observe the same signal $z_j = 0$ and the aggregate shock $\theta = 0$, but there is still uncertainty about the local shock realization ϵ_j. This risk is priced in the steady state spread $r_j > r^f$, meaning there is a positive steady state risk premium. In this section, I assume for simplicity no adjustment cost $\phi = 0$, no limited liability $\psi = 0$ and no default cost $c_d = 0$. Because of these assumptions, in equilibrium the perceived default risk and risk premium are constant (while the actual default risk may not be), but the other qualitative implications of the model are unaffected. I relax all these assumptions in Section 4.2 where I solve the full model numerically.

Proposition 1 (Linearized model) *Consider a first order approximation of the second-stage equilibrium defined by equations (13) and (14) assuming $\phi = 0$, $\psi = 0$ and $c_d = 0$. Let $\hat{x}$ indicate the log-deviation of any variable x from its steady state value and with $\tilde{x}$ the level deviation from steady state.*

- *Equilibrium local investment equals*

$$\hat{k}_j = \frac{1}{1-\alpha}(E[lnA_j|\Omega_j] - \gamma E[\hat{M}|\Omega_j]) \tag{18}$$

where $\hat{M} = \mu(\theta + \alpha\hat{K})$, with $\mu > 0$ and $\hat{K} = \int^j \hat{k}_j dj$. Let Ω_j denote the information set of island j (bank and firm) and $\gamma \equiv \frac{\nu-\xi}{1-(1-\alpha)\xi}$ the elasticity of the operating profit

[14] While an economy near the steady state is not suitable to study large and rare financial crises like the one considered in this paper, the basic model's mechanism does not rely on nonlinearities and its intuition remains intact in the linearized version

$\pi_j(A_j, k_j, M)$ *with respect to aggregate production* M*. if* $\nu < \xi$*, then*$\gamma < 0$ *and the economy exhibits strategic substitutability in firms investment decisions. If* $\nu > \xi$*, then* $\gamma > 0$ *and the economy exhibits strategic complementarity in firms investment decisions.*

- *The loan rate is proportional to perceived default risk*

$$\hat{r}_j \propto -\hat{p}(def_j|\Omega_j) \tag{19}$$

where $\hat{p}(def_j|\Omega_j)$ *is the perceived default risk of island* j *conditioning on information set* Ω_j*.*

- *Equilibrium perceived default risk is constant*

$$\hat{p}(def_j|\Omega_j) = 0 \tag{20}$$

- *Equilibrium aggregate banks' profits in state* θ *equal*

$$E[\tilde{\pi}_{bank}|z_j, \theta] \propto -\int^j [\hat{p}(def_j|z_j, \theta) - E[\hat{p}(def_j|\Omega_j)|\theta]]dj \tag{21}$$

where $\hat{p}(def_j|z_j, \theta)$ *is the actual default risk conditional on signal* z_j *and aggregate shock* θ*.*

See Online Appendix B for the proof.

Proposition 1 highlights some interesting results. First, the equilibrium loan rate $\hat{r}_j$ is negatively related to the perceived probability of default. This result follows directly from the pricing equation 13 and implies that changes in risk premia reflect only changes in perceived quantity of risk. Second, perceived default risk is constant in equilibrium (i.e. zero in log-deviation from the steady state). This is a knife-edge result and it depends on the simplifying assumptions introduced in this section, which I relax in the numerical solution. Third, since the loan pricing condition implies no expected profits for the bank, aggregate banks' profits in state θ depend on whether agents perceived risk correctly, i.e. whether the loan is correctly priced conditioning on θ.

PE vs GE A positive aggregate shock θ has two effects on equilibrium investment: a partial equilibrium (PE) effect and a general equilibrium (GE) effect.[15]

$$\frac{\partial \hat{k}_j}{\partial \theta} = \frac{1}{1-\alpha} \left(\underbrace{\frac{\partial E[lnA_j|\Omega_j]}{\partial \theta}}_{\text{PE effect}} - \gamma \underbrace{\frac{\partial E[\hat{M}|\Omega_j]}{\partial \theta}}_{\text{GE effect}} \right) \tag{22}$$

First, local productivity A_j in each island increases. Because firm's fundamental is higher, island j's posterior probability of default decreases, boosting borrowing and investment $\hat{k}_j$. This is the standard channel of productivity shocks examined in the existing literature and it does not depend on the interaction between islands (PE). Second, higher aggregate supply of intermediates can imply lower or higher demand for intermediate good j depending on the degree of decreasing return to scale (ν) with respect to the elasticity of substitution between intermediates (θ).

Assumption 1 (Strategic substitutability) *Assume that $\nu < \xi$: firms exhibit strategic substitutability in investment decisions.*

In section 4.2, I show that this assumption holds under fairly mild conditions, such as a similar or higher markup in intermediate compared to final good sector, which is supported by existing empirical evidence. Because of this assumption, higher aggregate investment $\hat{K}$ implies a lower selling price p_j and revenue for island j and as a result a lower optimal investment $\hat{k}_j$.

While λ depends endogenously on the sage-1 information choice, I consider here two limit cases to illustrate the mechanism of the model. First, I assume all islands decide to pay attention to aggregates in the first stage ($\lambda = 1$, i.e. full information). Second, I assume no island decides to pay attention to aggregates in the first stage ($\lambda = 0$, i.e. dispersed information).

[15] Here I use the term"partial equilibrium" to refer to an effect related only to island j's problem, and the term "general equilibrium" to refer to an effect related to the interaction between the islands (Angeletos and Lian, 2017).

4.1.1 Full information $\lambda = 1$

Consider the full information case, in which all islands decide to observe aggregate shock θ in the first stage in addition to the free signal z_j defined in equation 9.

Proposition 2 (Full information) *If $\Omega_j = \{z_j, \theta\}$, the solution to the linear game of proposition 1 is*

$$\hat{K}^{fi} = \frac{1-\gamma\mu}{1-\alpha+\gamma\mu\alpha}\theta \tag{23}$$

See Online Appendix B for the proof.

After an aggregate shock, the increase in local technology leads to higher aggregate debt and investment, but its effect is dampened by the endogenous decline in intermediate goods prices, which lowers firms' optimal investment. The stronger the elasticity of intermediate prices with respect to the increase in aggregate intermediate supply $0 < \gamma < 1$, the stronger the dampening force of the GE effect.

Corollary 1 (Actual default rate in FI) *If $\Omega_j = \{z_j, \theta\}$, actual default risk coincides with perceived default risk, which is constant by Proposition 1.*

$$\hat{p}(def_j|z_j, \theta) = \hat{p}(def_j|\Omega_j) = 0 \tag{24}$$

As a result the default rate (equal to the average actual default risk across firms) is also constant.

Notice that the negative endogenous GE effect on the firm's expected revenue can not be larger than the positive PE effect in full information, which means that the actual default risk can not be larger either. If this were the case, then the lower expected revenues would cause firms to reduce their debt and investment (Proposition 1), resulting in lower aggregate supply, higher price, and a positive endogenous GE effect. In other words: If default risk were higher, the agents would optimally limit and reduce risk. This is a consequence of the strategic substitutability between firms.[16] As a result, the full information

[16] A large body of research instead focuses on strategic complementarity in full information to rationalize the procyclical leverage (Gertler and Kiyotaki, 2010; Brunnermeier and Sannikov, 2014; He and Krishnamurthy, 2019; Bianchi and Mendoza, 2020).

economy is not riskier during credit booms, which is inconsistent with existing empirical evidence (Schularick and Taylor, 2012; Krishnamurthy and Muir, 2017).

Corollary 2 (Bank's profit in FI) *If $\Omega_j = \{z_j, \theta\}$, bank's profit are zero conditioning on z_j and θ.*

$$E[\tilde{\pi}_{bank}|z_j, \theta] = 0 \tag{25}$$

Since perceived risk equals actual risk, default risk is correctly priced conditioning on aggregate economic conditions. In other words: since banks observe θ, they do not make systematic errors conditioning on it. The zero expected profit condition implies that, on average, banks make zero excess return in each aggregate state θ. While this model implies zero expected profits for banks, a different bargaining power could lead to positive profits. However, bank shareholders would not accept predictable losses, which is at odds with the evidence of systematic negative excess returns on bank stocks after large credit booms (Baron and Xiong, 2017).

4.1.2 Dispersed information $\lambda = 0$

Consider the dispersed information case, in which no island decides to pay the cost to observe aggregate shock θ in the first stage, so they only observe the free signal z_j defined by equation 9.

Proposition 3 (Dispersed information) *If $\Omega_j = \{z_j\}$, the solution to the linear game of Proposition 1 is*

$$K^{di} = \frac{(m - \gamma\mu\delta)}{1 - \alpha + \gamma\mu\alpha\delta}\theta \tag{26}$$

where $m = \frac{\sigma_e^2 + \sigma_\theta^2}{\sigma_e^2 + \sigma_\theta^2 + \sigma_\eta^2}$ and $\delta = \frac{\sigma_e^2}{\sigma_e^2 + \sigma_\theta^2 + \sigma_\eta^2}$ are the Bayesian weights on signal z_j in the posterior means of $ln(A_j)$ and θ respectively, with $0 < \delta < m < 1$.

See Online Appendix B for the proof.

Agents do not observe aggregates, but only the local signal, which provides information about the local technology. Since the local technology is the sum of local and aggregate shocks, they can not distinguish between the two without additional information.

Agents are rational and form Bayesian posterior beliefs that assign a positive probability to both shocks. This is consistent with the empirical evidence that firms' expectations about macroeconomic conditions are sensitive to industry-specific shocks, even though these shocks do not have aggregate effects (Andrade et al., 2022).

Corollary 3 (Boom amplification) *The difference in aggregate investment in dispersed information 26 and full information 23 depends positively on θ, and therefore the information friction leads to an amplification of credit booms if*

$$(m - \gamma\mu\delta)(1 - \alpha + \gamma\mu\alpha) > (1 - \gamma\mu)(1 - \alpha + \gamma\mu\alpha\delta) \tag{27}$$

Assume that the condition in Corollary 3 is satisfied. Then, after a positive aggregate shocks agents observe a signal about higher local technology and partially mistake it for a local shock. As a result, they underestimate the endogenous increase in aggregate output and the associated decrease in selling price. Incomplete information therefore dampens the negative general equilibrium effect on investment and leads to an amplifications of individual borrowing and investment.[17]

The above intuition is correct only if condition 27 is satisfied. In general, aggregate shock θ affects both local fundamentals (PE effect) and aggregate output (GE effect). As a result, not observing θ leads to underestimating of both, with opposite effects on optimal investment. Whether investment is higher with dispersed information than with full information depends on how much observing aggregates increases (i) posterior beliefs about local productivity (PE) and (ii) posterior beliefs about aggregate intermediate output (GE). First, suppose the signal z_j is infinitely noisy, $\sigma_\eta \to \infty$, then $m = \delta = 0$ and condition 27 is not satisfied. The intuition is as follows. Without signals on local productivity, the aggregate shock is the only source of information. If agents do not observe this shock either, investment in all states is equal to the steady state level. If agents are instead able to observe it, a higher aggregate shock θ increases their posterior beliefs on both local technology (PE) and aggregate investment (GE), but the only existing equilibrium is one in

[17] The amplifying effect of dispersed information in presence of strategic substitutability between agents is explored also in Angeletos and Lian (2017), Benhima (2019) and Kohlhas and Walther (2021).

which the first outweighs the second and optimal local investment increases.[18] Second, suppose the signal z_j is noiseless, $\sigma_\eta \to 0$, then $m = 1, \delta < 1$ and condition 27 is satisfied. In this case, agents observe local productivity perfectly, independent of their information about the aggregate shock. However, observing aggregates provides information about the investment decisions of the other firms, and hence about the negative endogenous GE effect. In the dispersed information setting, agents underestimate the increase in competition after an aggregate shock and over-invest relative to the economy with informed agents.

