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Rational Exuberance Booms and Asymmetric Business Cycles

Bank of Finland Research
Discussion Papers
24 • 2015

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October 27, 2015

Abstract

I propose a theory of information production and learning in credit markets in which the incentives to engage in activities that reveal information about aggregate fundamentals vary over the business cycle and may account for both the excessive optimism that fueled booms preceding financial crises and the slow recoveries that followed. In my theory, information about aggregate fundamentals is produced along two dimensions. First, optimistic beliefs lead to a fall in private investment in information reducing the quality of information available, an intensive margin. This gives rise to episodes of rational exuberance where optimism sustains booms even as fundamentals decline in the buildup to crises. Second, the quantity of information is increasing in the level of economic activity, an extensive margin. Thus, recoveries are slow since the low levels of investment and output provide little information about improvements in the state of the economy. Consistent with model predictions, I find supporting evidence in terms of a U-shaped pattern in macro-uncertainty measures over the business cycle. I also discuss the implications on endogenous information production on cyclical macro-prudential policy.

Keywords: Business cycle asymmetry, Macro-uncertainty, Social learning

JEL Codes: D83, E32, E44, G01, G14

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* I thank Alberto Martin, Fernando Broner, Jose Luis Peydro, Xavier Freixas, Kristoffer Nimark, and participants at the CREI International Lunch, the UPF Finance Lunch, HECER and Bank of Finland seminars for their comments on earlier versions of this paper.

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1. Introduction

Modern business cycles are asymmetric. Although recessions are typically sharp and short, the recovery process tends to be prolonged and gradual. One theory to account for this is that the speed of learning co-varies with economic activity.[1] Expansions are slow to start because they do so from periods of low economic activity which reveal little about the state of the economy. The opposite is true at the height of expansions, when production and investment are high and learning is quick. Although very insightful, this theory has an important limitation. In many instances, expansions that end in financial crises seem *ex post* to have been fueled by excessive optimism, which sustained economic activity and led agents to disregard negative signals about the state of the economy. The recent Financial Crisis is a case in point. According to the report of the Financial Crisis Inquiry Commission: *"this financial crisis was avoidable.... there were warning signs. The tragedy was that they were ignored or discounted"*. This is of course problematic for the theory of learning mentioned above. After all, should not the high levels of investment and production at the height of an expansion produce a very precise signal of any changes in the underlying economic fundamentals? In this paper, I develop a model of information production to show why this may not be the case.

The main feature of my model is that the precision of information about the state of the economy depends on two channels. On the one hand, the state of the economy is partially revealed by observing the outcome from running investment opportunities. This is the channel emphasized in the literature, in which the production of information is increasing in the level of economic activity - *an extensive margin.* On the other hand, agents in my model can also invest in producing information about each project, and ultimately about the state of the economy, before undertaking them - *an intensive margin.* The key result is that this type of information production may decline once beliefs become highly optimistic. The reason is simple: economic agents have little reason to invest in more information about projects if they expect that most of them will do well. Therefore, a central prediction of my model is that the amount of information produced on the underlying state of the economy may decline as the economy approaches the peak of an expansion.

To formalize this theory, I embed these mechanisms in a simple model of credit markets with Bayesian learning about an unobserved aggregate fundamental and where there are no other distortions to financial intermediation. Resources and investment opportunities (projects) are separately endowed to two types of agents, financiers and entrepreneurs. A cycle emerges in that the fundamental, the aggregate quality of the pool of entrepreneurs, may be in one of two states, a high state

[1] See for example Veldkamp (2005); Van Nieuwerburgh and Veldkamp (2006); Ordonez (2013), and Fajgelbaum et al. (2013).

with a large proportion of good projects and a low state with less. The fundamental is persistent and the transition between the two states is symmetric. Agents learn about the aggregate state by observing past credit market and production outcomes. In this environment I include a costly screening technology by which an individual lender may produce information about a particular borrower's type increasing the quality of information revealed in markets.

In this setting, the acquisition of private information today (a particular borrower's type) affects the quality of public information available tomorrow (the average quality of all borrowers). In turn prior beliefs determine how much information will be generated the next period. To simplify the narrative, I abstract from conventional frictions to financial intermediation such as asymmetric information and imperfect banking competition. In the model, agents make choices to maximize the expected returns from running these projects where the only constraint to achieving the first-best outcome is imperfect information about the aggregate state and the quality of individual projects.

As in the current literature, my model generates asymmetric business cycles with slow recoveries. Nevertheless, once the economy enters a period of high optimism, it tends to stay there. When fundamentals deteriorate in these periods, the low levels of investment in private information generate weak signals. Agents are less likely to perceive the fall in fundamentals and remain optimistic - what I refer to as rationally exuberant. These episodes are likely to occur in economies and periods of time where the relative cost to producing information is within intermediate levels. This implies that financial development, by gradually easing the cost to private information production, may entail a transition period where business cycles are more volatile and crises episodes occur more frequently. Further, information is under-produced in the competitive equilibrium. This occurs both at the onset of recoveries and at the height of optimistic booms. Thus, policies which promote credit and investment during recessions, by generating more information, can help speed up the recovery process. In addition, macro-prudential policies which effectively limit the expected volatility of financial intermediary profits during credit booms may also help mitigate the likelihood of rational exuberance booms and crises episodes.

