Rational Overoptimism and Moral Hazard in Credit Booms*

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Job Market Paper

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October 2021

Abstract

I develop a framework in which over optimism in credit booms originates from rational decisions of managers. Because of moral hazard, managers pay too little attention to the aggregate conditions that generate risk, leading them to over borrow and over invest during booms. Periods of low risk premia predict higher default rates, higher probability of crises and systematic negative banks excess returns, in line with existing evidence. I document a positive relation between the convexity of CEO's compensation and their information on a larger sample of firms, which is consistent with my theory. My model implies that compensation regulation can play an important role in macro prudential policy.

Keywords: Overoptimism, expectations, imperfect information, moral hazard, credit cycles

JEL classification: D83, D84, E32, G01

*I am grateful to Ryan Chahrour, Jaromir Nosal and Rosen Valchev for their invaluable guidance and support. I also thank Marco Brianti, Ilaria D'Angelis, Tarek Hassan (discussant), Pierre de Leo, Fabio Schiantarelli, Juhana Siljander (discussant) and seminar and conference participants at Boston College, European Central Bank, Spring Green Line Macro Meeting 2021, Young Economist Symposium 2021 for helpful comments. All errors are my own.

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1 Introduction

Recent empirical works has revived the longstanding hypothesis that boom-and-bust credit cycles are driven by overoptimistic beliefs (Minsky, 1977; Kindleberger, 1978). In particular, empirical evidence documents that high credit growth and low risk premia significantly predict subsequent financial crises (Schularick and Taylor, 2012; Jordà et al., 2013; Krishnamurthy and Muir, 2017; Greenwood et al., 2020). Two additional facts point towards overoptimistic beliefs as an explanation for this evidence. First, credit booms also predict low and even negative excess returns on bank stocks (Baron and Xiong, 2017). 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 in explaining such systematic bias in belief formation (Maxted, 2019; Bordalo et al., 2021; Krishnamurthy and Li, 2021).

While existing theories of overoptimism preserve full information and depart from rational expectations, I provide evidence on the importance of information frictions during booms. I compare actual real GDP growth with survey forecasts during booms and NBER recessions, and show that panelists consistently underestimate real output in booms and overestimate it in recessions. I document a similar pattern of belief underestimation in housing starts growth during the housing bubble that preceded the financial crisis of 2008-2009. This evidence on systematic belief under-reaction is consistent with imperfect information about aggregate quantities and in line with a recent literature on information dispersion (Coibion and Gorodnichenko, 2015; Coibion et al., 2018; Gemmi and Valchev, 2021).

First, I develop a theory of credit booms where overoptimism originates from rational inattention to aggregate risk factors. In my model credit, an aggregate productivity shock leads to an increase in borrowing and production of firms who face the same downward sloping demand for their combined output. Because higher aggregate production implies lower selling price, inattention to competitors' investment decisions cause firms to form overoptimistic expectations about their own revenues. Inattentive firms over borrow and over invest, causing an excess supply in the good market which further amplifies the decline in price. As firms' revenues are lower than expected, their default risk increases. My model implies that even fully rational agents can be systematically overoptimistic in credit booms and overpessimistic in busts. Moreover, because inattentive banks underestimate borrower's probability of default, they misprice risk and register negative excess returns after credit booms, consistently with the existing evidence.

Second, I show that inattention to risk factors can be ascribed to moral hazard incentives in information choice. Because managers with convex compensation structures are less exposed to company's losses, they have a lower marginal benefit of information, resulting in lower attention to aggregate conditions. Uninformed managers underestimate the increase in competition and decline in revenues after booms and are overoptimistic about their company's revenues. As a result, moral hazard incentives don't just lead to excessive risk taking given beliefs, but also inattention to risk and overoptimistic beliefs in boom periods. This result helps connect the two narratives of excess risk taking before the financial crisis of 2008-2009: the initial criticisms toward managers' moral hazard incentives (e.g. Blinder 2009) and the following behavioral overoptimism view (e.g., Gennaioli and Shleifer 2018). I show that overoptimism is in fact a consequence of moral hazard incentives.

Finally, I provide empirical evidence on the relation between manager's compensation and information choice on a large sample of US firms. I look at the relation between firm's CEO compensation and its earning guidance and document that higher compensation asymmetry, measured as share of stock options for a given stock of shares, is positively correlated with inattention, measured as squared forecast errors on future profits. The evidence documents a negative relation between moral hazard incentive in information choice, consistently with my model.

Because beliefs are rational, my model implies that policy makers can reduce overoptimism in credit booms by regulating manager's incentives to collect information. Informed managers reduce borrowing and investment in credit booms, mitigating economic fluctuations. However information provision through public announcement or direct communication would still be costly for managers to process. Instead, solving the moral hazard by regulating managers' compensation would not only solve their excess risk taking in investment, but also encourage them to pay attention to aggregate risk factors.

Model I embed compensation incentives and information choice in a macroeconomic model with endogenous default. The model features a continuum of bank-firm pairs, which I refer as islands. Firms demand loans from banks in order to finance investment, while banks get funding at a constant risk free rate on international markets. Firms and banks are run by managers with a convex compensation scheme.

I introduce two important elements to an otherwise standard setting. First, strategic substitutability between islands. I assume each firm produces intermediate goods, which are acquired by a unique aggregate final good producer with downward sloping demand. Aggregate credit booms lead to an increase in aggregate supply of intermediate goods, which lowers the individual firm's selling price and therefore its revenues. Second, I introduce incomplete information. Following the Lucas island framework, I assume agents are not able to freely observe aggregates prices and quantities.[1] However, I allow bank and firm managers on each island to pay an information cost to observe aggregate shocks and therefore investment decisions of competitors.[2]

Firm's productivity depends on local and aggregate shocks but, because of the competition in the intermediate goods market, firms benefit more from local than aggregate shocks. Local shocks improve firm's fundamentals and reduce its default probability, resulting in higher equilibrium debt and lower spreads. On the other hand, aggregate shocks also increase production of competitors and therefore lower firm's expected revenue and increase its default probability relative to a local shock with the same magnitude. While the first effect is standard in the literature that abstracts from competition between islands, the second effect is novel and implies a strategic interaction between islands.

First, I show that the full information model is not able to qualitatively match the existing evidence on risk premia in a credit boom. If managers observe aggregate shocks, the economy is always safer in credit booms, which implies lower risk premia. Even if the negative price externality has a dampening effect on the credit boom, the model is qualitative similar to a standard model without this additional channel (Strebulaev and Whited, 2011). Because the economy is safer after a boom, the model does not match the existing evidence.

I show that the model with dispersed information is instead able to match the existing evidence on credit cycles. If managers do not observe aggregate shocks, they incorrectly attribute the boom primarily to a local shock and underestimate the increase in production of competitors. As a result, they over-borrow and over-invest, further overheating the

[1] This assumption is consistent with the decentralized nature of bank credit market.

[2] 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.

economy. Even if perceived risk and risk premia decline, default rate increases. The model is consistent with the existing empirical evidence. First, credit growth predicts higher average probability of default (Krishnamurthy and Muir, 2017). Second, low risk premia also predict 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 endogenize information and show that moral hazard incentives discourage information acquisition. Because managers with convex compensation structures are less exposed to company's losses, their marginal benefit of information is lower and they decide to collect less information. As a result, they will be inattentive to the endogenous increase in risk during credit booms. Importantly, the excess risk taking in booms depends on managers' inattention to risk and not simply on higher risk taking in investment choice. In order to isolate the information channel of moral hazard, I shut down information choice and allow managers to observe aggregates. I show that standard compensation risk taking incentives alone without information choice are not able to qualitatively match the data.

Finally, I embed the model in a infinite-period framework to study its implication for credit cycles and relate it to the existing evidence. I show that the model with a realistic calibration is able to reproduce two important sets of moments in the data. First, my model matches the systematic decrease in spreads and increase in credit growth before financial crises. Second, it reproduces the predictive power of decline in spreads and increase in credit in forecasting financial crises.

Empirics I find empirical evidence on the model's implied positive relation between CEO's compensation convexity and squared forecast errors. I measure CEOs' beliefs with firm's forecasts on future earnings per share from the *IBES Guidance* database.[3] I measure CEOs' compensation convexity as options stock holding controlling for equity shares holding and additional CEO and firm controls. I find that higher compensation convexity is associated with larger manager's squared forecast errors, in line with the model's implication.

[3] The underlying assumption is that the earning projection released by the firm, even if not personally computed by the CEO, has been approved by him (Otto, 2014).

Contribution to the literature This paper contributes to several strands of the literature. First, the growing body of research about credit cycles. In addition to the already mentioned empirical work (Schularick and Taylor, 2012; Jordà et al., 2013; Krishnamurthy and Muir, 2017; Baron and Xiong, 2017; López-Salido et al., 2017; Mian et al., 2017; Greenwood et al., 2020), this paper relates to 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), which embeds 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 originates instead from underreaction to bad news. As a result, forecast errors exhibits 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. Differently from them, in my model financial fragility originates from strategic substitutability and incomplete information. If agents knew about the increase in aggregate risk, they would reduce leverage and therefore reduce risk. In fact, in my model financial fragility increases because managers do not pay attention to it. As a result, while Fisherian models exhibit cooperation among investors who ride the bubble as long as other ride it, my model exhibits competition between investors, as they want to exit the bubble before it burst.

My paper also relates to the literature on strategic games with incomplete information (Woodford, 2001; Coibion and Gorodnichenko, 2012; Maćkowiak and Wiederholt, 2015). While dispersed information and strategic substitutability lead to amplification of partial equilibrium effects as in Angeletos and Lian (2017), I study its implication for pricing of risk in credit booms. Similarly to Kohlhas and Walther (2020), 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 moral hazard incentives.

Finally, this paper contributes to the literature on compensation incentives. In addition to the large body of research on CEO compensation (see Edmans et al. 2017 for a review), I mostly relate to the works studying the impact of compensation on information. Mackowiak and Wiederholt (2012) show that limited liability reduces optimal information choice, while Lindbeck and Weibull (2017) study optimal contracts between principal and manager in rational inattention setting. Differently form them, this paper abstracts from optimal contracts, but contributes by documenting the impact of compensation on information in the data and studying its implication on credit cycles. My empirical results are complementary to Cole et al. (2014), which provides experimental evidence on the impact of compensation on loan officer's screening effort.

2 Motivational Evidence on Beliefs in Booms

While existing theories of overoptimism preserve full information and depart from rational expectation, in this section I provide evidence which points towards the importance of information frictions in business cycles. In particular, I document that aggregate beliefs under-react to changes in macroeconomic quantities in booms and busts, consistent with models of dispersed information.[4]

First, I look at business cycle frequency fluctuations of forecast errors on real GDP growth by comparing the average errors in booms and recessions. 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 at the same horizon. Forecast data are from the Survey of Professional Forecasters, and a positive forecast errors imply that the consensus forecast underestimate the actual GDP growth. Figure 1 shows that forecasters underestimate real output during booms and overestimate them during NBER recessions. This evidence suggests that at the aggregate level expectations display underreaction, and not overreaction, to changes in macroeconomic quantities.

In addition to the business cycle frequency, I provide evidence for belief under-reaction in the most recent credit boom-and-bust episode. Financial crises are less frequent than

[4] A leading 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).

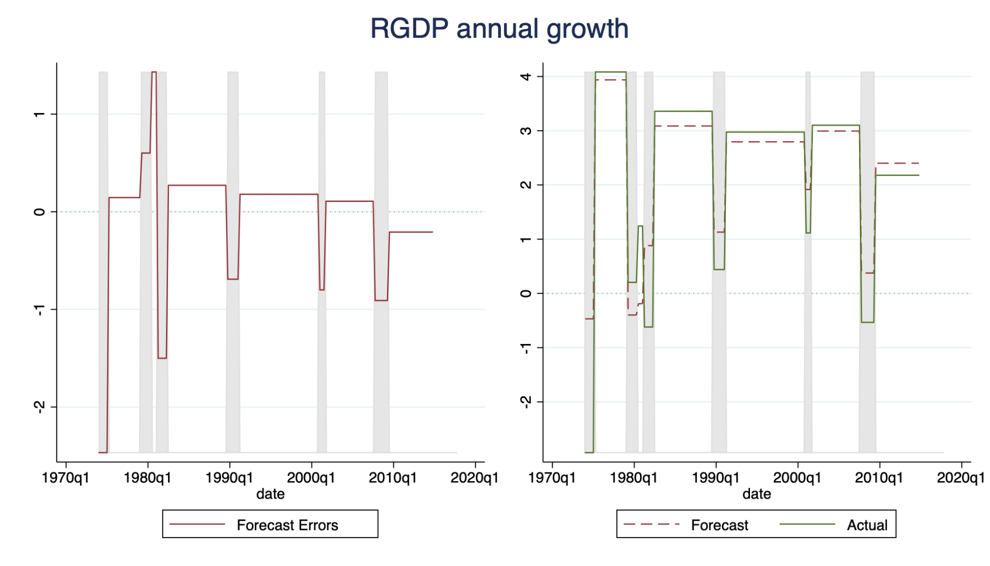

Figure 1: Forecast errors on Real GDP growth

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

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 growth forecasts and realizations of housing starts, averaged across the current and the next three quarters. The pattern is similar to the previous figure and it suggests that forecasters underestimated housing starts growth during the boom. In the next section I show how underestimation of an increase in supply leads to overestimation of the equilibrium market price, which might shed some light on the apparent overoptimism that boosted the housing bubble in the years preceding the crisis.