Now consider the case of an individual island, consisting of both bank and firm, forming expectation on local firm's operating profit. Define the forecast errors as the difference between realized and expected revenue, $fe \equiv \widehat{\pi}(A_j, k_j, M) - E[\widehat{\pi}(A_j, k_j, M)|\Omega_j]$.

Corollary 4 (Rationally extrapolative beliefs and underreaction) *If $\Omega_j = \{z_j\}$, the average forecast errors on firm j's revenue in state θ is proportional to*

$$E[\widehat{\pi}_j|z_j, \theta] - E[E[\widehat{\pi}_j|z_j]|\theta] =\propto -[(m - \gamma\mu\delta)(1 - \alpha + \gamma\mu\alpha) - (1 - \gamma\mu)(1 - \alpha + \gamma\mu\alpha\delta)]\theta \quad (28)$$

while the forecast error on aggregate output is

$$E[\widehat{Y}|z_j, \theta] - E[E[\widehat{Y}|z_j]|\theta] = (1 - \gamma\mu)\left(\frac{1 - \alpha + \alpha m}{1 - \alpha + \gamma\mu\alpha\delta}\right)\theta \quad (29)$$

If condition 27 holds, then

- $\theta > 0$*: agents underestimate aggregate output and overestimate individual revenues (overoptimism in booms).*
- $\theta < 0$*: agents overestimate aggregate output and underestimate individual revenues (overpessimism in busts).*

The firm's revenue depends positively on the PE effect and negatively on the GE effect. Since agents do not observe aggregates, they rationally confuse an aggregate shock with

[18] To see this, suppose that the negative GE effect from higher aggregate investment were stronger than the positive PE effect from higher local technology, and optimal local investment fell in θ. Aggregate investment would then be inversely proportional to θ, and the GE force would be positive, not negative, for the island, leading to a contradiction.

a local shock and underestimate the negative GE effect. The lack of information leads to extrapolative-like beliefs, as agents are systematically overoptimistic after positive aggregate shocks and overpessimistic after negative shocks. Differently from behavioral models, where extrapolation results from overreaction to positive news (Bordalo et al., 2018b, 2019), here it is due to rational underreaction to the endogenous negative general equilibrium effect. As a result, booms are associated with both overoptimism about local revenues and underestimation of aggregate quantities, consistent with the evidence in Section 2. Importantly, even if agents are rational and correct on average conditioning on their information set, they are consistently mistaken conditioning on unobserved aggregate states.

Figure 3 illustrates this mechanism. The dotted line represents the prior belief about the firm's revenue before receiving any information. A positive aggregate technology shock increases the firm's fundamentals and implies on average a good signal z_j that shifts the posterior beliefs on revenue to the blue solid line (positive PE effect). However, because of the endogenous increase in the supply of intermediate goods, the price of good j will be lower and the actual posterior revenue of an informed agent would shift back to the middle dashed line (negative GE effect). However, if agents do not observe aggregates, they underestimate this last shift and consequently the left tail risk, shown in the figure as the shaded area between their posterior and the actual posterior distribution of revenues.[19]

Corollary 5 (Actual default rate in DI) *If $\Omega_j = \{z_j\}$, the equilibrium default rate is proportional to*

$$\hat{p}(def|\theta) \propto [(m - \gamma\mu\delta)(1 - \alpha + \gamma\mu\alpha) - (1 - \gamma\mu)(1 - \alpha + \gamma\mu\alpha\delta)]\theta \tag{30}$$

where $\hat{p}(def|\theta) = \int^j \hat{p}(def_j|z_j, \theta)dj$. If condition (27) holds, default rate increases in aggregate shock θ

See Online Appendix B for the proof.

As dispersed information amplifies booms, the higher supply of intermediate goods further lowers prices and firms' revenues. Market participants confuse aggregate shocks

[19] Notice that more information also means lower posterior uncertainty. Thus, the difference between informed and non-informed posteriors is not only a lower posterior mean but also a lower posterior variance.

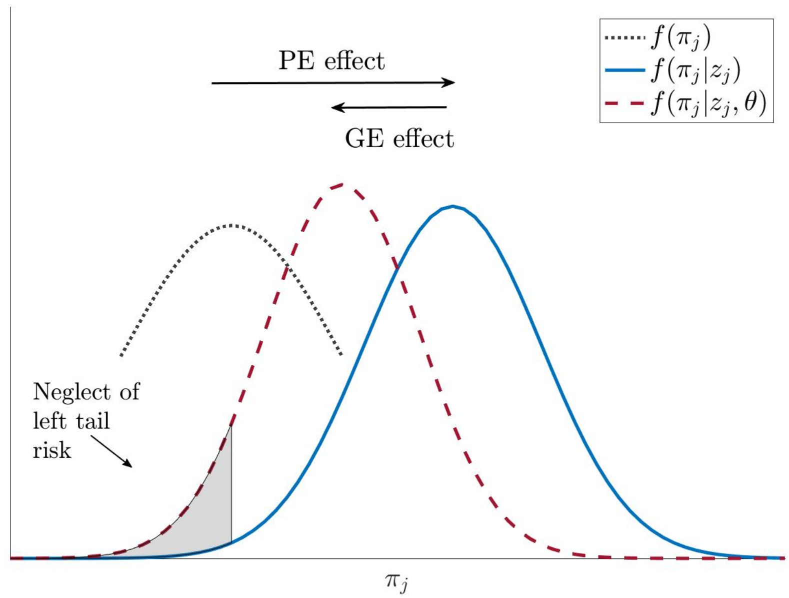

Figure 3: Rationally extrapolative beliefs in booms

Notes: The figure illustrates the posterior belief on firm's operating profits after a positive aggregate shock under three different information sets. The black dotted line represents the posterior of an agent not observing any new information. The blue solid line represents the posterior of an agent obsereving only local signal z_j. The red dashed line represents the posterior of an agent observing both local signal z_j and aggregate shock θ. Not observing aggregate shock θ leads to overestimating equilibrium price p_j and therefore individual revenues π_j.

with local shocks and increase debt too much relative to their future revenues, leading to a higher default rate. As a result, credit booms are times when default risk is greater. This is consistent with the existing evidence that low risk premia and high credit growth predict higher financial fragility (Krishnamurthy and Muir, 2017).

Corollary 6 (Bank's profit in DI) *If $\Omega_j = \{z_j\}$, the equilibrium average bank profits are proportional to*

$$E[\tilde{\pi}_{bank}|z_j,\theta] \propto [(m-\gamma\mu\delta)(1-\alpha+\gamma\mu\alpha)-(1-\gamma\mu)(1-\alpha+\gamma\mu\alpha\delta)]\theta \tag{31}$$

If condition 27 holds, average bank profits are negative after a credit boom.

Since the risk premium in equilibrium is such that, on average, banks earn a zero expected profit, when banks underestimate default risk they misprice loans and earn negative profits. This result is consistent with the evidence that credit booms generate negative returns for bank stocks documented by Baron and Xiong (2017).

Information choice In the first stage, firms and banks on each island decide whether to observe aggregates based on their expected profits in the final stage. In general, a share $\lambda \in [0,1]$ of the islands chooses to acquire the information. While Figure 3 illustrates individual beliefs for a given aggregate output M, this quantity is endogenous to the aggregate amount of information in the economy. If all agents in each island are informed, $\lambda = 1$, Proposition 3 states that the increase in aggregate supply during boom is smaller, and therefore the decrease in price as well. In Figure 3, this would imply a shorter distance between informed and uninformed posteriors, since the neglected GE effect is smaller. On the other hand, if agents on each island are uninformed, $\lambda = 0$, the credit boom is amplified, and the price decline is larger. In Figure 3, this would imply a larger gap between informed and uninformed posteriors, as the neglected GE effect is higher. Therefore, the benefit of information for the individual island depends negatively on the average level of information in the economy. In particular, there is strategic substitutability in information choice, since a higher aggregate information implies lower individual benefit of information. In Section 5, I illustrate numerically how risk taking incentives also affect benefit of information and equilibrium λ.

4.2 Numerical illustrations

I provide a numerical illustration of the nonlinear model. The contribution of examining numerical solutions of the model is twofold. First, I relax some parametric assumptions that are necessary to keep the analytical model tractable. Second, nonlinear global solutions are better suited than approximations around the steady state to examine the nature of large and rare credit booms such as those considered in this paper.

Calibration Table 1 reports the model's calibration. First, I set $\xi = 0.833$ to match a markup of 20%, which is inside the set of values estimated in the macro literature (for a review, see Basu (2019)). Together with a capital share $\tilde{\alpha} = 0.33$, it implies $\alpha = \frac{\tilde{\alpha}\xi}{1-(1-\tilde{\alpha})\xi} = 0.624$. The return to scale of final good producer ν can be expressed similarly as a function of the final good sector markup and the intermediate good share in production. Assuming the latter equal 0.5 (approximately the average value for the US economy over a long period of time) and a markup of 50% gives $\nu = 0.5$. The larger markup in the retail and wholesale sectors with respect to other sectors is in line with the evidence in De Loecker et al. (2020). However, the condition $\nu < \xi$ would be satisfied by any final good sector markup larger than 13%.[20]

Since TFP in my model is i.i.d., I set the aggregate volatility equal to the unconditional volatility implied by a standard autoregressive process with quarterly shock volatility 0.02 and autoregressive coefficient 0.995, which gives $\sigma_\theta = 0.2$. I set the idiosyncratic TFP volatility $\sigma_e = 3\sigma_\theta$, where the ratio 3 is somewhere between the macro structural estimates (e.g. ≈ 15, Maćkowiak and Wiederholt (2015)) and the micro empirical estimates (e.g. ≈ 1.1, Castro et al. (2015)). Moreover, I set the private noise $\sigma_\eta = \sigma_a$, where σ_a is the total volatility of TFP. Because the model aims to capture low frequency credit boom&busts as in the macro-finance empirical literature, I set the risk free rate to the 5-year implied return from a one-year T-bill of 2%, which gives $r^f = 0.1$. The corporate tax rate is set to 20% (CBO, 2017).

In this section, I abstract from limited liability and set $\psi = 0$. In section 5, I do comparative statics on this parameter to study how risk taking incentives affect lending and information choice. Finally, I calibrate the cost of information c such that with no limited liability it is optimal for all islands to collect information ($\lambda = 1$), which corresponds to around 3% of firm's dividends in the full information economy.

Full information $\lambda = 1$ Consider the full information, in which all islands decide to observe the aggregate shock θ in the first stage. The blue dashed lines in Figure 4 show the response of aggregate credit $B = \int^j b_j dj$ (proportional to aggregate investment), average risk premium $R - r^f$, default rate, and average bank profits in this economy as functions of the standard deviations of aggregate shock θ. The figure confirms the analytical results in Section 4.1, as higher aggregate shock θ leads to a credit boom. Differently from the linear model in Section 4.1, I allow for nonzero investment adjustment costs. As a result,

[20] Assume the final good sector face a demand given by $P = Y^{\tilde{\xi}-1}$ and have a production function $Y = M^{\tilde{\nu}} X^{1-\tilde{\nu}}$, where X is some other variable input. After maximizing X out, the profit function would be proportional to $\pi \propto M^{\frac{\tilde{\nu}\tilde{\xi}}{1-(1-\tilde{\nu})\tilde{\xi}}} \equiv M^{\nu}$. Given an intermediate share of $\tilde{\nu} = 0.5$ and $\xi = 0.833$, the condition $\nu < \xi$ implies a final good sector markup $\frac{1}{\tilde{\xi}} > 1.13$.

Table 1: Calibration

Parameter	Interpretation	Value
α	Return to scale intermediate good sector	0.624
ν	Return to scale final good sector	0.5
r^f	Risk free rate	0.1
ϕ	Investment adj cost coefficient	1
σ_θ	Volatility aggregate shock	0.2
σ_e	Volatility local shock	0.6
σ_η	Volatility signal noise	0.64
ψ	Limited liability	0
c_d	Default cost	0.5
τ	Corporate tax	0.20
c	Information cost	0.0017

the probability of default is not constant but falls after the boom, and since agents know that the risk of default risk is lower, the risk premium also falls. Risk is priced correctly and banks make zero average profits conditional on the aggregate state. The implications of the model are qualitatively similar to a benchmark model that abstracts from strategic interactions between firms, as the price externality only dampens the boom.

The model is not consistent with the existing evidence. First, Schularick and Taylor (2012) show that booms are times when financial risk accumulates, which in my model would imply a higher default rate after a credit boom. Second, Krishnamurthy and Muir (2017) document that low risk premia predict financial crises, but in the full information model, because risk is correctly priced conditioning on aggregates, risk premia are positively correlated with default risk. Finally, Baron and Xiong (2017) document that average excess return on bank stocks after large booms is negative, while informed banks in the model would not accept to make average negative returns.[21]

[21] While it would be possible to set up a model in which firms had higher risk tolerance and were willing to take on more risk during credit booms, the pricing equation 13 implies that the risk premium would rise as a result, which is inconsistent with the evidence in Krishnamurthy and Muir (2017). If banks had higher risk tolerance in booms as well, risk premia could be lower in times of high risk (e.g. Krishnamurthy and Li 2021), but it would still not be possible for rational bankers to accept negative excess returns on average, as documented in Baron and Xiong (2017).

Dispersed information $\lambda = 0$ Consider the dispersed information case, where no island decides to observe the aggregate shock θ in the first stage. The red solid lines in Figure 4 show the response of aggregate credit $B = \int^j b_j dj$, average risk premium $R - r^f$, default rate, and average bank profits in this economy as functions of the standard deviations of aggregate shock θ. The figure confirms the analytical results from section 4.1. As agents underestimate the magnitude of the negative GE effect, the credit boom is amplified, as shown by the solid red line in the upper left panel. The excess supply of intermediate goods lowers intermediate goods prices and revenues, but firms do not observe aggregates and take on too much debt. Default risk peaks after a credit boom, consistent with the evidence on credit boom-and-busts (Schularick and Taylor, 2012). Banks are also inattentive to aggregates and confuse the aggregate shock with a local shock. As a result, the risk premium on loans is lower in credit booms when default risk is larger. The model is consistent with existing evidence that high credit and low risk premia predict subsequent financial downturns (Krishnamurthy and Muir, 2017).

The decline in risk premia is not due to a change in risk tolerance, but to an underestimation of the endogenous increase in default risk. Figure 5 illustrates this point by plotting actual bank profit (solid red) and mean expected bank profit (dotted blue) in the left panel, and actual average default rate (solid red) and mean expected default rate (dotted blue) in the right panel. Banks do not internalize the increase in default risk and expect a zero average excess return. However, because of the increase in default risk, excess returns are negative on average after a credit boom. Assuming that the bank stock price is correlated with its operating profit, the results are consistent with the evidence of average negative returns on bank stocks during booms in Baron and Xiong (2017).

5 Information choice with limited liability

The previous section demonstrates how overoptimism during credit booms can be caused by information frictions. In this section, I explore the determinants of these information frictions. Specifically, I show that limited liability leads agents to pay less attention to aggregate risk factors, even for a low information cost. As a result, they become overoptimistic in booms and overpessimistic in busts. In order to do that, I allow for limited

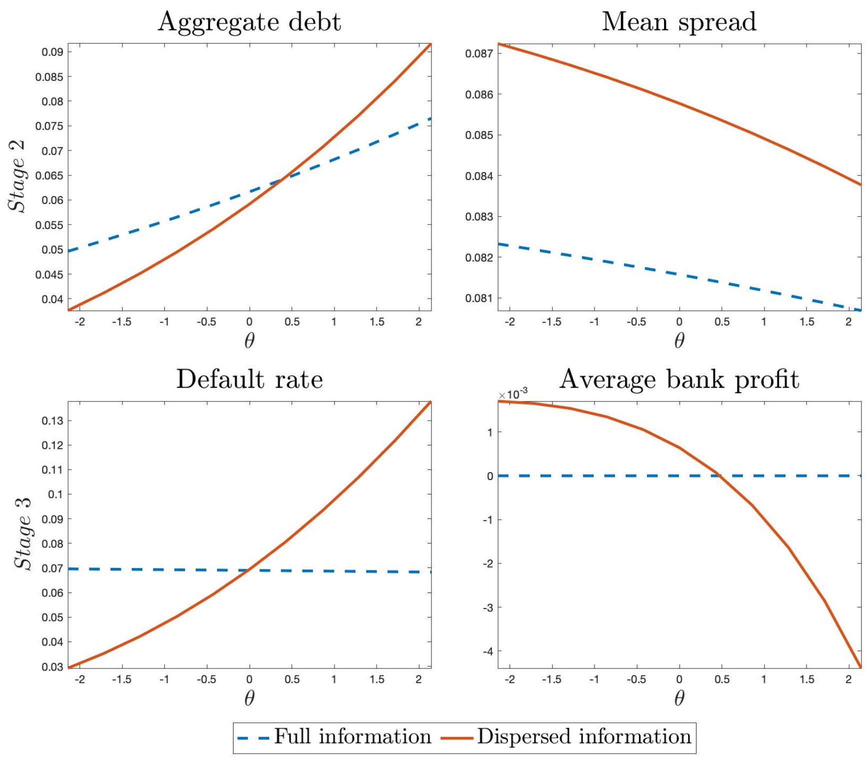

Figure 4

Notes: The figure illustrates the equilibrium of stage-2 investment and borrowing choice in the full information ($\theta \in \Omega_j$) and dispersed information economy ($\theta \notin \Omega_j$). The aggregate shock θ in the x-axis is expressed in standard deviations.

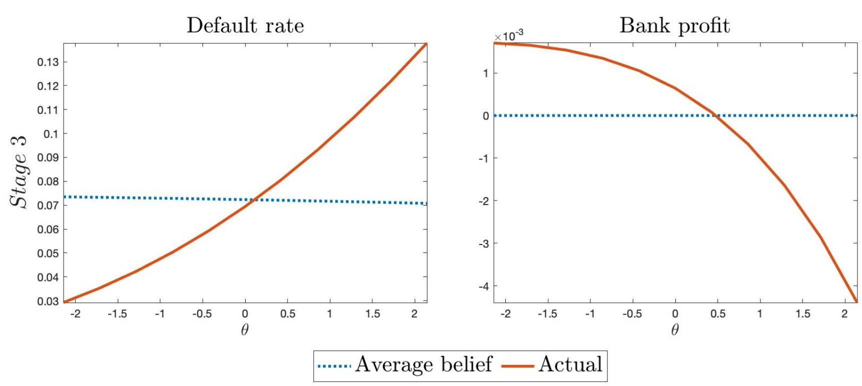

Figure 5

Notes: The figure illustrates the actual and the average expectation of bank excess return and default rate in the dispersed information economy ($\theta \notin \Omega_j$). The aggregate shock θ in the x-axis is expressed in standard deviations.

liability in payoffs $\psi > 0$ and study its implications on stage 2 and stage 1 equilibrium allocations.

Stage 2: Risk taking in lending An increase in limited liability has a standard risk-taking effect on stage-2 borrowing and lending decisions. First, consider firms' decision. As described in equation 14, there is a trade-off between the expected profits in the absence of default and the probability of default when determining the amount of debt to issue b_j. Higher payoff convexity ψ lowers firms' losses in case of default, encouraging them to take on more risk. Second, consider banks' decision. As described in equation 13, a higher payoff convexity ψ implies lower losses in the event of default, and therefore lower elasticity of credit spread with respect to default risk. This is the typical effect of risk-taking incentives for a given information structure, i.e. "informed" risk taking.

To isolate the effect of limited liability on borrowing decisions, I first shut down the information choice in stage 1. Figure 6 shows the equilibrium debt, average spread, default rate, and bank's profits in the full information economy for various level of limited liability ψ. A higher payoff convexity leads to more risk-taking and a lower price of risk, resulting in a higher unconditional default rate. However, similar to the full information model in the previous section, in the baseline calibration, credit booms are periods where the economy is safer and the default rate decreases, which does not align with empirical evidence (Schularick and Taylor, 2012; Krishnamurthy and Muir, 2017). Therefore, the full information model with only moral hazard incentives in stage-2 borrowing decisions is not able to reproduce the qualitative patterns of credit cycles seen in the data.

Stage 1: Risk taking in information In the first stage, banks and firms in each island decide whether to pay the cost of observing aggregate shocks in the second stage. Both agents benefit from information, as not observing aggregate shocks leads to higher default risk and losses. I set the attention cost such that, with no limited liability $\psi = 0$, it is optimal for all islands to pay the cost and be fully informed in next stage, $\lambda = 1$. Figure 7 shows that the equilibrium share of informed island λ decreases in limited liability ψ.[22] Intuitively, the higher is payoff convexity, the lower is exposure to losses and therefore the

[22] This result relies on the simultaneous increase in both firm and bank limited liability. Consider an increase in only firm limited liability. Firms with higher payoff convexity take on more risk and collect less information for a given credit spreads. However, lower information also leads to higher uncertainty and therefore higher average credit spreads charged by banks. Depending on the calibration, firms may still prefer to collect more information to lower the price of risk. On the other hand, if banks' payoff convexity also increases, the price of risk decreases, and the island as a whole is better off with less information.