In addition to the evidence reported here, a growing literature employs surveys of professional forecasters to document the importance of information frictions against the full information hypothesis (Coibion and Gorodnichenko, 2012, 2015; Gemmi and Valchev, 2021).[5] The evidence of aggregate stickiness in belief updating supports model of dis-

[5] Bordalo et al. (2018a) provides evidence supporting behavioral overreaction in survey individual-level forecasts on financial and macroeconomic variables. However, they still find dispersed information and belief stickiness at the consensus level. Moreover, Gemmi and Valchev (2021) provide further evidence on survey

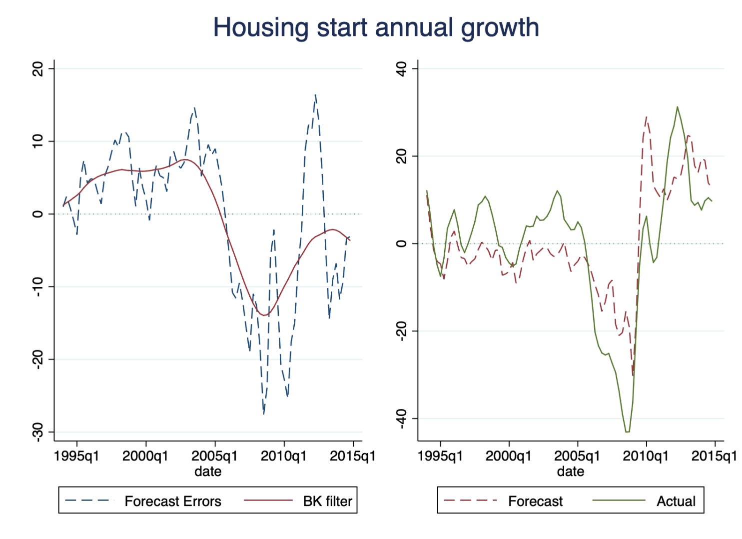

Figure 2: Forecast errors on Housing Start

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.

persed information, where agents have access to different information and are always in disagreement about the fundamentals. Moreover, the professional forecaster's expectations data I use here are likely to underestimate the amount of information friction of firms. In line with this, Coibion et al. (2018) study firm's level expectation and find stronger results. Managers' expectations display much more disagreement than professional forecasters, and this disagreement applies to both future and current economic condition. Moreover, they find that their belief updating is consistent with the Bayesian framework and their attention allocation to aggregates depends on incentives.

In summary, the evidence on aggregate expectations are consistent with information frictions that hinder the diffusion of information or the incorporation of new information in agent's beliefs (Sims, 2003; Woodford, 2001). In the following section I present a model consistent with the data, where overoptimism originates from incomplete information about aggregate quantities.

individual forecast which are inconsistent with the diagnostic expectation framework.

3 Model of inattentive credit booms

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

The model is divided in three stages. First, before receiving any information each bank-firm pair decides whether they want to observe aggregate shocks in the next stage. Second, they observe information and bargain on loans and loan rates. Finally, shocks realize and firms repay or default. Rather than a description of business cycles, the model is intended to describe 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, acquiring a bundle of intermediate goods $M = \left[\int^j M_j^\xi dj\right]^{\frac{1}{\xi}}$ with elasticity of substitution $\frac{1}{1-\xi}$, in order to produce final good $Y = M^\nu$. Therefore, the demand function for intermediate goods M_j in stage 3 equals:

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

The demand for intermediate good M_j could increase or decrease in aggregate production M depending on the degree of decreasing return to scale in final good production and the elasticity of substitution between goods. If $\nu < \xi$, higher aggregate supply of intermediates M lead to lower price p_j and therefore lower revenues for intermediate producer j. Conversely, if $\nu < \xi$, higher aggregate supply of intermediates M lead to higher price p_j and therefore higher revenues for intermediate producer j. opposite. I assume $\nu < \xi$ and in section 4.2 I show that this condition holds under fairly mild assumptions, such as an equal markup in intermediate and final good sectors.

[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 happens before markets open and information is observed, when there is no heterogeneity in firms and banks characteristics.

Firms In the second stage, firms in island j borrows b_j from the bank in order 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

$$M_j = A_j^{\zeta} k_j^{\tilde{\alpha}} l_j^{1-\tilde{\alpha}} \tag{2}$$

The parameter $\tilde{\alpha} \in (0,1)$ 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 profits of the firm as $\pi_j = p_j M_j - wl_j$. We 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

$$\pi(A_j, k_j, M) = \Lambda(M) A_j k_j^{\alpha} \tag{3}$$

where $\alpha = \frac{\tilde{\alpha}\xi}{1-(1-\tilde{\alpha})\xi}$, $\Lambda(M) = \nu^{\frac{1}{1-(1-\alpha)\xi}} M^{\frac{\nu-\xi}{1-(1-\alpha)\xi}}$ and $M = \left\{ \left[\frac{w}{(1-\alpha)\xi\nu}\right]^{\frac{(1-\alpha)}{(1-\alpha)\xi-1}} \left[\int^N A_j k_j^{\alpha} dj\right]^{\frac{1}{\xi}} \right\}^{\frac{1-(1-\alpha)\xi}{1-(1-\alpha)\nu}}$. 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 keep the difference as dividends, minus a tax rate τ. If the profits are not enough to repay the outstanding debt, the firm pays a default cost c_d proportional to installed capital, which can be thought as a liquidation or reorganization cost following the bankruptcy procedure.[7]

[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. This procedure implies some cost such as reputation costs, asset fire sales, loss of customer or supplier relationships, legal and accounting fees, and costs of changing management, which I assume depend on the size of the firm (Branch, 2002; Bris et al., 2006).

Banks Banks in each island j are deep-pocketed and risk-neutral. In the second stage they borrow at risk free rate r^f in the international market to finance the risky loan 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. Because firm's revenues are lost when the firm defaults, default is inefficient in this economy.

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 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 $\theta \sim N(0,\sigma_\theta^2)$. Both shocks realize in stage 3 and determine aggregate and local production.

3.1 Firm Manager's compensation

I assume that firms and banks are not run by the shareholders but by risk-neutral managers, who receives a compensation in shares and stock options. In particular, the manager gets $1-\psi$ shares of company's equity and ψ stock options. I consider manager's compensation convexity as a source of moral hazard incentives in the model for three reasons. First, it is one of the most studied source of moral hazard incentives (Edmans et al., 2017).[8] Second, in the aftermath of the financial crisis of 2008-2009 compensation policies have been suggested as likely culprits for the excessive risk-taking that led to the crisis (e.g. Bebchuk et al. (2010)). Third, I am going to test the model's implications in the data using option holdings in section 7.

[8] 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).

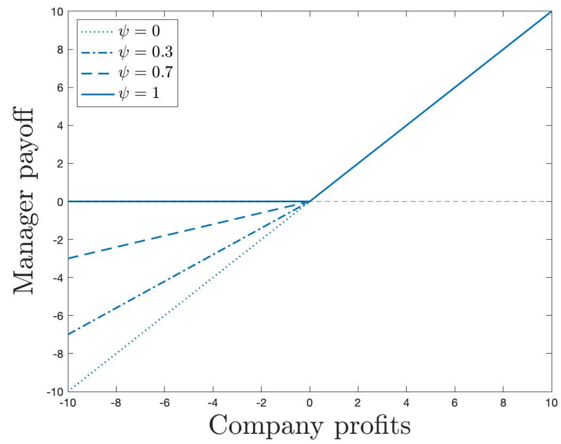

Figure 3

The manager's compensation structure is as follows:

$$w = \begin{cases} (1-\psi)d_j + \psi(d_j - \tilde{P}) & \text{if } d_j \geq \tilde{P} \\ (1-\psi)d_j & \text{if } d_j < \tilde{P} \end{cases} \tag{7}$$

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. Figure 3 illustrates the relation between company and manager's payoffs. 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.[9]

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 firm manager's

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

$$w_j = \begin{cases} \beta_m(1-\psi)d_j + \beta_m\psi(d_j - \tilde{P}) & \text{if } d_j \geq \tilde{P} \\ \beta_m(1-\psi)d_j & \text{if } d_j < \tilde{P} \end{cases} \tag{8}$$

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.

final payoff is given by

$$w_{firm,j} = \begin{cases} (1-\tau)[\pi(A_j, k_j, M) - (1+r_j)b_j] & \text{if } \pi(A_j, k_j, M) \geq (1+r_j)b_j \\ -(1-\psi)c_d k_j, & \text{if } \pi(A_j, k_j, M) < (1+r_j)b_j \end{cases} \tag{9}$$

Even if here I follow the interpretation of ψ as option share of firm manager, one can also simply interpret it as decrease in firm's default cost c_d. In other words, while I focus on the moral hazard problem between shareholder and manager, one can similarly think about the moral hazard problem between lender and borrower.

Bank manager compensation is given by

$$w_{bank,j} = \begin{cases} [(1+r_j) - (1+r^f)]b_j & \text{if } \pi(A_j, k_j, M) \geq (1+r_j)b_j \\ -(1-\psi)(1+r_j)b_j & \text{if } \pi(A_j, k_j, M) < (1+r_j)b_j \end{cases} \tag{10}$$

One can also interpret ψ more generally as the degree of limited liability of the bank, which could be due to the share of funds coming from insured deposit versus equity (Dell'Ariccia et al., 2014) or as the share of the loan value covered by government guarantees, a major part of the COVID-19 support packages offered by European governments to companies (OECD, 2020).

3.2 Stage 2: lending problem

Before shocks realize and production take place, bank and firm managers in each island decide loan quantity b_j and rate r_j based on their expectation about profits in stage 3. They share the island's surplus by Nash bargaining with the firm holding all the bargaining power, which implies a zero expected profit condition on the lender in line with the literature (e.g. Strebulaev and Whited (2011)).

Information structure The bank and firm on island j share the same information, as any private information would be perfectly revealed by local prices. Before making their borrowing and lending decision, they receive up to two signals. First, they observe a free noisy signal about local productivity:

$$z_j = ln(A_j) + \eta_j \tag{11}$$

with $\eta_j \sim N(0, \sigma_\eta^2)$ and $ln(A_j) = \epsilon_j + \theta$.

Second, they may perfectly observe aggregate productivity. Following the Lucas island setting, I assume managers in each islands do not observe aggregate quantities and prices for free. However, in stage 1 bank and firm managers in island j can decide whether to pay a cost to perfectly observe the aggregate shock θ. Let Ω_j be the (common) stage-2 information set of managers in island j: if they pay the cost in stage 1, $\Omega_j = \{z_j, \theta\}$, otherwise $\Omega_j = \{z_j\}$.

Notice that even in absence of direct observation on aggregate technology, the signal is still informative about θ, since as local technology is the sum of local and aggregate components. The local component ϵ_j acts as a nested noise weakening the inference.