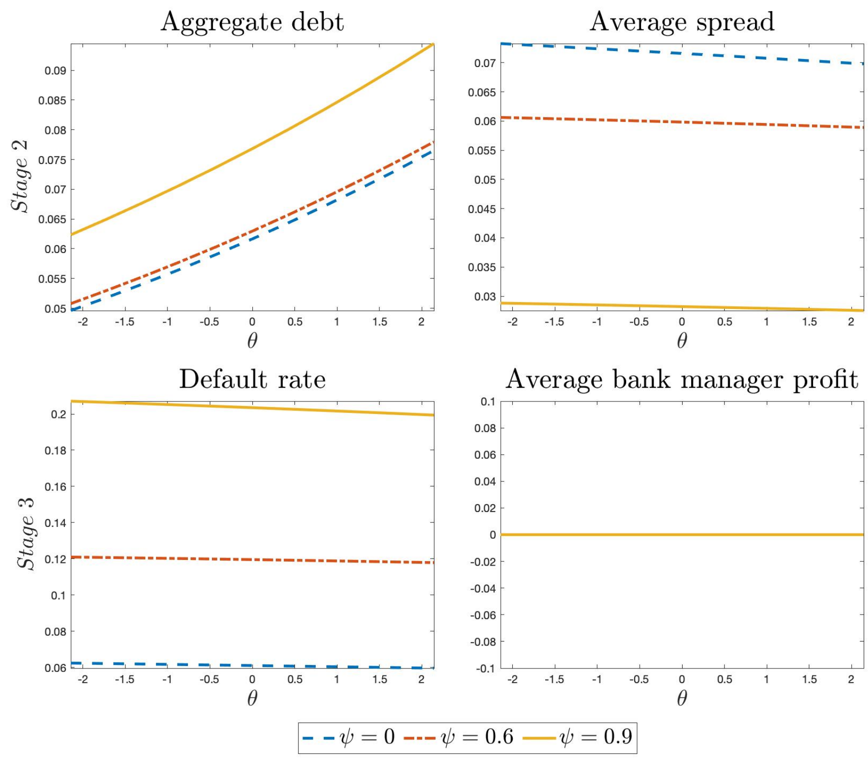

Figure 6: Full information and limited liability

Notes: The figure illustrates the stage-2 investment and borrowing choice in full information economy ($\theta \in \Omega_j$) for different values of limited liability parameter ψ. The aggregate shock θ in the x-axis is expressed in standard deviations.

lower is marginal benefit of information. [23]

Figure 8 shows the equilibrium debt, average spread, default rate, and bank profit for different values of limited liability ψ, which in turn lead to different levels of attention λ. As limited liability increases, optimal attention choice decreases, resulting in higher default rate and lower bank profit during booms, as discussed in the previous section. As a result, credit booms are period of higher default risk but lower risk premia, which is consistent with the empirical evidence on credit cycles. Comparing Figure 6 with Figure 8 we can see that risk taking in information choice can explain the patterns of credit cycles observed in the data, while "informed" risk-taking in investment decision alone can not.

[23] The intuition behind this result is similar to the findings of Mackowiak and Wiederholt (2012), who show that limited liability reduces optimal information choice in a general setting. Lindbeck and Weibull (2017) also study optimal contracts between principals and managers in rational inattention setting.

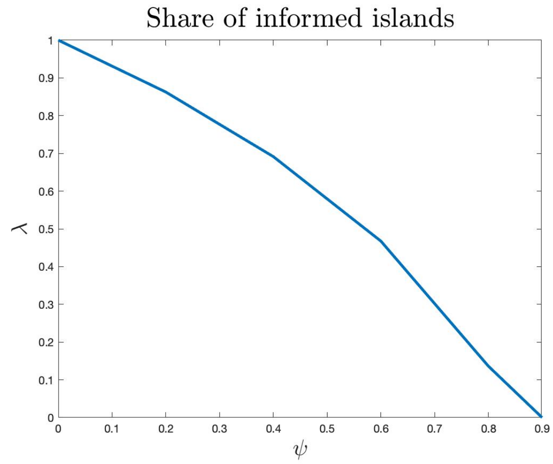

Figure 7: Limited liability and information choice

Notes: The figure illustrates the result of stage-1 information choice under different calibration for payoff convexity ψ. It shows that higher payoff convexity is associated with lower information choice.

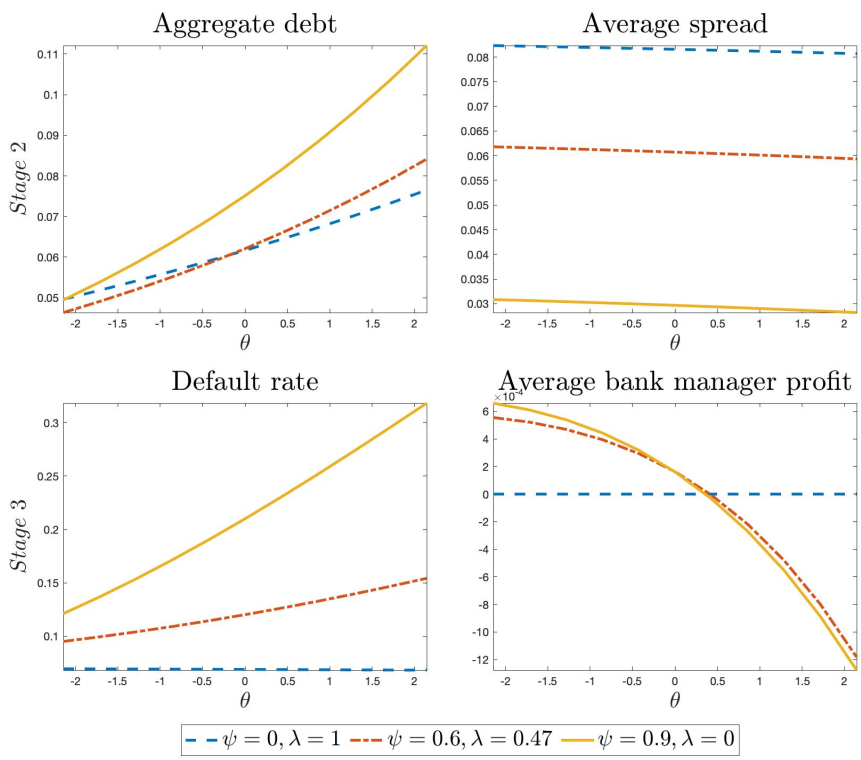

Figure 8: Information Choice and limited liability

Notes: The figure illustrates the equilibrium of the model (both stage 1 and stage 2) for different values of the limited liability parameter ψ. The aggregate shock θ in the x-axis is expressed in standard deviations.

6 Infinite-period extension

I extend the model to an infinite-period setting to compare its predictions to the existing evidence on credit cycles. First, I review the existing evidence on the paths of spreads and credit before financial crises, and then I compare the performance of my model to the data. While a full quantitative estimation of the model is beyond the scope of this paper, I demonstrate that the model with a standard calibration is able to generate realistic boom-and-busts dynamics.

I focus on financial crises, defined by the literature "as events during which a country's banking sector experiences bank runs, sharp increases in default rates accompanied by large losses of capital that result in public intervention, bankruptcy, or forced merger of financial institutions" (Jordà et al., 2013). I compare my model to two sets of evidence from Krishnamurthy and Li (2021): first, the pre-crisis path of spreads and credit; second, the predictive power of spreads and credit growth in forecasting financial crises.

Pre-crisis period Conditioning on a crisis at time t, consider the path of spreads and credit in the 5-years preceding the crisis. First, credit spreads are 0.34σs below their country mean, where the mean is defined to exclude the crisis and the 5 years after the crisis. Second, credit/GDP is 5% above the country mean.

Predicting crises The most important evidence for the scope of this paper is the ability of spreads and credit growth to predict crises. First, Krishnamurthy and Muir (2017) find that conditioning on an episode where credit spreads are below their median value 5 years in a row, the probability of a financial crisis increase by 1.76%. Second, Schularick and Taylor (2012) shows that a one standard deviation increase in credit growth over the preceding 5 years implies an increased in probability of a crisis of 2.8% over the next year.

Model I consider an overlapping generation of bank and firm managers living for two periods. In each period a new generation of managers is born and decide information (stage 1) and lending and borrowing (stage 2). In the following period, the shocks described in equation 6 realize, production take place and firms either repay or default (stage 3). In this period, the old generation of managers receive their payoffs and die, while a new

Table 2: Model and Data Moments

	Data	Model	
		$\psi = 0$	$\psi = .8$
Pre-crisis period (5 years)			
Credit spreads (σ below mean)	0.34	0.00	0.06
Credit/GDP (% above mean)	5	0	7
Predicting crises (5 years)			
Credit spreads (% increase in probability)	1.76	0.00	2.02
Credit/GDP (% increase in probability)	2.8	0.00	4.8

generation is born and the cycle repeats.

I assume that in case of default, firms can not re-enter the economy immediately as it takes one period for the firm to re-build its productive capacity. This simple constraint can be interpreted as time needed for new firms to secure funding to cover fixed costs of production or to set up the production process. Define the number of defaulted firms $N_{def,t}$ as the default rate times the number of firms in the economy N_t. Then the number of firms operating in period t is given by $N_t = N_{t-1} - N_{def,t} + N_{def,t-1}$. As illustrated in the previous section, in presence of limited liability credit booms are followed by a higher default rate, which implies a lower number of productive firms in the economy active in the following period. As a result, booms are followed by a burst, which is consistent with existing evidence.[24]

In order to relate to the existing evidence on credit cycles, I calibrate one period in the model to represent a 5-years time span in the data. I follow Krishnamurthy and Li (2021) and target an annual unconditional frequency of financial crisis of 4%, which is the average value of the different estimates in the literature. I define as financial crisis an event in which the output drops below the 20% percentile. I solve for the model equilibrium stage-1 information and stage-2 aggregate quantities and prices for each node

[24] While in the framework considered here booms translates into busts through a credit demand channel, one could think of an alternative setting where the mechanism works instead through a credit supply channel. As showed in the previous section, banks balance sheets are also impaired after booms as they suffer losses on their loans.

in 15x9 grid of aggregate shock θ_t and number of firms N_t, then I simulate 100,000 periods by drawing from the distribution of θ and interpolating from the grid. I simulate the theoretical moments for both the baseline model without payoff convexity $\psi = 0$ and with payoff convexity $\psi > 0$.

Table 2 compares the empirical moments to those generated by the model in two different calibrations. First, the baseline model without limited liability is unable to produce systematic movement in spreads or credit before crises or to predict financial crisis with movements in spreads or credit. In this model, crises occur only when the economy is hit by negative technological shocks, without any boom-and-bust dynamics. In contrast, the model with limited liability is qualitatively consistent with the evidence. Specifically, crises are systematically preceded by credit booms characterized by increase in credit and a decline in spreads. Similarly, increases in credit and declines in spreads have predictive power for the probability of future crises. Inattentive managers neglect default risk and over-invest, leading to an overheated economy that will eventually experience a recession in the following period.

7 Discussion

My model suggests that inattentive agents over-accumulate debt and investment during booms, which increases default risk and economic fragility. While this results is similar to a large strand of the macroeconomic literature on financial frictions, differently from it information here plays a central role and points towards novel macro-prudential policy implications.

A large class of models in the macro-financial literature rationalizes the over-accumulation of debt during booms as a result of strategic complementarity in leverage choices with full information: it is individually optimal to increase leverage when other agents do it, as individuals do not internalize the impact of their decision on the aggregate economy (Gertler and Kiyotaki, 2010; He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014; He and Krishnamurthy, 2019; Bianchi and Mendoza, 2020). However, it is socially suboptimal, as it leads to high levels of leverage and financial fragility. In this framework, a Pigouvian tax on investment corrects this externality by mitigating the increase in leverage

(Jeanne and Korinek, 2019).

In my model, the socially suboptimal high borrowing and investment during booms results from the combination of strategic substitutability and imperfect information. If firms and banks were fully informed about the increase in aggregate investment, they would decrease their own lending and investment, making the economy safer. However, because they are not informed, they contribute to aggregate financial fragility by increasing their own lending and investment. Providing information would then mitigate the overoptimism and therefore the boom-and-busts cycles.

The model suggests two alternative policies to mitigate the credit boom-and-bust. First, an increase in public information about accumulation of risk. Second, a change in individual incentives to privately collect information.