Lending decision The bank's expected excess return is

$$\begin{aligned} E[w_{bank,j}|\Omega_j] =& b_j[1 - p(default_j|\Omega_j)](1 + r_j)b_j \\ & - [(1 - \psi) + \psi[1 - p(default_j|\Omega_j)]](1 + r^f)b_j \end{aligned} \tag{12}$$

where the posterior default risk equals

$$p(default_j|\Omega_j) = \int_0^\infty \int_{-\infty}^{ln\left(\frac{b_j}{\Lambda(M)k(b_j)^\alpha}\right)} f(ln(A_j), M|\Omega_j) dA_j dM \tag{13}$$

where Ω_j is the information set of island j, $f(ln(A_j), M|\Omega_j)$ the joint posterior density function of $ln(A_j)$ and M_j and $k(b_j) = \phi^{-1}(\sqrt{1 + 2b_j\phi} - 1)$. The loan rate is implicitly determined by the zero expected profit condition on the bank

$$\frac{1 + r_j}{1 + r^f} = \frac{(1 - \psi) + \psi[1 - p(default_j|\Omega_j)]}{[1 - p(default_j|\Omega_j)]} \tag{14}$$

The loan rate is proportional to the perceived probability of default, implying that the risk premium on the loan is only proportional to the perceived risk with no time-varying price of risk.[10] A higher compensation convexity ψ lowers the elasticity of the spread with respect to perceived risk.

[10] This result derives from the assumption that the firm retains all the bargaining power, which implies a no expected profits condition for the bank. A non-zero bargaining power on the bank will not change the mechanism of the model, but it will change the determination of the risk premium, which could decline for higher quantity of risk if the price of risk decline as well. See appendix for an alternative calibration of the model where the bank has a non-zero bargaining power.

The expected payoff of the firm's manager conditioning on second stage information set is

$$
\begin{aligned}
E[w_{firm,j}|\Omega_j] =&(1-\tau)\int_0^\infty \int_{ln\left(\frac{b_j}{\Lambda(M)k(b_j)^\alpha}\right)}^\infty \Lambda(M)A_j k_j^\alpha f(ln(A_j), M|\Omega_j)dA_j dM \\
&- \left[1-p\left(default_j|\Omega_j\right)\right](1+r_j)b_j - \left[p\left(default_j|\Omega_j\right)\right](1-\psi)c_d k_j
\end{aligned}
\tag{15}
$$

An increase in options ψ decreases manager's losses in case of firm's default, increasing moral hazard incentives. The firm manager internalizes the bank's supply of loan $r_j(b_j)$ and decides the optimal borrowing b_j to maximize expected payoff

$$
k_j = argmaxE[w_{firm,j}(r_j(b_j), M_j, ln(A_j))|\Omega_j] \tag{16}
$$

Appendix B describes in the detail the bargaining process and the stage-2 equilibrium.

Strategic substitutability in production If $\nu < \xi$, the demand function for good j (1) is decreasing in aggregate production of intermediates M. For a given level of local production M_j, a lower price p_j implies lower revenues for firm j. As a result, island j's equilibrium debt b_j and loan rate r_j depend positively on the realization of local technology A_j, but negatively on the aggregate production M.

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 is informative about aggregate production M. Similarly to the lending decision in sage 2, I assume bank and firm managers share information and decide cooperatively through Nash bargaining with the firm holding all the bargaining power.[11] As a result, island j decides collectively to pay the attention cost if

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

[11] Any private information between agents in the same island would be perfectly revealed by local prices. Therefore any individual decision on whether to observe private information would need to account for this information spillover, introducing strategic considerations between agents in the same island. To avoid this, I use a Nash bargaining setting where the decision is taken cooperatively with the same bargaining power as in stage-2 bargaining. As a result, the firm manager gets the surplus and pay the information cost. I allow for a different split of surplus and cost in the appendix.

where w^*_{firm} are the equilibrium payoffs of firm managers in the second stage and expectation are conditional only on priors, as agents have no access to any signal at this stage. Expected profits depends on local and aggregate information choice: (i) whether managers in j will be able to observe aggregate shocks in the next stage, $\theta \in \Omega_j$, or not, $\theta \notin \Omega_j$; (ii) on the total share of islands deciding to observe aggregate shocks in the next stage $\lambda \in [0, 1]$, where $\lambda = 1$ 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 the cost or not, $E[w^*_{firm,j}(\theta \in \Omega_j, \lambda^*) - c] = E[w^*_{firm,j}(\theta \notin \Omega_j, \lambda^*)]$.

Information choice also exhibits strategic substitutability, meaning that a higher share of informed island λ decreases island j's incentive of paying the information cost. I provide intuition for this in the next section.

4 Credit booms and Inattention

4.1 Analytical results

In order to provide intuition for the model mechanism, I consider a first order approximation of the second stage model around the risky steady state (Coeurdacier et al., 2011).[12] At the steady state, all islands observes 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 moral hazard $\psi = 0$ and no default cost $c_d = 0$. Because of these assumptions, the equilibrium perceived default risk and risk premium are constant (while actual default risk might not be), but the remaining 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 the first order approximation of the second-stage equilibrium defined by equations (14) and (16) 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.*

[12] While the economy at the proximity of the steady state is not suitable to study large and rare financial crises like the one considered in this paper, the basic model mechanism does not rely on non-linearity and there preserve its main idea in the linearized version

- *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* $\pi_j(A_j, k_j, M)$ *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 bank's 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 default risk conditional on signal* z_j *and aggregate shock* θ, *which I define as actual default risk.*

See the appendix for the derivations.

First, notice that since I assume $\nu < \xi$, then $\gamma > 0$ and therefore equation (18) represents a linear game with strategic substitutability: higher aggregate investment (or debt) $\hat{K}$ lowers island j's optimal investment $\hat{k}_j$. Second, the equilibrium loan rate $\hat{r}_j$ is negatively related to the perceived default probability. This result follows directly from the price equation (14) and it implies that changes in risk premia only reflects changes in perceived quantity of risk. Second, perceived default risk is constant in equilibrium (or zero in log-deviation from the steady state). This is a knife-edge result that depends on the simplifying assumptions introduced in this section, which I relax in the numerical solution. Finally, as the loan pricing condition implies no expected profits for the bank, aggregate bank profits in state θ depend on whether agents correctly perceived risk, i.e. 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 effect and a general equilibrium effect.[13]

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

First, local productivity A_j in each island increases. Because firm's fundamental is higher, island j manager's posterior probability of default decreases, boosting borrowing and investment $\hat{k}_j$. This is the standard positive channel of productivity shocks 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). Since I assume $\nu < \xi$, $\gamma > 0$ and the higher competition in the intermediate good market implies a lower demand and revenues for firm j. As a result, optimal investment $\hat{k}_j$ is lower.

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 ($\lambda = 1$, *full information*). Second, I assume no island decide to pay attention to aggregates in the first stage ($\lambda = 0$, *dispersed information*).

4.1.1 Full information $\lambda = 1$

Consider the full information case, meaning all islands decide to observe aggregate shock θ in the first stage in addition to the free signal z_j defined by equation (11).

Proposition 2 (Full information) *If $\Omega_j = \{z_j, \theta\}$, the solution to the linear game in propo-*

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

sition 1 is

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

See the appendix for the proof.

After an aggregate shock, the improvement in local technology increases equilibrium aggregate debt and investment, but its effect is dampened by the endogenous decrease in intermediate good prices, which lower firms' optimal investment. The stronger the elasticity of intermediate price with respect to the increase in aggregate supply of intermediate $0 < \gamma < 1$, the stronger is 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, which equals the average actual default risk across firms, is also constant.

Notice that the negative endogenous GE effect on expected firm's revenue can not be larger than the positive PE effect in full information, which implies that the actual default risk can not be larger either. If that was the case, then the lower expected revenues would lead the managers to decrease debt and investment (proposition 1), resulting in lower aggregate supply, higher price and a positive endogenous GE effect. In other words, if the default risk was higher, the agents in the economy would optimally limit leverage and reduce it.[14] As a result, the full information economy is not riskier in credit boom, which is at odds with the 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.*

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

[14] This is a consequence of the strategic substitutability game between firms. A large body of research focuses instead on strategic complementarity to rationalize the procyclical leverage in full information (Gertler and Kiyotaki, 2010; Brunnermeier and Sannikov, 2014; He and Krishnamurthy, 2019; Bianchi and Mendoza, 2020).

Because perceived risk coincides with actual risk, default risk is correctly priced conditioning on aggregate economic conditions. In other worlds, because banks observe θ, they do not make systematic errors conditioning on it. The zero expected profit condition implies that banks make zero excess return on average for each θ. While this model implies zero expected profits for banks, a different bargaining power could imply positive profits. However bank shareholders would not accept predictable losses, which is at odds with the evidence in Baron and Xiong (2017).

4.1.2 Dispersed information $\lambda = 0$

Consider the dispersed information case, meaning no island decides to observe aggregate shock θ in the first stage, so they only observe the free signal z_j defined by equation 11.

Proposition 3 (Dispersed information) *If $\Omega_j = \{z_j\}$, the solution to the linear game in 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 the appendix for the proof.

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*

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

The aggregate shock θ affect both the local fundamental (PE effect) and the aggregate production (GE effect). As a result, not observing θ leads to an underestimation of both, with opposite effects on optimal investment. Whether investment in dispersed information is larger than in full information depends on how much observing aggregates increases (i) posterior belief on local productivity (PE) and (ii) posterior belief on aggregate production of intermediates (GE).

First, suppose the signal z_j is infinitely noisy, $\sigma_\eta \to \infty$, then $m = \delta = 0$ and the condition doesn't hold. Without signals on local productivity, the aggregate shock is the only source of information. If agents do not observe it either, investment equals the steady state level in every states. If agents are instead able to observe it, higher aggregate shock θ increases their posterior on both local technology (PE) and aggregate investment (GE), but the only equilibrium is one in which the first prevails on the second and optimal local investment increases.[15] Second, suppose the signal z_j is noiseless, $\sigma_\eta \to 0$, then $m = 1, \delta < 1$ and the condition holds. In this case agents observe perfectly local productivity regardless of their information on aggregate shock. However, observing aggregates is informative on the investment decisions of the other firms in the economy, and therefore on the negative endogenous GE effect. In the dispersed information setting, after an aggregate shock agents underestimate the increase in competition and over-invest with respect to the economy with informed agents. This result suggests that information frictions can lead to amplification by dampening negative GE effect, similarly to Angeletos and Lian (2017).

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

Corollary 4 (Rationally extrapolative beliefs and underreaction) *If $\Omega_j = \{z_j\}$, the average forecast errors on firm's revenues 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).*
- $\theta < 0$*: agents overestimate aggregate output and underestimate individual revenues (overpessimism).*

[15] To see it, suppose that the negative GE force from higher aggregate investmentt was stronger than the positive PE effect from higher local technology an optimal local investment decreased in θ. Aggregate investment would then be inversely related to θ, and the GE force would be positive for the island and not negative, leading to a contradiction.

Equilibrium revenues depend positively on the PE effect and negatively on the GE effect. Because agents do not observe aggregates, they rationally confound an aggregate shock for a local shock and underestimate the negative GE effect. The information incompleteness produces extrapolative-like beliefs, as agents are systematically overoptimistic after a positive shock and overpessimistic after a negative shock. Differently from behavioral models where overoptimism originates 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, in booms we observe both overoptimism about local revenues and underestimation of aggregate quantities, consistently with the evidence in section 2. Even if agents are rational and correct on average conditioning on their information set, they can be consistently mistaken conditioning on unobserved aggregate states.

Figure 4 illustrates the intuition. The dotted line represents the prior belief about firm's revenues before receiving any information. A positive technology shock increases firm's fundamentals and implies on average a good signal z_j that shifts the posterior beliefs on revenues to the blue solid line (positive PE effect). However, because of the endogenous increase in intermediate good supply, price of good j will be lower and the actual posterior revenues of an informed agent would shift back to the middle dashed line (negative GE effect). Inattentive agents underestimate left tail risk, illustrated in the figure as the shaded area between their posterior and the actual posterior distribution of revenues.[16]

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 the appendix for the proof.

As dispersed information amplifies the credit boom, the larger supply of intermediates lowers further prices and firms' revenues. As agents confound the aggregate for a local shock, they do not internalize this risk and increase leverage too much with respect to

[16] Notice that, because more information also implies lower posterior uncertainty, the difference between informed and non-informed posterior is not only lower posterior mean but also lower posterior variance.