Public communication The procyclical aggregate fragility in the model stems from a lack of coordination due to information dispersion. Policy makers can attenuate this problem by providing free public information about the accumulation of risk. A recent and growing literature studies central banks' financial stability communication and their impact on financial stability (Born et al., 2014; Harris et al., 2019; Londono et al., 2021). While the literature on financial stability communication is still developing, this paper highlights how information about the aggregate economic fragility can attenuates credit boom-and-busts. However, even if the central bank can provide free public information, agents might still have to pay a cognitive cost to process this information, as suggested by the rational inattention literature (Sims, 2003; Mackowiak et al., 2018).

Risk taking incentives My model highlights how risk taking incentives discourage agents from correctly assess risk, leading to procyclical overoptimistic beliefs. Policy makers can then encourage information collection by altering agents' incentives, and in particular lowering risk-taking incentives. An example is the regulation of managers' compensation structure, e.g. limiting stock options compensation. An example of this policy is the Tax Cuts and Jobs Act (TCJA), that in 2017 reduced the scope of tax deductability for performance-based compensation as stock options (Durrant et al., 2020). On the empirical side, Cole et al. (2014) provides experimental evidence on the impact of compensation incentives, and in particular limited liability, on loan officers' effort to asses risk of borrower of a commercial bank.

8 Conclusions

I have presented a theoretical framework in which overoptimism during credit booms originates from risk taking incentives in information choice. While existing models attribute overoptimism to behavioral extrapolation of good news, I propose a rational framework in which overoptimism results from inattention to negative news. Specifically, large credit booms are associated with an increase in aggregate supply and decrease in selling prices, and therefore inattention to aggregates leads to an overestimation of own revenues. As a result, agents over-borrow and over-invest, further overheating the economy. Periods of low risk premia predict higher default rate and systematic bank losses, consistent with empirical evidence. Additionally, I show that such information frictionss can result from limited liability in payoffs, as convex payoff structures discourage managers from collecting information. Because beliefs depend on incentives, my model suggests that compensation regulation has important role in terms of macro-prudential policy.

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Rational Overoptimism and Limited Liability: Online Appendix

Appendix A Stage-2 equilibrium

The stage-2 equilibrium can be equivalently expressed in terms of firm's issuance of bond $\tilde{b}_j$ and bond price q_j instead of loan rate r_j and loan quantity b_j, where $q_j = \frac{1}{1+r_j}$, and $\tilde{b}_j = \frac{b_j}{q_j}$.

Information Agents observe the signal $z = \epsilon_j + \theta + \eta_j$, with $\epsilon_j \sim N(0, \sigma_\epsilon^2)$ and $\eta_j \sim N(0, \sigma_\eta^2)$, and may observe $\theta \sim N(0, \sigma_\theta^2)$. Therefore information set of agent j is $\Omega_j = \{z_j, \theta\}$ or $\Omega_j = \{z_j\}$ depending on their choice in the first stage.

Define $\tilde{z} = z - \theta$. Posteriors are $e|\tilde{z} \sim N(E[e|\tilde{z}], Var[e|\tilde{z}])$ with $E[e|\tilde{z}] = \tilde{m}\tilde{z}$ with $\tilde{m} = \frac{\sigma_e^2}{\sigma_e^2+\sigma_\eta^2}$ and $Var[e|\tilde{z}] = \frac{\sigma_e^2\sigma_\eta^2}{\sigma_e^2+\sigma_\eta^2}$, and $\theta|z \sim N(E[\theta|z], Var[\theta|z])$ with $E[\theta|z] = \delta z$ with $\delta = \frac{\sigma_\theta^2}{\sigma_e^2+\sigma_\eta^2+\sigma_\theta^2}$ and $Var[e|\tilde{z}] = \frac{\sigma_\theta^2(\sigma_e^2+\sigma_\eta^2)}{\sigma_e^2+\sigma_\eta^2+\sigma_\theta^2}$.

Bargaining process Define $C(\theta) = ln\left(\frac{k+\frac{1}{2}\phi k^2}{q\Lambda(M)k^\alpha}\right) - \theta$. The expected payoff of firm manager conditioning on stage-2 information set Ω_j is

$$\begin{aligned}
E[w_{firm,j}|\Omega_j] = &- \left[1 - \int_{-\infty}^{\infty}\int_{-\infty}^{C(\theta)} \phi(\epsilon_j|\theta, z_j)d\epsilon_j\phi(\theta|\Omega_j)d\theta\right]\tilde{b}_j \\
&- \left[\int_{-\infty}^{\infty}\int_{-\infty}^{C(\theta)} \phi(\epsilon_j|\theta, z_j)d\epsilon_j\phi(\theta|\Omega_j)d\theta\right]\psi c_d k_j(q_j, \tilde{b}_j) \\
&+ k_j(q_j, \tilde{b}_j)^\alpha \int_{-\infty}^{\infty}\int_{C(\theta)}^{\infty} \Lambda(\theta)e^{\epsilon_j}\phi(\epsilon_j|\theta, z_j)d\epsilon_j e^\theta\phi(\theta|\Omega_j)d\theta
\end{aligned}$$

while the expected payoff of the bank manager conditioning on stage-2 information set Ω_j is

$$\begin{aligned}
E[w_{bank}|\Omega_j] = &b_j\left(\left[1 - \int_{-\infty}^{\infty}\int_{-\infty}^{C(\theta)} \phi(\epsilon_j|\theta, z_j)d\epsilon_j\phi(\theta|\Omega_j)d\theta\right]\right) \\
&- b_j\left(1 - \psi\left[\int_{-\infty}^{\infty}\int_{-\infty}^{C(\theta)} \phi(\epsilon_j|\theta, z_j)d\epsilon_j\phi(\theta|\Omega_j)d\theta\right]\right)\frac{q_j}{q}
\end{aligned} \tag{32}$$

where $\phi(\epsilon_j|\theta, z_j) = \phi\left(\frac{C-E[\epsilon_j|\theta,z_j]}{\sqrt{Var[\epsilon_j|\theta,z_j]}}\right)$ is the posterior distribution of ϵ_j conditioning on θ and z_j, and $\phi(\theta|\Omega_j) = \phi\left(\frac{\theta-E[\theta|\Omega_j]}{\sqrt{Var[\theta|\Omega_j]}}\right)$ is the posterior distribution of θ conditioning on information set Ω_j, which may or not include θ.

Bank and firm manager decide collectively bond issued $\tilde{b}_j$ and price q_j through Nash Bargaining

$$max_{q_j,\tilde{b}_j}\ (E[w_{firm,j}|\Omega_j])^{\beta}(E[w_{bank,j}|\Omega_j])^{1-\beta} \tag{33}$$

Since I assume $\beta \to 1$, the problem becomes becomes

$$\begin{aligned} &max_{q_j,b_j}\ E[w_{firm,j}|\Omega_j] \\ &s.t. \quad E[w_{bank,j}|\Omega_j] \geq 0 \end{aligned} \tag{34}$$

Note that maximizing in terms of k_j is equivalent to maximizing in terms of $\tilde{b}_j$. The resulting first order conditions are given by

$$\begin{aligned} &E[w_{bank,j}|\Omega_j] = 0 \\ &\frac{\frac{\partial E[w_{firm,j}|\Omega_j]}{\partial \tilde{b}_j}}{\frac{\partial E[w_{bank,j}|\Omega_j]}{\partial \tilde{b}_j}} = \frac{\frac{\partial E[w_{firm,j}|\Omega_j]}{\partial q_j}}{\frac{\partial E[w_{bank,j}|\Omega_j]}{\partial q_j}} \end{aligned} \tag{35}$$

where each term is defined as follow. Define $pdef_j = \left[\int_{-\infty}^{\infty}\int_{-\infty}^{C(\theta)} \phi(\epsilon_j|\theta, z_j)d\epsilon_j\phi(\theta|\Omega_j)d\theta\right]$. Then,

$$\begin{aligned} \frac{\partial E[w_{firm,j}|\Omega_j]}{\partial \tilde{b}_j} = &-[1-pdef_j] - [pdef_j]\,\psi c_d \frac{\partial k_j}{\partial \tilde{b}_j} - \left[\int_{-\infty}^{\infty} \phi(C|\theta, z_j)\frac{\partial C}{\partial \tilde{b}_j} d\epsilon_j \phi(\theta|\Omega_j)d\theta\right]\psi c_d k_j \\ &+ \alpha k_j^{\alpha-1}\frac{\partial k_j}{\partial \tilde{b}_j}\int_{-\infty}^{\infty}\int_{C(\theta)}^{\infty} \Lambda(\theta)e^{\epsilon_j}\phi(\epsilon_j|\theta, z_j)d\epsilon_j e^{\theta}\phi(\theta|\Omega_j)d\theta \end{aligned} \tag{36}$$

where $\frac{\partial k_j}{\partial \tilde{b}_j} = \frac{q_j}{\sqrt{1+2\phi\tilde{b}_j q_j}}$, and $\frac{\partial C}{\partial \tilde{b}_j} = \frac{1}{\tilde{b}_j} - \alpha\frac{1}{k_j}\frac{\partial k_j}{\partial \tilde{b}_j}$.

$$\frac{\partial E[w_{firm,j}|\Omega_j]}{\partial \tilde{q}_j} = -\left[pdef_j\right]\psi c_d \frac{\partial k_j}{\partial q_j} - \left[\int_{-\infty}^{\infty}\phi(C|\theta,z_j)\frac{\partial C}{\partial q_j}d\epsilon_j \phi(\theta|\Omega_j)d\theta\right]\psi c_d k_j + \alpha k_j^{\alpha-1}\frac{\partial k_j}{\partial q_j}\int_{-\infty}^{\infty}\int_{C(\theta)}^{\infty}\Lambda(\theta)e^{\epsilon_j}\phi(\epsilon_j|\theta,z_j)d\epsilon_j e^{\theta}\phi(\theta|\Omega_j)d\theta \tag{37}$$

where $\frac{\partial k_j}{\partial q_j} = \frac{\tilde{b}_j}{\sqrt{1+2\phi\tilde{b}_j q_j}}$, and $\frac{\partial C}{\partial q_j} = -\alpha\frac{1}{k_j}\frac{\partial k_j}{\partial q_j}$.

$$\frac{\partial E[w_{bank,j}|\Omega_j]}{\partial \tilde{b}_j} = \left[(1-pdef_j) - (1-\psi pdef_j)\frac{q_j}{q^f}\right] + \tilde{b}_j\left[-\frac{\partial pdef_j}{\partial \tilde{b}_j} + \psi\frac{q_j}{q^f}\frac{\partial pdef_j}{\partial \tilde{b}_j}\right] \tag{38}$$

where

$$\frac{\partial pdef_j}{\partial \tilde{b}_j} = \left[\int_{-\infty}^{\infty}\phi(C|\theta,z_j)\frac{\partial C}{\partial \tilde{b}_j}d\epsilon_j\phi(\theta|\Omega_j)d\theta\right] \tag{39}$$

Finally,

$$\frac{\partial E[w_{bank,j}|\Omega_j]}{\partial q_j} = +\tilde{b}_j\left[-\frac{\partial pdef_j}{\partial q_j} + \psi\frac{q_j}{q^f}\frac{\partial pdef_j}{\partial q_j} - (1-\psi pdef_j)\frac{1}{q^f}\right] \tag{40}$$

where

$$\frac{\partial pdef_j}{\partial q_j} = \left[\int_{-\infty}^{\infty}\phi(C|\theta,z_j)\frac{\partial C}{\partial q_j}d\epsilon_j\phi(\theta|\Omega_j)d\theta\right] \tag{41}$$

Appendix B Proofs

Proposition 1. Assume no limited liability and no investment adjustment cost $c_d = \psi = \phi = 0$. To simplify the exposition, I drop the subscript j. Use the definition of $q = \frac{1}{1+r}$ and $q\tilde{b} = k$. As a result, $C = \left(\frac{k^{1-\alpha}}{q\Lambda(\theta)}\right) - \theta$.