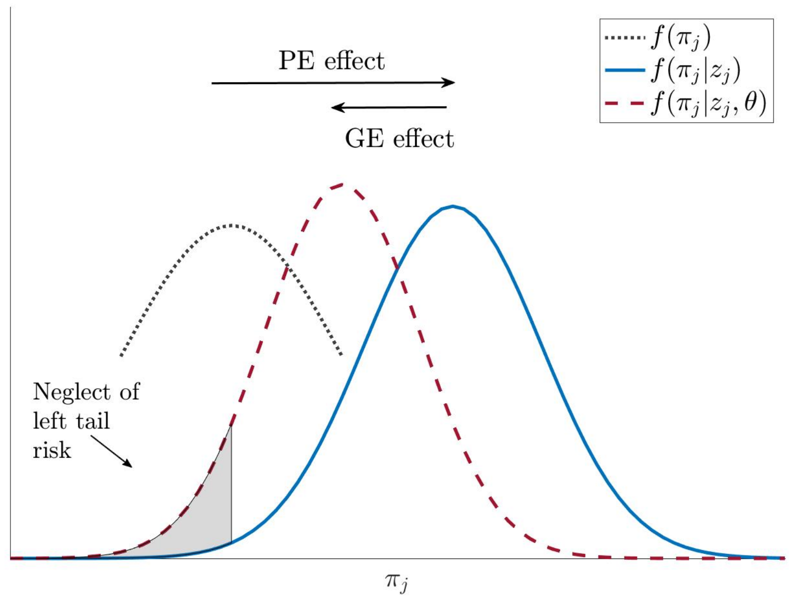

Figure 4: Rationally extrapolative beliefs in booms

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.

their repayment capacity, leading to higher default rate. As a result, credit booms are period in which default risk is larger, consistent with the evidence that low risk premium 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.

Because in equilibrium the risk premium is such that banks get zero expected profit on average, when banks underestimate default risk they misprice loans and get negative profits.[17] This result is consistent with the evidence that credit booms predict negative

[17] Since I assumed $\alpha = 0$, the condition applies to both shareholders and managers. If $\alpha > 0$, then the pricing condition is on manager's profits.

returns on bank stocks in Baron and Xiong (2017).

Information choice In the first stage, managers decide whether they want to observe aggregates based on their expected profits in the final stage. In general, a share $\lambda \in [0, 1]$ of islands decides to acquire the information. While figure 4 illustrates individual beliefs for a given aggregate production M, this quantity is endogenous to the aggregate amount of information in the economy. If all managers in each island are informed, $\lambda = 1$, proposition 3 states that the increase in aggregate supply in boom is lower, and the decrease in price as well. In figure 4, this would mean a shorter distance between informed and uninformed posterior, as the neglected GE effect is lower. On the other hand, if managers and firms in each island are uninformed, $\lambda = 0$, the credit boom is amplified, and the decline in price is larger. In figure 4, this would mean a larger distance between informed and uninformed posterior, 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, as higher aggregate information implies lower individual benefit of information. In section 5 I illustrate numerically how moral hazard incentives also affect benefit of information and equilibrium λ.

4.2 Numerical illustrations

I provide a numerical illustration of the non-linear model. The contribution of studying numerical solutions of the model is twofold. First, I relax some parametric assumptions needed to keep the analytical model tractable. Second, non-linear global solution are more suitable than approximation around the steady state to analyze the nature of large and rare credit booms, as the ones 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, my modeling assumption of $\nu < \xi$ would be satisfied by any final good sector markup larger than 13%.[18]

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 manager convex compensation incentives and set $\psi = 0$. In section 5 I increase convex compensation incentives and study its implications on lenidng and information choice. Finally, I calibrate the cost of information c such that with no convex compensation incentives it is optimal for all islands to be 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 case, where all islands decide to observe aggregate shock θ in the first stage. The blue dashed lines in figure 5 reports 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 standard deviations of the aggregate shock θ. The figure confirms the analytical results in the previous section, as large values of aggregate shock θ are associated with a credit boom. Differently from the linear model in the previous section, I allow for a non-zero investment adjustment cost. As a consequence, the probability of default is not constant but declines after boom and, because agents know the risk is lower, the risk premium declines as well. Risk is correctly priced and banks make zero average profits in boom-and-busts.

[18] 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	Compensation convexity	0
c_d	Default cost	0.5
τ	Corporate tax	0.20
c	Information cost	0.0017

The model's implications are qualitatively similar to a benchmark model that abstracts from strategic interactions between firms, but with the price externality dampening the boom.

The model is not consistent with the existing evidence. First, Schularick and Taylor (2012) show that booms are periods where financial risks accumulates, which in my model would imply a larger default rates after a credit boom. Second, Krishnamurthy and Muir (2017) document that low risk premium predict financial crisis, but in full information, 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 is negative after a boom, while informed bank in the model would not accept to make average negative returns.[19]

Dispersed information $\lambda = 0$ Consider the dispersed information case, where no island decides to observe aggregate shock θ in the first stage. The red solid lines in figure 5 reports the response of aggregate credit $B = \int^j b_j dj$, average risk premium $R - r^f$, default rate and

[19] While it would be possible to set up a model where firms had higher risk tolerance and were willing to take on more risk during credit booms, bond pricing equation (14) implies that the risk premium would increase as a consequence, inconsistently with the evidence in Krishnamurthy and Muir (2017). If the bankers had higher risk tolerance in booms as well, risk premia could be lower in periods of high risk (e.g. Krishnamurthy and Li 2021), but it would still not be possible to have rational bankers accepting negative excess returns on average, as documented in Baron and Xiong (2017).

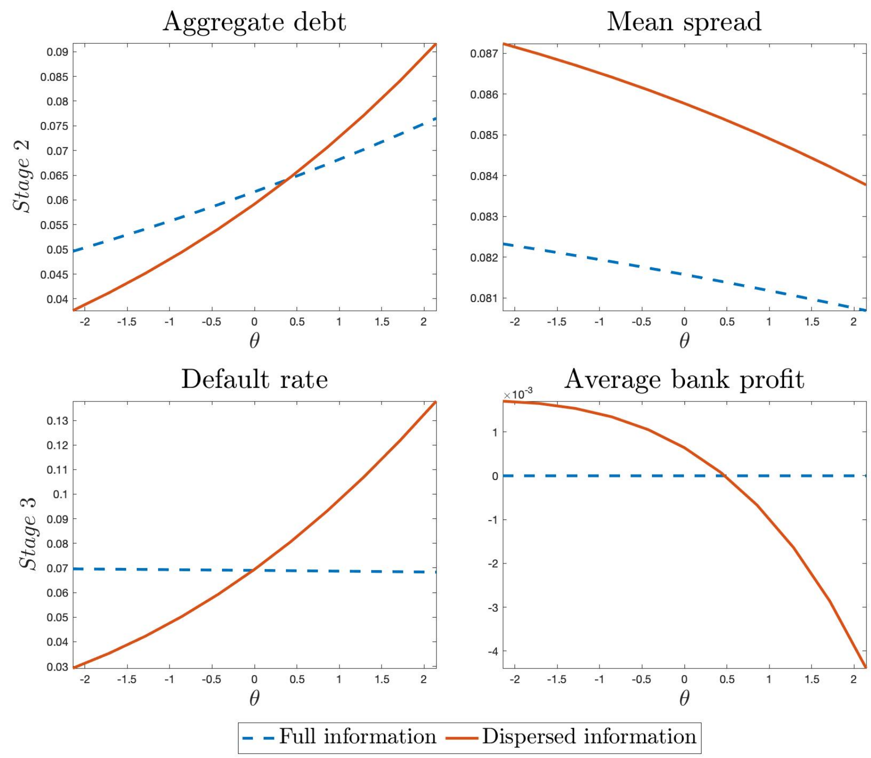

Figure 5

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.

average bank profits in this economy as functions of standard deviations of the aggregate shock θ. The figure confirms the analytical results in the previous section. Because agents are unaware of the negative GE effect, the credit boom is amplified, as depicted by the solid red line in the upper left panel . The excess supply of intermediate goods lowers the price and revenues, but firms are inattentive to aggregates and take on too much debt. Default risk now peaks after credit booms, consistent with the evidence on credit boom-and-busts (Schularick and Taylor, 2012). Banks are also inattentive to aggregates and they confound the aggregate shock for a local shock. As a result, the risk premium on lending is lower in credit booms when the default risk is larger. The model's results are consistent with existing evidence that high credit and low risk premia predict subsequent financial downturn (Krishnamurthy and Muir, 2017).

The decline in risk premium is not due to a change in risk tolerance, but to the underestimation of the endogenous increase in default risk. Figure 6 clarifies this point by

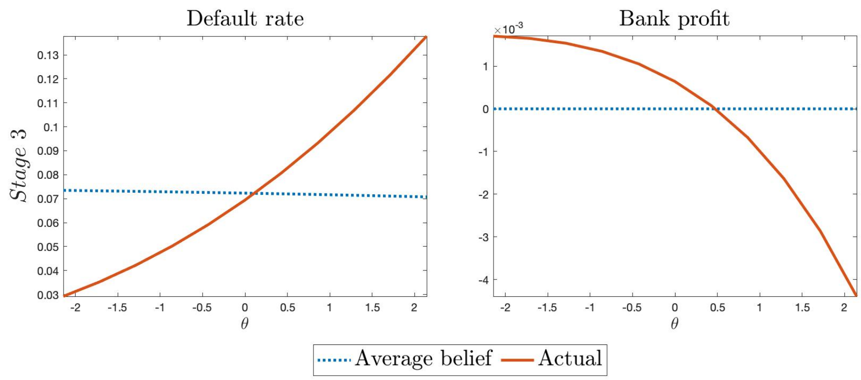

Figure 6

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.

plotting actual bank's profits (solid red) and mean bank's expected profits (dotted blue) in the left panel and actual average default rate (solid red) and mean expected default rate (dotted blue) on the right. Managers do not internalize the increase in default risk and expect zero average excess return. However, because of the increase in default risk, excess returns during credit booms are negative on average. Under the assumption that bank's stock price is correlated with operating profits, the results is in line with the evidence of average negative returns on bank's stock during booms in Baron and Xiong (2017).

The equilibrium share of informed islands λ is endogenous and depends on the optimal attention decisions in stage 1. While it would be possible to rationalize a high level of information friction with a high enough information cost c, such high cost might not be realistic. I the next section I show how moral hazard incentives lead to lower optimal attention choices and therefore explain a high level of information dispersion in the model even when information costs are low.

5 Inattention and moral hazard

While the previous section illustrates how information frictions explain the observed frothiness and overoptimism in credit booms, I now turn to the determinant of such information friction. I show that managers with moral hazard incentives optimally decide to be inattentive to aggregates even for low information costs, causing them to be overoptimistic in booms and overpessimistic in busts. I connect the moral hazard narratives of the excessive risk taking before the financial crisis of 2008-2009 (e.g. Blinder 2009) with the behavioral overoptimism view (e.g., Gennaioli and Shleifer 2018) by showing that overoptimism is in fact a consequence of moral hazard.

Stage 2: Moral hazard in lending An increase in compensation convexity has a standard moral hazard incentive channel on stage-2 borrowing and lending decisions. First, consider the firm manager's decisions. For a given interest rate schedule $r_j(b_j)$, the firm faces a trade-off in their debt issuance b_j between higher expected profits in the no-default states and higher default probability (equation (16)). Higher compensation convexity ψ lowers firm managers' losses in case of default, encouraging them to take on more risk. Second, consider bank managers' decisions. Higher compensation convexity ψ implies lower losses in case of default and therefore lower elasticity of credit spread $\frac{1+r^i}{1+r^f}$ with respect to default risk (equation (14)).

In order to isolate the effect of moral hazard on borrowing decisions, I initially shut down the information choice in stage 1. Figure 7 reports the equilibrium debt, average spread, default rate and bank's profits in an economy in full information for different values of compensation asymmetry ψ. Higher moral hazard incentives lead to higher risk taking by firm managers and lower price of risk by bank managers, resulting in higher unconditional default rate. However, similarly to the full information model in the previous section, credit booms are period where the economy is safer and default rate decreases, which is not consitent with the 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 match qualitatively the empirical evidence on credit cycles.

Stage 1: Moral hazard in information In the first stage, bank and firm managers in each island decide whether to pay or not the information cost to observe aggregate shocks in stage 2. Both agents benefit from information, as neglecting aggregate shocks leads to higher default risk and losses. I set the attention cost such that, with no compensation convexity $\psi = 0$, it is optimal for all islands to pay the cost and be fully informed in next stage, $\lambda = 1$. Figure 8 shows that the equilibrium share of informed island λ declines in compensation convexity ψ.[20] Intuitively, the larger is the manager's compensation convex-

[20] This result relies on the contemporaneous increase both firm and bank moral hazard incentives. First, higher firm managers' compensation convexity leads to higher risk taking and lower optimal information for a given credit spreads, but lower information also results in higher uncertainty and higher average credit spreads. Because firm managers want to take on more risk, depending on the calibration they might prefer to

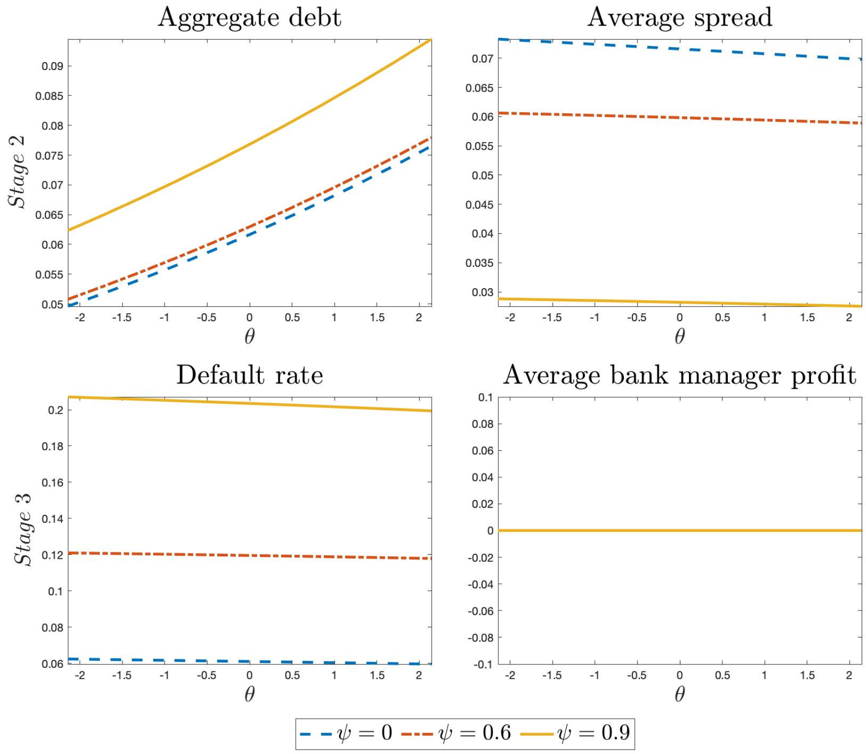

Figure 7: Full information and Moral hazard

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

ity, the lower is their exposure to losses and therefore the lower is their marginal benefit of information. [21]

Figure 9 reports the equilibrium debt, average spread, default rate and bank's profits for different values of compensation asymmetry ψ, which endogenously lead to different value of attention λ. The higher is managers' moral hazard, the lower is the optimal attention choice, which leads to higher default rate and lower bank's profits in booms as discussed in the previous section. As a consequence, credit booms are period where default risk is larger but risk premium lower, consistently with the empirical evidence on credit cycles. The comparison between figure 7 and figure 9 reveals that moral hazard in information choice is able to explain the existing evidence on credit cycles, while moral

collect more information just to decrease price of risk. However, if bank managers' compensation convexity increases as well, then price of risk declines and the island collectively is better off with lower information.

[21] The intuition behind this result is similar to Mackowiak and Wiederholt (2012), who show that limited liability reduces optimal information choice in a general setting, while Lindbeck and Weibull (2017) study optimal contracts between principal and manager in rational inattention setting.

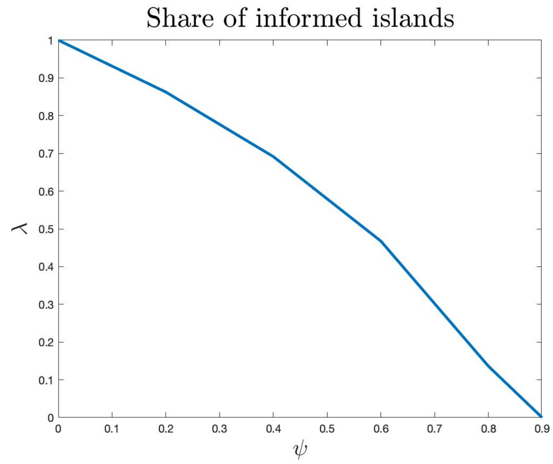

Figure 8: Compensation and information choice

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

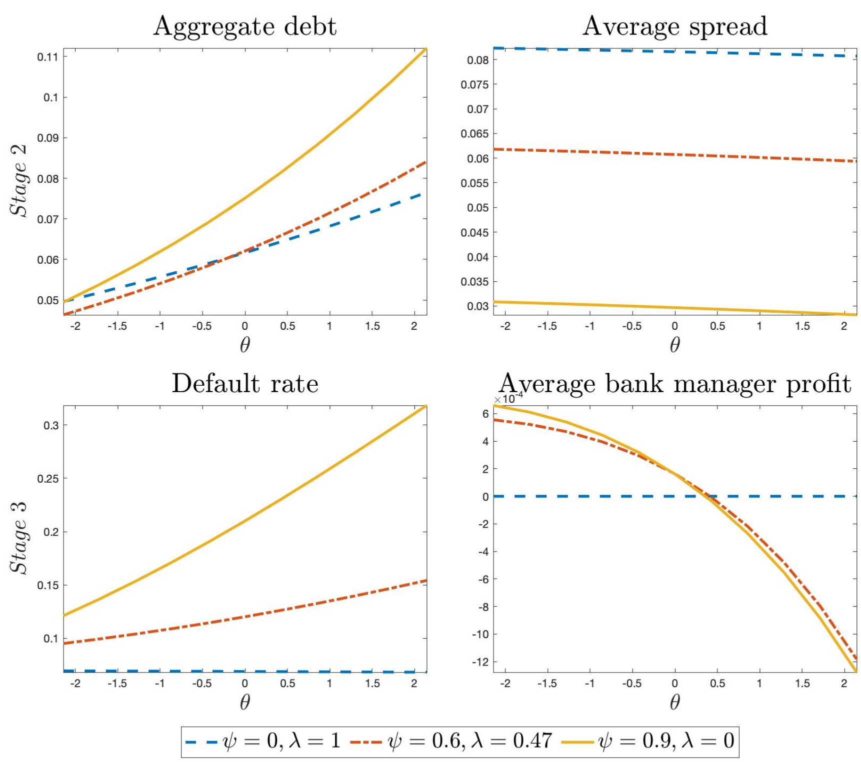

Figure 9: Information Choice and Moral hazard

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

hazard in investment decision alone is not.

6 Dynamic extension

In this section I extend the model to an infinite-periods 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, then I compare the performance of my model against the data. While a full quantitative match of the data is beyond the scope of this paper, I show that the model is nonetheless able to produce 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 against 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.

Dynamic model In order to related my model to the existing evidence, I embed my three-stage game in a infinite period setting. 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, shocks described in equation (6) realize, production take place and firms repay or default (stage 3). In this period, the old generation of managers receive their payoffs and die, while a new generation of managers is born and repeats the cycle.

I assume that in case of default, firms can not re-enter in the economy immediately as

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

it takes one period for the firm to re-build its productive capacity. This simple friction can be interpreted as time needed for new firms to collect the funding to cover some fixed cost of production or to organize 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

$$N_t = N_{t-1} - N_{def,t} + N_{def,t-1} \tag{32}$$

As illustrated in the previous section, in presence of moral hazard credit booms are followed by a larger default rate, which implies a lower number of productive firms in the economy in the following period. As a result, booms are followed by a burst as in the existing evidence.[22]

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 mean value of the different frequencies estimated in the literature. As a result, I define a financial crisis as 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

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

for each node 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 compensation convexity $\psi = 0$ and with compensation convexity $\psi > 0$.

Table 2 reports the empirical moments and the ones generated by the model in the two different calibrations. First, the baseline model without convex compensation is not able 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 happens only when the economy is hit by negative technological shock, with no boom-and-bust dynamics. On the other hand, the model with convex compensation is qualitatively consistent with the evidence. First, crises are systematically preceded by credit boom with an increase in credit and a decline in spreads. Similarly, increase in credit and decline in spreads have predictive power on the probability of a crises in the future. Inattentive managers neglect default risk and over-invest, over-heating the economy which will end up in a recession in the following period.

7 Compensation and information in the data

I provide empirical support for the negative effect of compensation convexity on information choice by relating compensation of CEOs with the forecast released by their company on own earnings.

I draw mainly on three datasets. First, I collect forecast data from Institutional Brokers Estimates System (I/B/E/S) manager guidance database. This panel records in each year the forecasts released by the firm's management about their own company annual profits or earnings.[23] Second, I collect data on CEO's compensation from Execucomp and finally I get annual financial data from the Compustat/CRSP merged database. After merging these datasets, I get a panel of around 1000 CEO-firm pairs from 2004 to 2018. Appendix A provides further details on the datasets and variable definition.

I define forecast errors as actual earning per share (EPS) registered by firm i in year t minus the forecasts released by firm i in year t about own EPS at the end of the same year. In order to make the errors comparable across firms, I normalize them by the standard

[23] I follow the literature in measuring CEO's beliefs using firm's forecast (Otto, 2014; Hribar and Yang, 2016). The underlying assumption is that these forecasts are approved by the CEOs or, alternatively, that CEO's incentives apply also to his subordinates.

deviation of the firm's detrended EPS.[24]

$$fe_{i,t} = \frac{eps_{i,t} - E_t[eps_{i,t}]}{sd_i} \tag{33}$$

I test the model's implication by regressing manager's squared forecast errors on compensation convexity.

$$\begin{aligned} fe_{i,t}^2 = \beta_0 + \beta_1 ln(Options_{i,t-1}) + \beta_2 ln(Shares_{i,t-1}) + \beta_3 ln(Salary_{i,t-1}) \\ + \beta_4 CEOcontrols_{i,t} + \beta_5 FirmControls_{i,t-1} + \eta_i + \gamma_t + \epsilon_{i,t} \end{aligned} \tag{34}$$

I measure compensation convexity as number of vested stock options for a given stock of equity shares and fixed salary. I use end of previous period stocks as they are more relevant for forecasts released at beginning of current period, and to minimize concerns about reverse causality. I control for CEO's age, tenure, forecast horizon and forecast width.[25] Moreover, I control for standard lagged firm financial variables.[26] Finally, I include time and CEO fixed effects.

The estimate of interest $\hat{\beta}_1$ represents the impact of an increase in stock options holding on squared forecast errors. In accordance to the model, I find a robust and statistically positive coefficient under different measures of option holdings. Table 3 reports the estimated $\hat{\beta}_1$ with different specifications. Column 1 uses the baseline specification, where I measure CEO's option holdings with a dummy equal to 1 if the CEO has a positive holding of stock options. Using a dummy lowers concerns about measurement errors on manager's compensation. However, In columns 2 and 3 I use respectively value of shares and the number of shares underlying the option contracts. In column 4 I saturate the model by including 2-digits industry times year fixed effect. In all the specifications, option holding is positively and significantly correlated to squared forecast errors. This finding support the model's implications, as larger compensation convexity leads the manager to take on more risk and neglect information.

[24] In order to get rid of the common trend in firm's EPS, I first subtract from each firm actual EPS the median of all other firms in the panel. Then I compute the standard deviation of the firm's EPS in on the available observations after 1985, considering only firms for which I have 10 or more years of data.

[25] As firms release forecast at different distances from the fiscal year ending date, I control for the horizon forecasted. Moreover, since some firms provide an interval and not a point forecast, I control for the forecast width.

[26] I control for annual stock return, standard deviation of returns, total assets, market capitalization, book value, leverage, stock price, total assets.

Table 3: Option compensation and squared forecast errors

	(1) fe^2 Coef./SE	(2) fe^2 Coef./SE	(3) fe^2 Coef./SE	(4) fe^2 Coef./SE	(5) fe^2 Coef./SE
OptionsDummy	0.134**			0.107**	0.038*
	(0.055)			(0.043)	(0.019)
lnOptionsVal		0.017**			
		(0.007)			
lnOptionsNum			0.028*		
			(0.013)		
R-squared	0.062	0.062	0.063	0.089	0.824
N	4482	4475	4475	4244	4455
Controls	Y	Y	Y	Y	Y
Year fe	Y	Y	Y	Y	Y
Ceo-firm fe	Y	Y	Y	Y	Y
Year$\times$industry fe				Y	

Note: the table reports the estimated $\hat{\beta}_1$ from regression 34. Column 1 reports the baseline model, where I measure options simply with a dummy having value 1 if vested option holding is positive. Column 2 measures options holding as the value of the stock underlying the option contracts. Column 3 measures options holding as the number of stocks underlying the option contracts. Column 4 includes analyst squared forecast errors as control. Column 5 includes 2-digit sector times year fixed effect. Additional controls include: CEO's characteristics, as lagged number equity shares (value in column 2), lagged fixed salary, age, tenure, forecast horizon and forecast width; lagged firm's financial variable, as stock annual return, standard deviation, market capitalization, book value, leverage, stock price (except column 2), total assets, EPS.