Foc 1 Consider the first first order condition in 35.

$$q = q^f\left[1 - \int_{-\infty}^{\infty}\Phi_e(C(\theta)|z,\theta)\phi_\theta(\theta|\Omega)d\theta\right] \tag{42}$$

In steady state

$$q^* = q^f \left[1 - \Phi\left(\frac{C^*}{\sqrt{Var[\epsilon|\theta,z]}}\right)\right] \tag{43}$$

where x^* is the steady state value of variable x. Differentiating

$$dq = -\, q^f \Phi\left(\frac{C^*}{\sqrt{Var[\epsilon|\theta,z]}}\right) \int_{-\infty}^{\infty} [dC - dE[e|z,\theta]]\, \phi_\theta\,(\theta|z)\, d\theta \tag{44}$$

where $dC = (1-\alpha)]\hat{k} - \hat{q} - (\eta_{\Lambda(M),\theta} - 1)d\theta$, where $\eta_{\Lambda(M),\theta} \equiv -\frac{1}{\Lambda(M)}\Lambda'(M)M'(\theta)$, and $dE[\epsilon|z,\theta] = \frac{\partial E[\epsilon|\tilde{z}]}{\partial\theta}d\theta + \frac{\partial E[\epsilon|\tilde{z}]}{\partial z}dz$. Therefore

$$dq = -q^f \Phi\left(\frac{C^*}{\sqrt{Var[\epsilon|\theta,z]}}\right) \int_{-\infty}^{\infty} \left[(1-\alpha)]\hat{k} - \hat{q} - \eta_{\Lambda(M),\theta}d\theta - \frac{\partial E[\epsilon|\tilde{z}]}{\partial\theta}d\theta - \frac{\partial E[\epsilon|\tilde{z}]}{\partial z}dz\theta\right] \phi_\theta\,(\theta|z)\, d\theta \tag{45}$$

Denote $a \equiv ln(A)$ and notice that

$$\begin{aligned} E[a|z,\theta] &= \tilde{m}(z-\theta) + \theta \\ &= \frac{\partial E[\epsilon|\tilde{z}]}{\partial z}z + \frac{\partial E[\epsilon|\tilde{z}]}{\partial\theta}\theta + \theta \end{aligned}$$

Moreover, $\hat{M} \equiv \frac{dM}{M} = \frac{M'(\theta)d\theta}{M}$ and therefore

$$\begin{aligned} \eta_{\Lambda(M),\theta}d\theta = &- \frac{M}{\Lambda(M)}\Lambda'(M)\frac{M'(\theta)d\theta}{M} \\ =&\eta_{\Lambda,M}\hat{M} \end{aligned} \tag{46}$$

where $\eta_{\Lambda,M} \equiv \frac{\nu-\xi}{1-(1-\alpha)\xi}$. Substitute back and divided by steady state value

$$\hat{q} = \tilde{L}_1 \left\{-\,(1-\alpha)\,\hat{k} + E[a|z] + \eta_{\Lambda,M}E[\hat{M}|z]\right\} \tag{47}$$

where $\tilde{L}_1 = \frac{\phi\left(\frac{C^*}{\sqrt{Var[\epsilon|\theta,z]}}\right)}{\left[1-\Phi\left(\frac{C^*}{\sqrt{Var[\epsilon|\theta,z]}}\right)-\phi\left(\frac{C^*}{\sqrt{Var[\epsilon|\theta,z]}}\right)\right]}$.

Foc 2 Differentiate the second first order condition in 35

$$\frac{d\frac{\partial E[w_{firm,j}|\Omega_j]}{\partial \tilde{b}_j}}{\frac{\partial E[w_{firm,j}|\Omega_j]}{\partial \tilde{b}_j}} - \frac{d\frac{\partial E[w_{bank,j}|\Omega_j]}{\partial \tilde{b}_j}}{\frac{\partial E[w_{bank,j}|\Omega_j]}{\partial \tilde{b}_j}} = \frac{d\frac{\partial E[w_{firm,j}|\Omega_j]}{\partial q_j}}{\frac{\partial E[w_{firm,j}|\Omega_j]}{\partial q_j}} - \frac{d\frac{\partial E[w_{bank,j}|\Omega_j]}{\partial q_j}}{\frac{\partial E[w_{bank,j}|\Omega_j]}{\partial q_j}} \tag{48}$$

and let's see each term individually.

- From equation 36, the derivative of expected firm manager payoff with respect to bond $\tilde{b}$ is given by

$$\begin{aligned}\frac{\partial E[w_{firm}|\Omega]}{\partial \tilde{b}} = &- \left[1 - \int_{-\infty}^{\infty} \Phi_e(C(\theta)|z,\theta)\phi_\theta(\theta|\Omega)d\theta\right] \\ &+ \alpha k_j^{\alpha-1} q \int_{-\infty}^{\infty} \Lambda(\theta) e^{\frac{Var[\epsilon|\theta,z]}{2}+E[\epsilon|\theta,z]} \Phi_\epsilon \left(\frac{Var[\epsilon|\theta,z]+E[\epsilon|\theta,z]-C(\theta)}{\sqrt{Var[\epsilon|\theta,z]}}\right) e^\theta \phi(\theta|\Omega_j)d\theta\end{aligned}$$

Differentiating,

$$\begin{aligned}d\frac{\partial E[w_{firm}|\Omega]}{\partial \tilde{b}} =& \phi_e\left(\frac{C^*}{\sqrt{Var[\epsilon|\theta,z]}}\right)\left\{\hat{q} - (1-\alpha)\hat{k} + E[a|z] + \eta_{\Lambda,M}E[\hat{M}|z]\right\} \\ &+ \alpha k_j^{\alpha-1} q\Lambda e^{\frac{Var[\epsilon|\theta,z]}{2}} \Phi_\epsilon(\cdot)\left\{\hat{q} - (1-\alpha)\hat{k} + E[a|z] + \eta_{\Lambda,M}E[\hat{M}|z]\right\} \\ &- \alpha k_j^{\alpha-1} q\Lambda e^{\frac{Var[\epsilon|\theta,z]}{2}} \phi_\epsilon(\cdot)\left\{-\hat{q} + (1-\alpha)\hat{k} - E[a|z] - \eta_{\Lambda,M}E[\hat{M}|z]\right\} \\ =& \left\{\alpha k_j^{\alpha-1} q\Lambda e^{\frac{Var[\epsilon|\theta,z]}{2}} \left[\Phi_\epsilon(\cdot) + \phi_\epsilon(\cdot)\right] + \phi_e\left(\frac{C^*}{\sqrt{Var[\epsilon|\theta,z]}}\right)\right\} \times \\ &\times \left\{\hat{q} - (1-\alpha)\hat{k} + E[a|z] + \eta_{\Lambda,M}E[\hat{M}|z]\right\}\end{aligned} \tag{49}$$

As a result,

$$\begin{aligned}\frac{d\frac{\partial E[w_{firm,j}|\Omega_j]}{\partial \tilde{b}_j}}{\frac{\partial E[w_{firm,j}|\Omega_j]}{\partial \tilde{b}_j}} =& \frac{\left\{\alpha k_j^{\alpha-1} q\Lambda e^{\frac{Var[\epsilon|\theta,z]}{2}} \left[\Phi_\epsilon(\cdot) + \phi_\epsilon(\cdot)\right] + \phi_e\left(\frac{C^*}{\sqrt{Var[\epsilon|\theta,z]}}\right)\right\}}{\frac{\partial E[w_{firm,j}|\Omega_j]}{\partial \tilde{b}_j}} \times \\ &\times \left\{\hat{q} - (1-\alpha)\hat{k} + E[a|z] + \eta_{\Lambda,M}E[\hat{M}|z]\right\} \\ =& L_1 \left\{\hat{q} - (1-\alpha)\hat{k} + E[a|z] + \eta_{\Lambda,M}E[\hat{M}|z]\right\}\end{aligned} \tag{50}$$

where $L_1 \equiv \frac{\left\{\alpha k_j^{\alpha-1} q \Lambda e^{\frac{Var[\epsilon|\theta,z]}{2}} [\Phi_\epsilon(\cdot)+\phi_\epsilon(\cdot)] + \phi_e\left(\frac{C^*}{\sqrt{Var[\epsilon|\theta,z]}}\right)\right\}}{\frac{\partial E[w_{firm,j}|\Omega_j]}{\partial \tilde{b}_j}}$.

- From equation 37, the derivative of expected firm manager payoff with respect to bond price q is given by

$$\frac{\partial E[d_{firm}|\Omega]}{\partial q} = \alpha k_j^{\alpha-1} \frac{k}{q} \int_{-\infty}^{\infty} \Lambda(\theta) e^{\frac{Var[\epsilon|\theta,z]}{2} + E[\epsilon|\theta,z]} \Phi_\epsilon \left(\frac{Var[\epsilon|\theta,z] + E[\epsilon|\theta,z] - C(\theta)}{\sqrt{Var[\epsilon|\theta,z]}} \right) e^\theta \phi(\theta|\Omega_j) d\theta \tag{51}$$

Differentiating,

$$\begin{aligned} d\frac{\partial E[d_{firm}|\Omega]}{\partial q} =& \alpha k_j^{\alpha-1} \frac{k}{q} \Lambda e^{\frac{Var[\epsilon|\theta,z]}{2}} \left[\Phi_\epsilon(\cdot) + \phi_\epsilon(\cdot)\right] \left\{ \hat{q} - (1-\alpha)\hat{k} + E[a|z] + \eta_{\Lambda,M} E[\hat{M}|z] \right\} \\ &+ \alpha k_j^{\alpha-1} \frac{k}{q} \Lambda e^{\frac{Var[\epsilon|\theta,z]}{2}} \Phi_\epsilon(\cdot)(\hat{k} - 2\hat{q}) \end{aligned} \tag{52}$$

therefore

$$\begin{aligned} \frac{d\frac{\partial E[w_{firm,j}|\Omega]}{\partial q}}{\frac{\partial E[w_{firm,j}|\Omega]}{\partial q}} &= \frac{\alpha k_j^{\alpha-1} \frac{k}{q} \Lambda e^{\frac{Var[\epsilon|\theta,z]}{2}} \left[\Phi_\epsilon(\cdot) + \phi_\epsilon(\cdot)\right]}{\frac{\partial E[w_{firm,j}|\Omega]}{\partial q}} \times \\ &\times \left\{ \hat{q} - (1-\alpha)\hat{k} + E[a|z] + \eta_{\Lambda,M} E[\hat{M}|z] \right\} + (\hat{k} - 2\hat{q}) \\ &= L_2 \left\{ \hat{q} - (1-\alpha)\hat{k} + E[a|z] + \eta_{\Lambda,M} E[\hat{M}|z] \right\} + (\hat{k} - 2\hat{q}) \end{aligned} \tag{53}$$

where $L_2 \equiv \frac{\alpha k_j^{\alpha-1} \frac{k}{q} \Lambda e^{\frac{Var[\epsilon|\theta,z]}{2}} [\Phi_\epsilon(\cdot)+\phi_\epsilon(\cdot)]}{\frac{\partial E[w_{firm,j}|\Omega]}{\partial q}}$.