While the theory implies that compensation convexity increases both risk taking and inattention to risk, I isolate the latter by controlling for the squared forecast error of analysts' mean forecast. Intuitively, since manager's option compensation does not affect information choice of analysts, their forecast errors reflect only the endogenous increase in the firm's EPS volatility due to manager's risk taking, but not his information choice. Therefore, controlling for analyst forecast errors help me isolating the information channel. Column 5 in table 3 reports the result by including this additional control. The impact of option on manager's squared errors is lower than in column 1, as expected, but still positive and significant.[27]

Since the seminal paper of Malmendier and Tate (2005), the behavioral corporate finance literature has used manager's decision to hold vested options instead of exercising them as a measure of CEO overconfidence (or overoptimism). The CEO fixed effects in my regressions take care of any non-time varying CEO characteristics, and therefore control for CEO's intrinsic overconfidence or risk aversion.

My findings are in line with a large body of empirical works on the impact of compensation incentives on risk taking (Edmans et al., 2017) and on the impact of CEO's overoptimism on risk taking (Ho et al., 2016). The result above suggests that both CEO's beliefs and risk taking are related to compensation.

8 Discussion and policy implications

My model implies that inattentive agents over-accumulate debt and investment during booms, which leads to higher default risk and economic fragility. While this results is similar to a large strand of the macroeconomic literature on financial frictions, the underlying mechanism is different and it highlights novel macro-prudential policy implications.

A large class of models in the macro-financial literature rationalizes the over-accumulation of debt during booms with 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

[27] The large R squared is due to the large explanatory power than analysts squared error has on manager's squared error. Nonetheless, option holding retains some explanatory power, which is due to the information effect alone.

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. As aggregate investment increases, informed firms and banks would decrease their own lending and investment, making the economy safer. However, because they can not perfectly observe aggregates, they contribute in making the economy riskier by increasing their own lending and investment. Information provision would then mitigate the overoptimism and therefore the boom-and-busts cycles.

The policy maker can solve the information friction and mitigate the boom-and-bust cycles by correcting managers' moral hazard. While the policy maker could provide free information though public announcements or direct communication with managers, they still have to pay a cognitive cost to process this information (Sims, 2003; Mackowiak et al., 2018). However, the policy maker can affect managers' incentives to collect information by making them accountable for their mistakes in belief formation. A feasible policy in this direction is regulating managers' compensation structure by 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).

9 Conclusions

I presented a theoretical framework where overoptimism originates from moral hazard incentives in information choice. While existing models explain overoptimism during credit booms with behavioral extrapolation to good news, I propose a rational framework where overoptimism originates instead from inattention to negative news. In particular, large credit booms are associated with an increase in aggregate supply and decrease in price, and therefore inattention to aggregates leads to overestimation of own revenues. As a result, managers over-borrow and over-invest, overheating further the economy. Periods of low risk premium predict higher default rate and systematic bank losses, in line with existing evidence. Moreover, I show that such information friction can result from moral hazard incentives, as convex compensation structures discourage managers to collect information. Finally, I document a positive relation between CEO's compensation incentives and information in a large sample of US firms. Because beliefs depend on incentives, my model suggests that compensation regulation has important implication in terms of macro-prudential policy.

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A Data

I combine data from two main sources: (1) Compustat for publicly listed US firms, (2) the Institutional Brokers Estimate System (I/B/E/S) Guidance database for manager's earnings forecast and actual earnings. In addition, I used the Execucomp database for executive compensation data and CRSP for monthly stock prices. To construct the sample, I discarded firm-year with negative values for assets and book value. Moreover, I consider only US firms reporting in US dollars and CEO compensation data.

A.1 Compustat and Execucomp

I downloaded the US Fundamentals Annual file in the CRSP/Compustat Merged dataset available through Wharton Research Data Services (WRDS). The variables I use are constructed from Compustat variables as follows:

- Annual return on stock: $\left(\dfrac{prcc\_f_t + dvpsx_t}{ajex_t}\right) / \left(\dfrac{prcc\_f_{t-1} + dvpsx_{t-1}}{ajex_{t-1}}\right) - 1$
- Leverage: $\dfrac{dltt}{at}$
- Market Value: $mktcap$
- Cash over assets: $\dfrac{ch}{at}$
- EBIT over assets: $\dfrac{ebit}{at}$
- Size: at
- Closing price (fiscal): $prcc_f$

I also use the CRSP database to compute the monthly stock return standard deviation as follows:

1. Monthly stock return: $\left(\dfrac{prccm_\tau + dvpsxm_\tau}{ajexm_\tau}\right) / \left(\dfrac{prccm_{\tau-1} + dvpsxm_{\tau-1}}{ajexm_{\tau-1}}\right) - 1$ with τ indicate month
2. Standard deviation of annual return in year t as the standard deviation of monthly return in last 60 months (minimum of 40 months).

From Execucomp, I considered only the current CEO from each firms and compute the following variables:

- CEO tenure: $year - becomeceo$ (drop if tenure¡0)
- Age: age
- Number of stock shares holding: $shrown\_excl\_opts$
- Value of stock shares holding: $shrown\_excl\_opts \times lprcc_f$
- Number of unexercised vested options: $opt\_unex\_exer\_num$
- Value of unexercised vested options: $opt\_unex\_exer\_est\_val$
- Dummy options: equal to 1 if number of unexercised vested options is larger than zero.
- Salary: $salary$

A.2 I/B/E/S

I downloaded I/B/E/S annual earnings per share (eps) forecast and realization data adjusted for stick-split from WRDS. I made the following sample restrictions

- I considered only US currency earnings ($curr = USD$), range and point forecast ($range\_desc = 01, 02$), comparable guidance ($diff\_code = 58$).
- I exclude observations where announcement dates is later than frecasted date; when firms issues multiple forecast in the same date on same horizon I keep the last forecast.

I consider forecasts released by firm i in year t about earnings of the same firm at the end of the same fiscal year. I compute forecast errors are realization minus forecasts. In order to make the errors comparable across firms, I normalize them by firm's earnings standard deviation.

- Standard deviation of realized earnings sd:
  - I first detrend each firm's earnings realization by subtracting the yearly median across firms. I use the median to lower the concerns about outliers

– I then compute the standard deviation of individual firm's detrended earnings from 1985. I consider only firms that reports more than 10 years of data.

- Firm's forecast $E_t[eps_{it}]$: val_1 if firm provides a point forecast, and $(val_1 - val_2)/2$ if the firm provides a range forecast.
- Manager's squared forecast errors fe^2: $\left(\frac{eps_{it}-E_t[eps_{it}]}{sd}\right)^2$,
- Analysts average forecast $\tilde{E}_t[eps_{it}]$: $mean\_at\_date$
- Analysts squared forecast errors $\tilde{fe}^2$: $\left(\frac{eps_{it}-\tilde{E}_t[eps_{it}]}{sd}\right)^2$
- Forecast width: zero if firm provides a point forecast, and $(val_1 - val_2)/sd$ if the firm provides a range forecast.
- Forecast lead: difference between fiscal year end month forecasted and month the forecast is released by the firm in months.

A.3 Summary statistics

Variable are winsorized before the analysis and I exclude firm with less than 5 observations. I am left with a sample of around 4500 firm-year observations from 2004 to 2018.

B 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 $\epsilon_j \sim N(0, \sigma^2_\epsilon)$ and $\eta_j \sim N(0, \sigma^2_\eta)$, and may observe $\theta \sim N(0, \sigma^2_\theta)$. 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 $\tilde{m} = \frac{\sigma^2_e}{\sigma^2_e+\sigma^2_\eta}$ and $Var[e|\tilde{z}] = \frac{\sigma^2_e\sigma^2_\eta}{\sigma^2_e+\sigma^2_\eta}$, and $\theta|z \sim N(E[\theta|z], Var[\theta|z])$ with $E[\theta|z] = \delta z$ with $\delta = \frac{\sigma^2_\theta}{\sigma^2_e+\sigma^2_\eta+\sigma^2_\theta}$ and $Var[e|\tilde{z}] = \frac{\sigma^2_\theta(\sigma^2_e+\sigma^2_\eta)}{\sigma^2_e+\sigma^2_\eta+\sigma^2_\theta}$.

Table 4: Summary statistics

	Mean	Median	Standard deviation
SquaredForError	0.16	0.02	0.72
SquaredForErrorAnalyst	0.20	0.02	0.80
ActualEPS	2.45	2.06	1.89
OptionsDummy	0.85	1.00	0.36
OptionsVal	28264.10	12902.38	43779.49
OptionsNum	665.81	376.67	911.93
Equity	39221.11	11310.77	128343.64
EquityNum	905.33	283.74	2180.37
Salary	892.97	893.75	316.59
ForLead	8.62	10.00	2.75
ForWidth	0.14	0.10	0.14
Age	56.21	56.00	6.70
Tenure	8.46	7.00	6.75
AnnualReturn	0.13	0.12	0.33
MonthlyReturnSd	0.09	0.09	0.04
MktCap	7119.60	2991.44	10584.35
BookVal	17.36	15.13	10.68
Leverage	0.20	0.20	0.14
StockPrice	44.02	39.36	24.73
TotalAssets	8090.72	2997.71	13642.88

Marginal effects

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

$$
\begin{aligned}
E[w_{bank}|\Omega_j] =& b_j \left(\left[1 - \int_{-\infty}^{\infty} \int_{-\infty}^{C(\theta)} \phi(\epsilon_j|\theta, z_j) d\epsilon_j \phi(\theta|\Omega_j) d\theta \right] \right) \\
& - b_j \left(1 - \psi \left[\int_{-\infty}^{\infty} \int_{-\infty}^{C(\theta)} \phi(\epsilon_j|\theta, z_j) d\epsilon_j \phi(\theta|\Omega_j) d\theta \right] \right) \frac{q_j}{q}
\end{aligned}
\tag{35}
$$

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

$$
max_{q_j, \tilde{b}_j} \ (E[w_{firm,j}|\Omega_j])^{\beta} (E[w_{bank,j}|\Omega_j])^{1-\beta} \tag{36}
$$

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

$$
\begin{aligned}
& max_{q_j, b_j} \ E[w_{firm,j}|\Omega_j] \\
& s.t. \quad E[w_{bank,j}|\Omega_j] \geq 0
\end{aligned}
\tag{37}
$$

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

$$
\begin{aligned}
& E[w_{bank,j}|\Omega_j] = 0 \\
& \frac{\frac{\partial E[w_{firm,j}|\Omega_j]}{\partial \tilde{b}_j}}{\frac{\partial E[w_{bank,j}|\Omega_j]}{\partial \tilde{b}_j}} = \frac{\frac{\partial E[w_{firm,j}|\Omega_j]}{\partial q_j}}{\frac{\partial E[w_{bank,j}|\Omega_j]}{\partial q_j}}
\end{aligned}
\tag{38}
$$

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,

$$\frac{\partial E[w_{firm,j}|\Omega_j]}{\partial \tilde{b}_j} = -\left[1-pdef_j\right] - \left[pdef_j\right]\psi c_d \frac{\partial k_j}{\partial \tilde{b}_j} - \left[\int_{-\infty}^{\infty} \phi(C|\theta, z_j)\frac{\partial C}{\partial \tilde{b}_j} d\epsilon_j \phi(\theta|\Omega_j) d\theta\right]\psi c_d k_j$$
$$+ \alpha k_j^{\alpha-1}\frac{\partial k_j}{\partial \tilde{b}_j}\int_{-\infty}^{\infty}\int_{C(\theta)}^{\infty} \Lambda(\theta) e^{\epsilon_j}\phi(\epsilon_j|\theta, z_j) d\epsilon_j e^{\theta}\phi(\theta|\Omega_j) d\theta \tag{39}$$