- From equation 38, the derivative of the expected bank manager payoff with respect to bond $\tilde{b}_j$ is given by

$$\begin{aligned} \frac{\partial E[d_{bank}|\Omega^i]}{\partial \tilde{b}} =& \left[\left(1 - \int_{-\infty}^{\infty} \Phi_e(C(\theta)|z,\theta) \phi_\theta(\theta|\Omega) d\theta \right) - \frac{q}{q^f} \right] \\ &- (1-\alpha) \int_{-\infty}^{\infty} \phi_e(C(\theta)|z,\theta) \phi_\theta(\theta|\Omega) d\theta \end{aligned}$$

Differentiating,

$$d\frac{\partial E[d_{bank}|\Omega]}{\partial \tilde{b}} = -\phi_e\left(\frac{C^*}{\sqrt{Var[\epsilon|\theta,z]}}\right)\left\{\hat{q} - (1-\alpha)\,\hat{k} + E[a|z] + \eta_{\Lambda,M}E[\hat{M}|z]\right\}$$
$$-\frac{q}{q^f}\hat{q} - (1-\alpha)\phi_e\left(\frac{C^*}{\sqrt{Var[\epsilon|\theta,z]}}\right)\frac{C^*}{Var[\epsilon|\theta,z]}\left\{\hat{q} - (1-\alpha)\,\hat{k} + E[a|z] + \eta_{\Lambda,M}E[\hat{M}|\right. \tag{54}$$

therefore

$$\begin{aligned}\frac{d\frac{\partial E[d_{bank}|\Omega]}{\partial \tilde{b}}}{\frac{\partial E[d_{bank}|\Omega]}{\partial \tilde{b}}} &= \frac{\phi_e\left(\frac{C^*}{\sqrt{Var[\epsilon|\theta,z]}}\right)(1+(1-\alpha)\frac{C}{Var[\epsilon|\theta,z]})}{\frac{\partial E[d_{bank}|\Omega]}{\partial \tilde{b}}}\left\{\hat{q} - (1-\alpha)\,\hat{k} + E[a|z] + \eta_{\Lambda,M}E[\hat{M}|z]\right\} \\ &- \frac{\frac{q}{q^f}}{\frac{\partial E[d_{bank}|\Omega]}{\partial \tilde{b}}}\hat{q} \\ &= L_3\left\{\hat{q} - (1-\alpha)\,\hat{k} + E[a|z] + \eta_{\Lambda,M}E[\hat{M}|z]\right\} - L_4\hat{q}\end{aligned} \tag{55}$$

where $L_3 \equiv \frac{\phi_e\left(\frac{C^*}{\sqrt{Var[\epsilon|\theta,z]}}\right)(1+(1-\alpha)\frac{C}{Var[\epsilon|\theta,z]})}{\frac{\partial E[d_{bank}|\Omega]}{\partial \tilde{b}}}\left\{\hat{q} - (1-\alpha)\,\hat{k} + E[a|z] + \eta_{\Lambda,M}E[\hat{M}|z]\right\}$ and $L_4 \equiv \frac{\frac{q}{q^f}}{\frac{\partial E[d_{bank}|\Omega]}{\partial \tilde{b}}}$.

- From equation 40, the derivative of the expected bank manager payoff with respect to bond price q_j is given by

$$\frac{\partial E[d_{bank}|\Omega]}{\partial q} = \frac{k}{q}\left[\alpha\int_{-\infty}^{\infty}\phi_e(C(\theta)|z,\theta)\phi_\theta(\theta|\Omega)d\theta\frac{1}{q} - \frac{1}{q^f}\right]$$

differentiating,

$$
\begin{aligned}
d\frac{\partial E[d_{bank}|\Omega]}{\partial q} &= \frac{k}{q}(\hat{k}-\hat{q})\left[\alpha\phi_e\left(\frac{C^*}{\sqrt{Var[\epsilon|\theta,z]}}\right)\frac{1}{q}-\frac{1}{q^f}\right]+ \\
&+\frac{k}{q}\alpha\phi_e\left(\frac{C^*}{\sqrt{Var[\epsilon|\theta,z]}}\right)\frac{C^*}{Var[\epsilon|\theta,z]}\frac{1}{q}\left\{\hat{q}-(1-\alpha)\,\hat{k}+E[a|z]+\eta_{\Lambda,M}E[\hat{M}|z]\right\} \\
&-\frac{k}{q}\alpha\phi_e\left(\frac{C^*}{\sqrt{Var[\epsilon|\theta,z]}}\right)\frac{1}{q}\hat{q}
\end{aligned}
$$

Therefore

$$
\begin{aligned}
\frac{d\frac{\partial E[d_{bank}|\Omega]}{\partial q}}{\frac{\partial E[d_{bank}|\Omega]}{\partial q}} &= (\hat{k}-\hat{q})-\frac{\frac{k}{q}\alpha\phi_e\left(\frac{C^*}{\sqrt{Var[\epsilon|\theta,z]}}\right)}{\frac{\partial E[d_{bank}|\Omega]}{\partial q}}\hat{q} \\
&-\frac{\frac{k}{q}\alpha\phi_e\left(\frac{C^*}{\sqrt{Var[\epsilon|\theta,z]}}\right)\frac{C^*}{Var[\epsilon|\theta,z]}}{\frac{\partial E[d_{bank}|\Omega]}{\partial q}}\left\{\hat{q}-(1-\alpha)\,\hat{k}+E[a|z]+\eta_{\Lambda,M}E[\hat{M}|z]\right\} \\
&=(\hat{k}-\hat{q})-L_5\left\{\hat{q}-(1-\alpha)\,\hat{k}+E[a|z]+\eta_{\Lambda,M}E[\hat{M}|z]\right\}-L_6\hat{q}
\end{aligned}
\tag{56}
$$

where $L_5=\frac{\frac{k}{q}\alpha\phi_e\left(\frac{C^*}{\sqrt{Var[\epsilon|\theta,z]}}\right)\frac{C^*}{Var[\epsilon|\theta,z]}}{\frac{\partial E[d_{bank}|\Omega]}{\partial q}}$ and $L_6=\frac{\frac{k}{q}\alpha\phi_e\left(\frac{C^*}{\sqrt{Var[\epsilon|\theta,z]}}\right)}{\frac{\partial E[d_{bank}|\Omega]}{\partial q}}$.

Finally, substitute equations 50, 53, 55, and 56 in equation 48 and get

$$
\begin{aligned}
(L_1-L_2-L_3-L_5+L_4+1-L_6)\hat{q} &= -(L_1-L_2-L_3-L_5)\left\{-(1-\alpha)\,\hat{k}+E[a|z]+\eta_{\Lambda,M}E[\hat{M}|z]\right\} \\
\hat{q} &= \tilde{L}_2\left\{-(1-\alpha)\,\hat{k}+E[a|z]+\eta_{\Lambda,M}E[\hat{M}|z]\right\}
\end{aligned}
\tag{57}
$$

where $\tilde{L}_2\equiv\frac{-(L_1-L_2-L_3-L_5)}{(L_1-L_2-L_3-L_5+L_4+1-L_6)}$.

Equilibrium Substitute equation 47 in 57

$$\tilde{L}_1 \left\{ -(1-\alpha)\hat{k} + E[a|z] + \eta_{\Lambda,M} E[\hat{M}|z] \right\} = \tilde{L}_2 \left\{ -(1-\alpha)\hat{k} + E[a|z] + \eta_{\Lambda,M} E[\hat{M}|z] \right\}$$
$$(\tilde{L}_1 - \tilde{L}_2) \left\{ -(1-\alpha)\hat{k} + E[a|z] + \eta_{\Lambda,M} E[\hat{M}|z] \right\} = 0 \tag{58}$$

therefore, the stage-2 equilibrium k and q are given by

$$\hat{k} = \frac{1}{1-\alpha}(E[a|z] - \gamma E[\hat{M}|z])$$
$$\hat{q} = 0 \tag{59}$$

Where $\gamma \equiv -\eta_{\Lambda(M),M} = -\frac{\nu-\xi}{1-(1-\alpha)\xi}$. If $\nu < \xi$, then $\gamma > 0$. Therefore $\hat{r}_j \propto \hat{q} = 0$.

Since $M = \left\{ \left[\frac{w}{(1-\alpha)\xi\nu}\right]^{\frac{(1-\alpha)}{(1-\alpha)\xi-1}} \left[\int^N A_j k_j^\alpha dj\right]^{\frac{1}{\xi}} \right\}^{\frac{1-(1-\alpha)\xi}{1-(1-\alpha)\nu}}$, log deviation of M around the stochastic steady state equals

$$\hat{M} = \mu(\alpha\hat{K} + \theta)$$

where $\mu \equiv \frac{1}{\xi}\frac{1-(1-\alpha)\xi}{1-(1-\alpha)\nu} > 0$ and $\hat{K} = \int^j k_j dj$. One can write

$$\hat{k} = \frac{1}{1-\alpha}(E[a|z] - \gamma\mu E[\theta + \alpha\hat{K}|z])$$
$$\hat{q} = 0$$

Moreover, from 42

$$\hat{q}_j = -\zeta\hat{p}(def_j|\Omega_j) = 0 \tag{60}$$

where $\zeta \equiv \frac{p^*(def|0)}{1-p^*(def|0)}$.

The expected level deviation of bank j profits from steady state conditioning on state θ equals

$$E[w_{bank,j}|z_j,\theta] = -p^*(def|0)\hat{p}(def_j|z_j,\theta) - \frac{q^*}{q_j}\hat{q}_j$$
$$= -p^*(def|0)[\hat{p}(def_j|z_j,\theta) - E[\hat{p}(def_j|\Omega_j)|\theta]] \tag{61}$$

which is zero for each θ if $\theta \in \Omega_j$. ■

Proposition 2. Consider the global game when θ is observed

$$\hat{k} = \frac{1}{1-\alpha}E[a_j|z] - \frac{1}{1-\alpha}\gamma\mu\left(\theta + \alpha\hat{K}\right) \tag{62}$$

where $E[a_j|z_j, \theta] = \tilde{m}(z_j - \theta) + \theta$, where $z_j = a_j + \eta_j$ and $\tilde{m} = \frac{\sigma_e^2}{\sigma_e^2+\sigma_\eta^2}$. Aggregating across islands

$$\begin{aligned} K &= \frac{1}{1-\alpha}(1-\gamma\mu)\theta - \frac{\alpha}{1-\alpha}\gamma\mu K \\ K &= \frac{(1-\gamma\mu)}{1-\alpha+\alpha\gamma\mu}\theta \end{aligned} \tag{63}$$

■

Proposition 3. Consider the global game when θ is not observed

$$\hat{k} = \frac{1}{1-\alpha}E[a_j|z_j] - \frac{1}{1-\alpha}\gamma\mu\left(E[\hat{\theta}|z_j] + \alpha E[\hat{K}|z_j]\right) \tag{64}$$

where $E[a_j|z_j] = mz_j$, where $m = \frac{\sigma_e^2+\sigma_\theta^2}{\sigma_e^2+\sigma_\theta^2+\sigma_\eta^2}$, and $E[\theta|z_j] = \delta z_j$ where $\delta = \frac{\sigma_e^2}{\sigma_e^2+\sigma_\theta^2+\sigma_\eta^2}$. Following Morris and Shin (2002), I guess the linear solution $k_j = \chi z_j$

$$\begin{aligned} k_j &= \frac{1}{1-\alpha}(m - \gamma\mu[1+\alpha\chi]\delta)z_j \\ \chi &= \frac{1}{1-\alpha}(m - \gamma\mu[1+\alpha\chi]\delta) \\ \chi &= \frac{(m-\gamma\mu\delta)}{1-\alpha+\gamma\mu\alpha\delta} \\ K &= \frac{(m-\gamma\mu\delta)}{1-\alpha+\gamma\mu\alpha\delta}\theta \end{aligned} \tag{65}$$

■

Corollary 4. The loglinearized individual revenues $\hat{\pi}_j$ if $\theta \notin \Omega_j$ equals

$$\begin{aligned} \widehat{\pi}_j &= -\gamma\hat{M} + a_j + \alpha k_j \\ &= -\gamma\mu\left(\theta + \alpha\frac{(m-\gamma\mu\delta)}{1-\alpha+\gamma\mu\alpha\delta}\theta\right) + a_j + \alpha k_j \end{aligned} \tag{66}$$

Since $E[a_j|z_j] = mz_j$ and $E[\theta|z_j] = \delta z_j$,

$$\begin{aligned} E[\widehat{\pi}_j|z_j,\theta] - E[E[\widehat{\pi}_j|z_j]|\theta] =& E[a_j|z_j,\theta] - E[E[a_j|z_j]|\theta] - \gamma(\hat{M} - E[\hat{M}|z_j]) \\ =& \left[(1-m) - \gamma\mu(1-\delta)\left(1 + \alpha\frac{(m-\gamma\mu\delta)}{1-\alpha+\gamma\mu\alpha\delta}\right)\right]\theta \end{aligned} \tag{67}$$

It implies that average forecast errors are a positive function of θ if

$$\begin{aligned} (1-m) - \gamma\mu(1-\delta)\left(1 + \alpha\frac{(m-\gamma\mu\delta)}{1-\alpha+\gamma\mu\alpha\delta}\right) > 0 \\ (m-\gamma\mu\delta)\left(1-\alpha+\alpha\gamma\mu\right) > (1-\gamma\mu)(1-\alpha+\gamma\mu\alpha\delta) \end{aligned} \tag{68}$$

■

Corollary 5. Consider actual probability of default of firm j in dispersed information conditioning on aggregate shock θ: $p(def_j|z_j,\theta) \equiv \Phi_{e|\tilde{z}}(C(\theta))$. The first order approximation around the risky steady state is

$$\hat{p}(def_j|z_j,\theta) = \frac{\phi_{e|0}(C^*)}{\Phi_{e_0}(C^*)}\left[(1-\alpha)\,\hat{k}_j - \hat{q}_j + \gamma\hat{M} - E[a_j|z_j,\theta]\right] \tag{69}$$

Aggregating across islands

$$\begin{aligned} \hat{p}(def|z_j,\theta) &= \xi\left[(1-\alpha)\,\hat{K} - \hat{Q} + \gamma\hat{M} - \theta\right] \\ \hat{p}(def|z_j,\theta) &= \xi\left[(1-\alpha+\alpha\gamma\mu)\,\hat{K} - (1-\gamma\mu)\theta\right] \\ \hat{p}(def|z_j,\theta) &= \xi\left[(1-\alpha+\alpha\gamma\mu)\,\frac{(m-\gamma\mu\delta)}{1-\alpha+\gamma\mu\alpha\delta} - (1-\gamma\mu)\right]\theta \end{aligned} \tag{70}$$

Then it implies that $\frac{\partial\hat{p}(def|\theta)}{\partial\theta} > 0$ if

$$(m-\gamma\mu\delta)\left(1-\alpha+\alpha\gamma\mu\right) > (1-\gamma\mu)(1-\alpha+\gamma\mu\alpha\delta) \tag{71}$$

■

Corollary 6. Consider the logdeviation of perceived probability of default from steady state, meaning conditioning on info set $\Omega_j = \{z_j\}$.

$$\hat{p}(def_j|z_j) = \frac{\phi_{e|0}(C^*)}{\Phi_{e_0}(C^*)}\left[(1-\alpha)\,\hat{k}_j - \hat{q}_j + \gamma E[\hat{M}|z_j] - E[a_j|z_j]\right] \tag{72}$$

Consider the logdeviation of actual probability of default from steady state, meaning conditioning on info set $\Omega_j = \{z_j, \theta\}$.

$$\hat{p}(def_j|z_j,\theta) = \frac{\phi_{e|0}(C^*)}{\Phi_{e_0}(C^*)}\left[(1-\alpha)\,\hat{k}_j - \hat{q}_j + \gamma\hat{M} - E[a_j|z_j,\theta]\right] \tag{73}$$

The average bank profits equal the difference between the two

$$\begin{aligned} E[\tilde{\pi}_{bank,j}|z_j,\theta] &\propto -[\hat{p}(def_j|z_j,\theta) - E[\hat{p}(def_j|z_j)|\theta]] \\ &\propto -[E[a_j|z_j,\theta] - E[E[a_j|z_j]|\theta] - \gamma(M - E[M|z_j])] \end{aligned} \tag{74}$$

from the proof of corollary 4, it follow that average bank profits are a negative function of θ if

$$(m-\gamma\mu\delta)\,(1-\alpha+\alpha\gamma\mu) > (1-\gamma\mu)(1-\alpha+\gamma\mu\alpha\delta) \tag{75}$$

■

Appendix C Manager compensation

Suppose we interpret the limited liability constraint as resulting from a manager's convex compensation structure. The structure is as follows:

$$w_j = \begin{cases} (1-\psi)d_j + \psi(d_j - \tilde{P}) & \text{if } d_j \geq \tilde{P} \\ (1-\psi)d_j & \text{if } d_j < \tilde{P} \end{cases} \tag{76}$$

where d_j is the company's payoff, bank or firm, and $\tilde{P}$ is the profit level corresponding to the exercise price of manager's options. The larger the amount of options in manager's compensation scheme ψ, the lower is his exposure to company's losses and therefore higher his insurance against company's losses.

I assume for simplicity $\tilde{P} = 0$, meaning that manager's options are in the money when the profits of the firm are positive, i.e. in the non-default state. Therefore the payoff structure is equivalent as in Section 3.1.

A more general compensation structure would consist of β_m shares of company's equity, of which ψ are options.

$$w_j = \begin{cases} \beta_m(1-\psi)d_j + \beta_m\psi(d_j - \tilde{P}) & \text{if } d_j \geq \tilde{P} \\ \beta_m(1-\psi)d_j & \text{if } d_j < \tilde{P} \end{cases} \tag{77}$$

The net profits for the shareholder are $(1-\beta_m)d_j$ if profit are positive and $\beta_m\psi d_j$ otherwise. In particular, $\beta_m < 1$ in order to ensure a positive expected leftover profit for the shareholders. However, setting $\beta_m = 1$ does not affect qualitatively the results. Moreover, an additional fixed compensation $\bar{w}$ would not affect the manager's incentives and therefore his decisions.

Appendix D Equal bargaining power

In the baseline model I assume firm and bank managers decide loan quantity and prices in the second stage and information in the first stage through Nash bargaining, with the firms retaining all bargaining power. This yields the standard implication that the price of the loan reflects only quantity of risk, with no changes in price of risk. I relax this assumption here by setting an equal bargaining power for bank and firm.

Second stage The second-stage optimal k_j^* and r_j^* maximize

$$max_{q_j,b_j} \ (E[w_{firm}|\Omega_j])^{\beta}(E[w_{bank}|\Omega_j])^{1-\beta} \tag{78}$$

Figure 9 and 10 illustrate the equilibrium where $\beta = 0.5$. Differently from the baseline model, risk premium increases in booms even if risk declines, as the bank extracts more profit from the firm. As a result, bank's profits increase in moderate booms, but decline for very large booms as the losses for mispricing of risk becomes larger than the rent extraction from the firm.

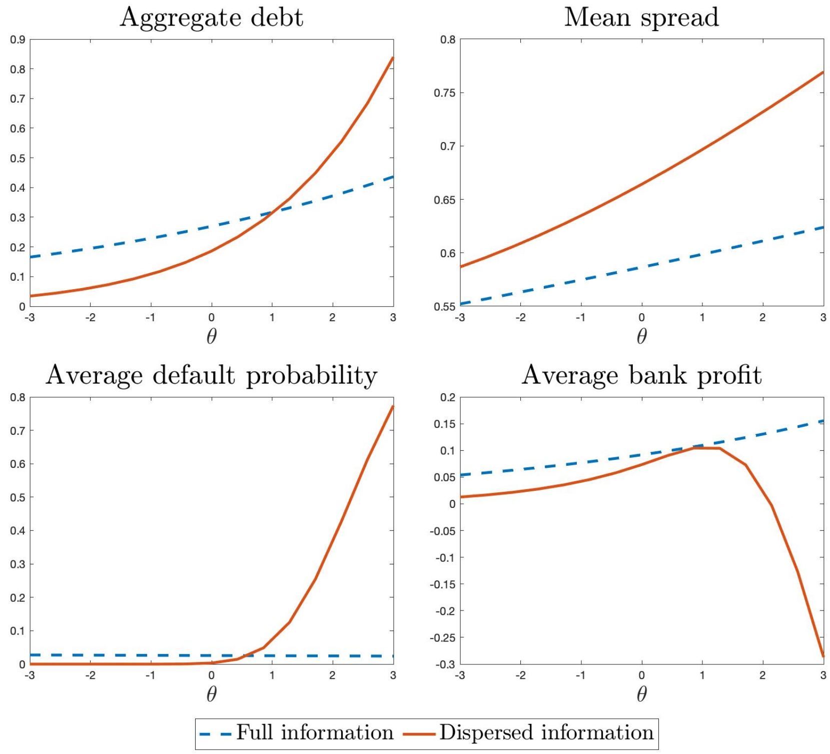

Figure 9

Notes: The figure illustrates the equilibrium of stage-2 investment and borrowing choice in the full information ($\theta \in \Omega_j$) and dispersed information economy ($\theta \notin \Omega_j$). The aggregate shock θ in the x-axis is expressed in standard deviations.

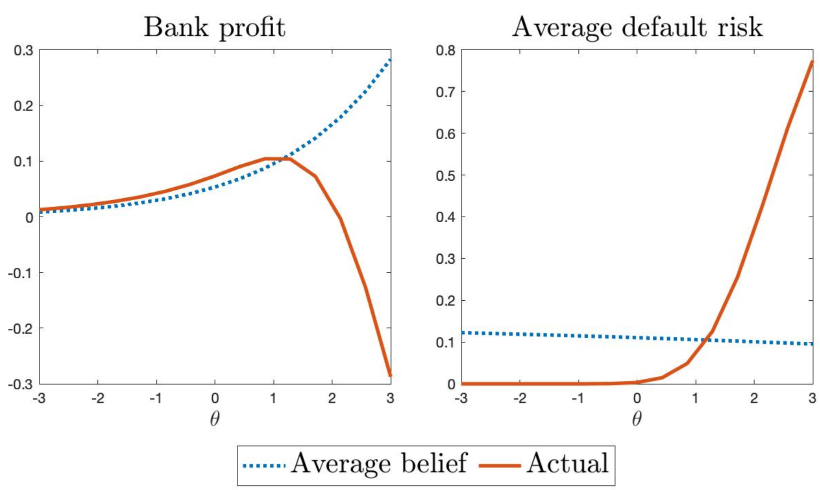

Figure 10

Notes: The figure illustrates the actual and the average expectation of bank excess return and default rate in the dispersed information economy ($\theta \notin \Omega_j$). The aggregate shock θ in the x-axis is expressed in standard deviations.