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

$$\frac{\partial E[w_{firm,j}|\Omega_j]}{\partial \tilde{q}_j} = -\left[pdef_j\right]\psi c_d \frac{\partial k_j}{\partial q_j} - \left[\int_{-\infty}^{\infty} \phi(C|\theta, z_j)\frac{\partial C}{\partial q_j} d\epsilon_j \phi(\theta|\Omega_j) d\theta\right]\psi c_d k_j$$
$$+ \alpha k_j^{\alpha-1}\frac{\partial k_j}{\partial q_j}\int_{-\infty}^{\infty}\int_{C(\theta)}^{\infty} \Lambda(\theta) e^{\epsilon_j}\phi(\epsilon_j|\theta, z_j) d\epsilon_j e^{\theta}\phi(\theta|\Omega_j) d\theta \tag{40}$$

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

$$\frac{\partial E[w_{bank,j}|\Omega_j]}{\partial \tilde{b}_j} = \left[(1-pdef_j) - (1-\psi pdef_j)\frac{q_j}{q^f}\right] + \tilde{b}_j\left[-\frac{\partial pdef_j}{\partial \tilde{b}_j} + \psi\frac{q_j}{q^f}\frac{\partial pdef_j}{\partial \tilde{b}_j}\right] \tag{41}$$

where

$$\frac{\partial pdef_j}{\partial \tilde{b}_j} = \left[\int_{-\infty}^{\infty} \phi(C|\theta, z_j)\frac{\partial C}{\partial \tilde{b}_j} d\epsilon_j \phi(\theta|\Omega_j) d\theta\right] \tag{42}$$

Finally,

$$\frac{\partial E[w_{bank,j}|\Omega_j]}{\partial q_j} = +\tilde{b}_j\left[-\frac{\partial pdef_j}{\partial q_j} + \psi\frac{q_j}{q^f}\frac{\partial pdef_j}{\partial q_j} - (1-\psi pdef_j)\frac{1}{q^f}\right] \tag{43}$$

where

$$\frac{\partial pdef_j}{\partial q_j} = \left[\int_{-\infty}^{\infty} \phi(C|\theta, z_j)\frac{\partial C}{\partial q_j} d\epsilon_j \phi(\theta|\Omega_j) d\theta\right] \tag{44}$$

C Proofs

Proposition 1. Assume no moral hazard 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 38.

$$q = q^f \left[1 - \int_{-\infty}^{\infty} \Phi_e(C(\theta)|z,\theta)\phi_\theta(\theta|\Omega)d\theta\right] \tag{45}$$

In steady state

$$q^* = q^f \left[1 - \Phi\left(\frac{C^*}{\sqrt{Var[\epsilon|\theta,z]}}\right)\right] \tag{46}$$

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

$$dq = -\, q^f \Phi\left(\frac{C^*}{\sqrt{Var[\epsilon|\theta,z]}}\right)\int_{-\infty}^{\infty}\left[dC - dE[e|z,\theta]\right]\phi_\theta\left(\theta|z\right)d\theta \tag{47}$$

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

$$dq = -q^f\Phi\left(\frac{C^*}{\sqrt{Var[\epsilon|\theta,z]}}\right)\int_{-\infty}^{\infty}\left[(1-\alpha)]\hat{k} - \hat{q} - \eta_{\Lambda(M),\theta}d\theta - \frac{\partial E[\epsilon|\tilde{z}]}{\partial\theta}d\theta - \frac{\partial E[\epsilon|\tilde{z}]}{\partial z}dz\theta\right]\phi_\theta\left(\theta|z\right)d\theta \tag{48}$$

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

$$\begin{aligned} \eta_{\Lambda(M),\theta}d\theta &= -\frac{M}{\Lambda(M)}\Lambda'(M)\frac{M'(\theta)d\theta}{M} \\ &= \eta_{\Lambda,M}\hat{M} \end{aligned} \tag{49}$$

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

$$\hat{q} = \tilde{L}_1\left\{-\left(1-\alpha\right)\hat{k} + E[a|z] + \eta_{\Lambda,M}E[\hat{M}|z]\right\} \tag{50}$$

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 38

$$\frac{d\frac{\partial E[w_{firm,j}|\Omega_j]}{\partial \tilde{b}_j}}{\frac{\partial E[w_{firm,j}|\Omega_j]}{\partial \tilde{b}_j}} - \frac{d\frac{\partial E[w_{bank,j}|\Omega_j]}{\partial \tilde{b}_j}}{\frac{\partial E[w_{bank,j}|\Omega_j]}{\partial \tilde{b}_j}} = \frac{d\frac{\partial E[w_{firm,j}|\Omega_j]}{\partial q_j}}{\frac{\partial E[w_{firm,j}|\Omega_j]}{\partial q_j}} - \frac{d\frac{\partial E[w_{bank,j}|\Omega_j]}{\partial q_j}}{\frac{\partial E[w_{bank,j}|\Omega_j]}{\partial q_j}} \tag{51}$$

and let's see each term individually.

- From equation 39, 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,

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

As a result,

$$\begin{aligned}\frac{d\frac{\partial E[w_{firm,j}|\Omega_j]}{\partial \tilde{b}_j}}{\frac{\partial E[w_{firm,j}|\Omega_j]}{\partial \tilde{b}_j}} =& \frac{\left\{\alpha k_j^{\alpha-1}q\Lambda e^{\frac{Var[\epsilon|\theta,z]}{2}}\left[\Phi_\epsilon(\cdot)+\phi_\epsilon(\cdot)\right]+\phi_e\left(\frac{C^*}{\sqrt{Var[\epsilon|\theta,z]}}\right)\right\}}{\frac{\partial E[w_{firm,j}|\Omega_j]}{\partial \tilde{b}_j}}\times\\ &\times\left\{\hat{q}-(1-\alpha)\hat{k}+E[a|z]+\eta_{\Lambda,M}E[\hat{M}|z]\right\}\\ =& L_1\left\{\hat{q}-(1-\alpha)\hat{k}+E[a|z]+\eta_{\Lambda,M}E[\hat{M}|z]\right\}\end{aligned} \tag{53}$$

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 40, the derivative of expected firm manager payoff with respect to bond price q is given by

$$\frac{\partial E[d_{firm}|\Omega]}{\partial q} = \alpha k_j^{\alpha-1}\frac{k}{q}\int_{-\infty}^{\infty}\Lambda(\theta)e^{\frac{Var[\epsilon|\theta,z]}{2}+E[\epsilon|\theta,z]}\Phi_\epsilon\left(\frac{Var[\epsilon|\theta,z]+E[\epsilon|\theta,z]-C(\theta)}{\sqrt{Var[\epsilon|\theta,z]}}\right)e^\theta\phi(\theta|\Omega_j)d\theta \tag{54}$$

Differentiating,

$$\begin{aligned} d\frac{\partial E[d_{firm}|\Omega]}{\partial q} =& \alpha k_j^{\alpha-1}\frac{k}{q}\Lambda e^{\frac{Var[\epsilon|\theta,z]}{2}}\left[\Phi_\epsilon\left(\cdot\right)+\phi_\epsilon\left(\cdot\right)\right]\left\{\hat{q}-\left(1-\alpha\right)\hat{k}+E[a|z]+\eta_{\Lambda,M}E[\hat{M}|z]\right\} \\ &+\alpha k_j^{\alpha-1}\frac{k}{q}\Lambda e^{\frac{Var[\epsilon|\theta,z]}{2}}\Phi_\epsilon\left(\cdot\right)(\hat{k}-2\hat{q}) \end{aligned} \tag{55}$$

therefore

$$\begin{aligned} \frac{d\frac{\partial E[w_{firm,j}|\Omega]}{\partial q}}{\frac{\partial E[w_{firm,j}|\Omega]}{\partial q}} &= \frac{\alpha k_j^{\alpha-1}\frac{k}{q}\Lambda e^{\frac{Var[\epsilon|\theta,z]}{2}}\left[\Phi_\epsilon\left(\cdot\right)+\phi_\epsilon\left(\cdot\right)\right]}{\frac{\partial E[w_{firm,j}|\Omega]}{\partial q}}\times \\ &\times\left\{\hat{q}-\left(1-\alpha\right)\hat{k}+E[a|z]+\eta_{\Lambda,M}E[\hat{M}|z]\right\}+(\hat{k}-2\hat{q}) \\ &= L_2\left\{\hat{q}-\left(1-\alpha\right)\hat{k}+E[a|z]+\eta_{\Lambda,M}E[\hat{M}|z]\right\}+(\hat{k}-2\hat{q}) \end{aligned} \tag{56}$$

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 41, 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,

$$d\frac{\partial E[d_{bank}|\Omega]}{\partial\tilde{b}} = -\,\phi_e\left(\frac{C^*}{\sqrt{Var[\epsilon|\theta,z]}}\right)\left\{\hat{q}-(1-\alpha)\,\hat{k}+E[a|z]+\eta_{\Lambda,M}E[\hat{M}|z]\right\}$$
$$-\,\frac{q}{q^f}\hat{q}-(1-\alpha)\phi_e\left(\frac{C^*}{\sqrt{Var[\epsilon|\theta,z]}}\right)\frac{C^*}{Var[\epsilon|\theta,z]}\left\{\hat{q}-(1-\alpha)\,\hat{k}+E[a|z]+\eta_{\Lambda,M}E[\hat{M}|\right. \tag{57}$$

therefore

$$\frac{d\frac{\partial E[d_{bank}|\Omega]}{\partial\tilde{b}}}{\frac{\partial E[d_{bank}|\Omega]}{\partial\tilde{b}}} = \frac{\phi_e\left(\frac{C^*}{\sqrt{Var[\epsilon|\theta,z]}}\right)(1+(1-\alpha)\frac{C}{Var[\epsilon|\theta,z]})}{\frac{\partial E[d_{bank}|\Omega]}{\partial\tilde{b}}}\left\{\hat{q}-(1-\alpha)\,\hat{k}+E[a|z]+\eta_{\Lambda,M}E[\hat{M}|z]\right\}$$
$$-\,\frac{\frac{q}{q^f}}{\frac{\partial E[d_{bank}|\Omega]}{\partial\tilde{b}}}\hat{q}$$
$$= L_3\left\{\hat{q}-(1-\alpha)\,\hat{k}+E[a|z]+\eta_{\Lambda,M}E[\hat{M}|z]\right\}-L_4\hat{q} \tag{58}$$

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 43, 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,

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

Therefore

$$\frac{d\frac{\partial E[d_{bank}|\Omega]}{\partial q}}{\frac{\partial E[d_{bank}|\Omega]}{\partial q}} = (\hat{k}-\hat{q}) - \frac{\frac{k}{q}\alpha\phi_e\left(\frac{C^*}{\sqrt{Var[\epsilon|\theta,z]}}\right)}{\frac{\partial E[d_{bank}|\Omega]}{\partial q}}\hat{q}$$
$$- \frac{\frac{k}{q}\alpha\phi_e\left(\frac{C^*}{\sqrt{Var[\epsilon|\theta,z]}}\right)\frac{C^*}{Var[\epsilon|\theta,z]}}{\frac{\partial E[d_{bank}|\Omega]}{\partial q}}\left\{\hat{q}-(1-\alpha)\hat{k}+E[a|z]+\eta_{\Lambda,M}E[\hat{M}|z]\right\}$$
$$= (\hat{k}-\hat{q}) - L_5\left\{\hat{q}-(1-\alpha)\hat{k}+E[a|z]+\eta_{\Lambda,M}E[\hat{M}|z]\right\} - L_6\hat{q} \tag{59}$$

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 53, 56, 58, and 59 in equation 51 and get

$$(L_1-L_2-L_3-L_5+L_4+1-L_6)\hat{q} = -(L_1-L_2-L_3-L_5)\left\{-(1-\alpha)\hat{k}+E[a|z]+\eta_{\Lambda,M}E[\hat{M}|z]\right\}$$
$$\hat{q} = \tilde{L}_2\left\{-(1-\alpha)\hat{k}+E[a|z]+\eta_{\Lambda,M}E[\hat{M}|z]\right\} \tag{60}$$

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 50 in 60

$$\tilde{L}_1\left\{-(1-\alpha)\hat{k}+E[a|z]+\eta_{\Lambda,M}E[\hat{M}|z]\right\} = \tilde{L}_2\left\{-(1-\alpha)\hat{k}+E[a|z]+\eta_{\Lambda,M}E[\hat{M}|z]\right\}$$
$$(\tilde{L}_1-\tilde{L}_2)\left\{-(1-\alpha)\hat{k}+E[a|z]+\eta_{\Lambda,M}E[\hat{M}|z]\right\} = 0 \tag{61}$$

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

$$\hat{k} = \frac{1}{1-\alpha}(E[a|z]-\gamma E[\hat{M}|z])$$
$$\hat{q} = 0 \tag{62}$$

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

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

Moreover, from 45

$$\hat{q}_j = -\zeta \hat{p}(def_j|\Omega_j) = 0 \tag{63}$$

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

$$\begin{aligned}
E[w_{bank,j}|z_j,\theta] &= -p^*(def|0)\hat{p}(def_j|z_j,\theta) - \frac{q^*}{q_j}\hat{q}_j \\
&= -p^*(def|0)[\hat{p}(def_j|z_j,\theta) - E[\hat{p}(def_j|\Omega_j)|\theta]]
\end{aligned} \tag{64}$$

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

Proposition 2. Consider the global game when θ is observed

$$\hat{k} = \frac{1}{1-\alpha}E[a_j|z] - \frac{1}{1-\alpha}\gamma\mu\left(\theta + \alpha\hat{K}\right) \tag{65}$$

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

$$\begin{aligned}
K &= \frac{1}{1-\alpha}(1-\gamma\mu)\theta - \frac{\alpha}{1-\alpha}\gamma\mu K \\
K &= \frac{(1-\gamma\mu)}{1-\alpha+\alpha\gamma\mu}\theta
\end{aligned} \tag{66}$$

■

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

$$\hat{k} = \frac{1}{1-\alpha}E[a_j|z_j] - \frac{1}{1-\alpha}\gamma\mu\left(E[\hat{\theta}|z_j] + \alpha E[\hat{K}|z_j]\right) \tag{67}$$

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 $k_j = \chi z_j$

$$\begin{aligned} k_j &= \frac{1}{1-\alpha}(m - \gamma\mu[1+\alpha\chi]\delta)z_j \\ \chi &= \frac{1}{1-\alpha}(m - \gamma\mu[1+\alpha\chi]\delta) \\ \chi &= \frac{(m-\gamma\mu\delta)}{1-\alpha+\gamma\mu\alpha\delta} \\ K &= \frac{(m-\gamma\mu\delta)}{1-\alpha+\gamma\mu\alpha\delta}\theta \end{aligned} \tag{68}$$

■

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

$$\begin{aligned} \widehat{\pi}_j &= -\gamma\hat{M} + a_j + \alpha k_j \\ &= -\gamma\mu\left(\theta + \alpha\frac{(m-\gamma\mu\delta)}{1-\alpha+\gamma\mu\alpha\delta}\theta\right) + a_j + \alpha k_j \end{aligned} \tag{69}$$

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

$$\begin{aligned} E[\widehat{\pi}_j|z_j,\theta] - E[E[\widehat{\pi}_j|z_j]|\theta] =& E[a_j|z_j,\theta] - E[E[a_j|z_j]|\theta] - \gamma(\hat{M} - E[\hat{M}|z_j]) \\ =& \left[(1-m) - \gamma\mu(1-\delta)\left(1+\alpha\frac{(m-\gamma\mu\delta)}{1-\alpha+\gamma\mu\alpha\delta}\right)\right]\theta \end{aligned} \tag{70}$$

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

$$\begin{aligned} (1-m) - \gamma\mu(1-\delta)\left(1+\alpha\frac{(m-\gamma\mu\delta)}{1-\alpha+\gamma\mu\alpha\delta}\right) > 0 \\ (m-\gamma\mu\delta)\left(1-\alpha+\alpha\gamma\mu\right) > (1-\gamma\mu)(1-\alpha+\gamma\mu\alpha\delta) \end{aligned} \tag{71}$$

■

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

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

Aggregating across islands

$$\begin{aligned}
\hat{p}(def|z_j,\theta) &= \xi\left[(1-\alpha)\,\hat{K}-\hat{Q}+\gamma\hat{M}-\theta\right]\\
\hat{p}(def|z_j,\theta) &= \xi\left[(1-\alpha+\alpha\gamma\mu)\,\hat{K}-(1-\gamma\mu)\theta\right]\\
\hat{p}(def|z_j,\theta) &= \xi\left[(1-\alpha+\alpha\gamma\mu)\,\frac{(m-\gamma\mu\delta)}{1-\alpha+\gamma\mu\alpha\delta}-(1-\gamma\mu)\right]\theta
\end{aligned} \tag{73}$$

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

$$(m-\gamma\mu\delta)\,(1-\alpha+\alpha\gamma\mu)>(1-\gamma\mu)(1-\alpha+\gamma\mu\alpha\delta) \tag{74}$$

■

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

$$\hat{p}(def_j|z_j)=\frac{\phi_{e|0}(C^*)}{\Phi_{e_0}(C^*)}\left[(1-\alpha)\,\hat{k}_j-\hat{q}_j+\gamma E[\hat{M}|z_j]-E[a_j|z_j]\right] \tag{75}$$

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

$$\hat{p}(def_j|z_j,\theta)=\frac{\phi_{e|0}(C^*)}{\Phi_{e_0}(C^*)}\left[(1-\alpha)\,\hat{k}_j-\hat{q}_j+\gamma\hat{M}-E[a_j|z_j,\theta]\right] \tag{76}$$

The average bank profits equal the difference between the two

$$\begin{aligned}
E[\tilde{\pi}_{bank,j}|z_j,\theta] &\propto -[\hat{p}(def_j|z_j,\theta)-E[\hat{p}(def_j|z_j)|\theta]]\\
&\propto -[E[a_j|z_j,\theta]-E[E[a_j|z_j]|\theta]-\gamma(M-E[M|z_j])]
\end{aligned} \tag{77}$$

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

$$(m-\gamma\mu\delta)\,(1-\alpha+\alpha\gamma\mu)>(1-\gamma\mu)(1-\alpha+\gamma\mu\alpha\delta) \tag{78}$$

■

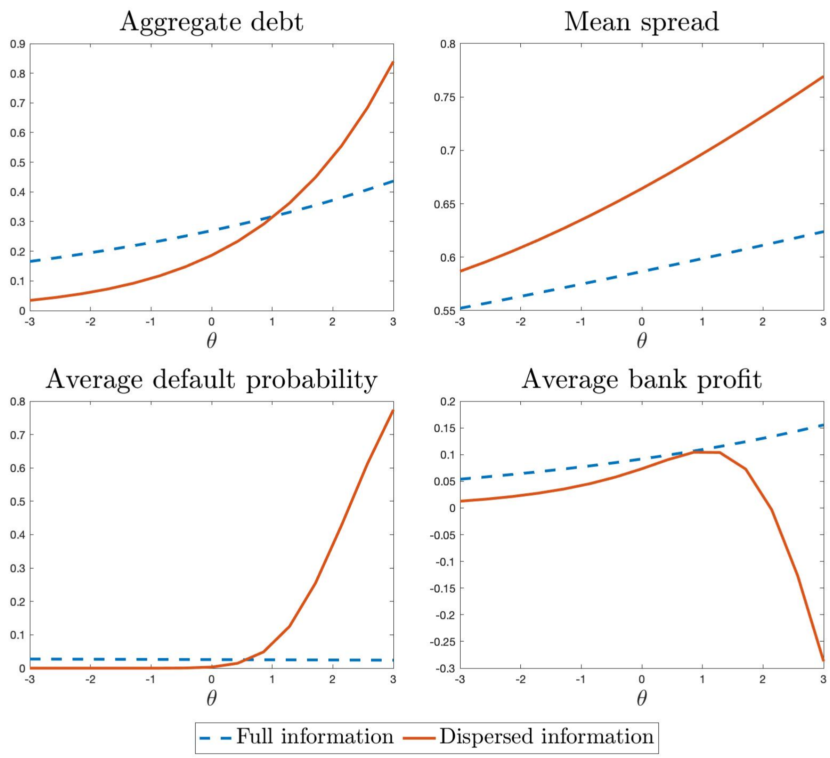

Figure 10

D Equal bargaining power

In the baseline model I assume firm and bank managers decide loan quantity and prices in 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 the same bargaining power on bank and firm.

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

$$max_{q_j,b_j}\ (E[w_{firm}|\Omega_j])^{\beta}(E[w_{bank}|\Omega_j])^{1-\beta} \tag{79}$$

Figure 10, and 11 illustrate the equilibrium where $\beta = 0.5$. Differently from the baseline model, risk premium increases in booms even if risk declines, as the bank extract 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.

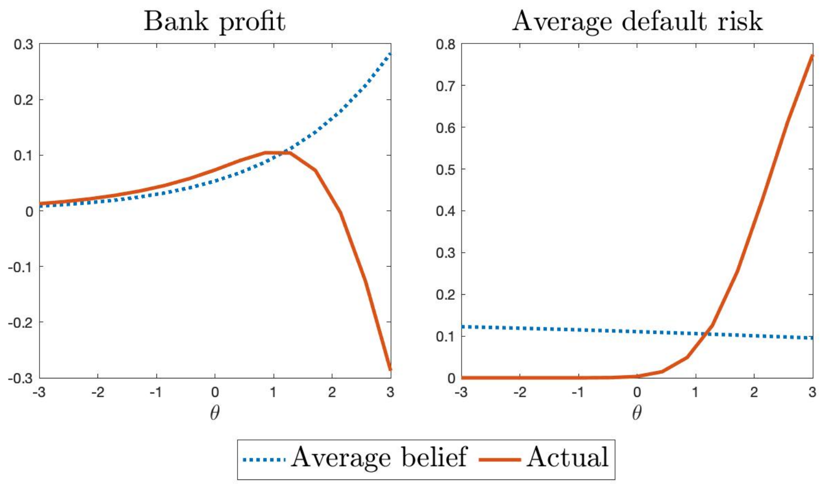

Figure 11

First stage Next , consider the same convex compensation structure 7 on the bank manager instead

$$w_{bank} = \begin{cases} b_j(1-q_j) - b^f(1-q^f) & \text{if } \Lambda(M)A_j{k_j}^{\alpha} \geq b_j \quad (repay) \\ (1-\alpha_b)[b_j(-q_j) - b^f(1-q^f)] & \text{if } \Lambda(M)A_j{k_j}^{\alpha} < b_j \quad (default) \end{cases} \tag{80}$$

where α_b is the option holding of the bank manager. In the first stage the island decide to pay the information cost if

$$\begin{aligned} &(E[\pi^*_{firm}(\theta \in \Omega_j, \lambda)] - \beta c)^{\beta}(E[w^*_{bank}(\theta \in \Omega_j, \lambda)] - (1-\beta)c)^{1-\beta} \\ &\geq (E[\pi^*_{firm}(\theta \notin \Omega_j, \lambda)])^{\beta}(E[w^*_{bank}(\theta \notin \Omega_j, \lambda)])^{1-\beta} \end{aligned} \tag{81}$$

where I assume that bank and firm split the information cost c according to their bargaining power β as well. Figure 12 reports the equilibrium information λ for different values of bank manager compensation convexity (assuming no convexity on firm manager's compensation). Higher moral hazard incentives on bank manager aalso reduces optimal information choice.

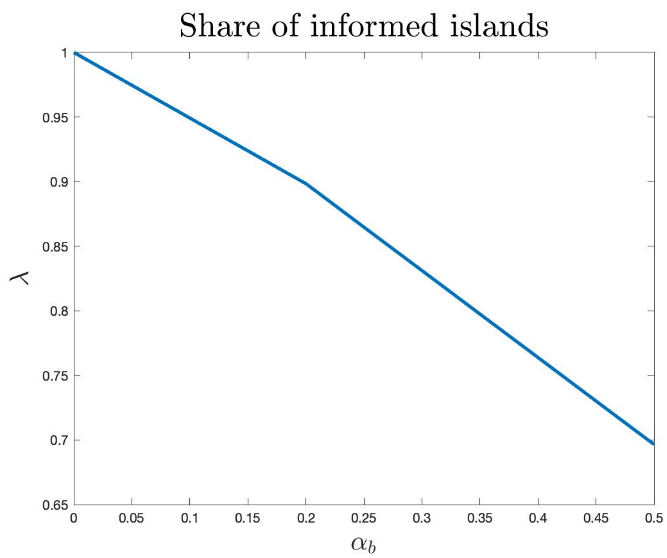
Share of informed islands
1
0.95
0.9
0.85
0.8
0.75
0.7
0.65
λ
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0.5
α_b

Figure 12