I also document evidence on macro-uncertainty measures from the U.S. consistent with the model mechanisms. I show that macro-uncertainty exhibits a U-shaped pattern over expansions, initially declining but then appear to increase prior to NBER-dated peaks in economic activity. This pattern is present in two widely used measures, forecaster disagreement and the *VIX*[2], which I complement with a forecast uncertainty index constructed from the average diffusion of individual forecasts.

[2]The *VIX* corresponds to the option-implied expected 30-day volatility of the *S&P 500 Index*.

Related Literature. The model presented here complements the literature on imperfect information and uncertainty as important drivers of short-run fluctuations.[3] It provides an information production mechanism as way to endogenize uncertainty *shocks*. Through the extensive margin to information production, I incorporate the positive feedback between economic activity and the precision of information in current models of social learning over the business cycle such as Veldkamp (2005); Van Nieuwerburgh and Veldkamp (2006); Ordonez (2013), and Fajgelbaum et al. (2013). Unlike these models which imply a monotonic relationship between beliefs and information production, the inclusion of the intensive margin in my model allows for the occasional highly optimistic boom where information production falls and generates rising uncertainty.[4]

The intensive margin in my model draws from the literature on boom-bust episodes as arising from informational cascades and herding.[5] In my model, a similar feature appears during periods of high optimism at the heights of expansions. I refer to these as episodes of rational exuberance where agents rationally discount warning signs because they are thought to be less precise. This is in contrast to models with adaptive or rules-based learning such as in Bullard et al. (2010) or behavioral biases as in Gennaioli et al. (2013). Further, agents in my model do not internalize the information benefits that accrue to agents in future periods and thus information is under-produced as in Burguet and Vives (2000).

I use screening in credit markets as the means by which private information is produced. A reduction in the incentives to use this technology at the height of booms appears prominently in the credit screening literature (Ruckes, 2004; Berger and Udell, 2004; Dell'Ariccia and Marquez, 2006; Gorton and Ordonez, 2014a). The particular screening mechanism I employ in the model is adapted from learning about collateral in Gorton and Ordonez (2014a,b). My mechanism differs in two key points. First, I introduce heterogeneity across entrepreneurs such that for any given point in time a proportion of borrowers gets screened. This smooths the transition between periods of high and low screening. Second, I focus on producing information about the productivity of projects themselves and effectively endogenize the formation of beliefs about the aggregate fundamental. As such, this paper complements crises models arising from a shock to beliefs or investor sentiment.[6] Unlike the majority of the literature on credit market screening, I have not included a role for externalities arising from competition in the banking sector (see Ruckes, 2004; Petriconi, 2012)or

[3] Examples are Beaudry and Portier (2006); Collard et al. (2009); Blanchard et al. (2013); Bloom (2009); Barsky and Sims (2011); Eusepi and Preston (2011); Bloom et al. (2012); Christiano et al. (2014).

[4] An alternative view is that uncertainty rises prior to or during crashes as these are realizations of unusual or rare events as in Nimark (2014) and Orlik and Veldkamp (2014).

[5] Related examples from the literature are Bikhchandani et al. (1992),Chamley and Gale (1994), Caplin and Leahy (1994), Chari and Kehoe (2003), Chamley (2004), and Broner (2008).

[6] For example see Boz (2009) for crises in developing economies, and Boz and Mendoza (2014), Martin and Ventura (2011), Gennaioli et al. (2013), and Gorton and Ordonez (2014a) for the recent U.S. Financial crisis.

information asymmetry between borrowers and lenders in the form of adverse selection (Broecker, 1990; Freixas et al., 2007) or costly state verification (Ordonez, 2013). This is done largely to simplify the model and isolate the effects of my mechanism. As the above-mentioned references would indicate, the inclusion of these frictions may amplify the pro-cyclicality of information production and asymmetry in business cycles.

The next section develops the model while Section 3 establishes the business cycle implications. Section 4 provides some evidence and Section 5 concludes.

2. Credit markets and information production

A. Setup

Let us focus on a simple economy where resources and investment opportunities are separately endowed to two types of risk-neutral agents who maximize end-of-period consumption. We have a set $M \in \mathbb{N}$ financiers with an initial endowment W of a consumption good at the beginning of the period. Then we have $N \in \mathbb{N}$ entrepreneurs each of which have an investment opportunity - a project - in which some investment K of the consumption good made at the beginning of the period can potentially yield Y consumption goods at the end of the period. A credit market exists to facilitate the transfer of resources from financiers to entrepreneurs.

However, the return to investing in each project depends on two factors which differ across entrepreneurs. In particular, if an entrepreneur i borrows K_i then he may obtain Y_i according to the following production function:

$$Y_i = \begin{cases} A_i K_i^{\alpha} & \text{with probability } \theta_i \quad 0 < \alpha < 1 \\ 0 & \text{with probability } 1 - \theta_i \end{cases}$$

The productivity parameter A_i differs across entrepreneurs and comes from some distribution with an upper and lower bound $F(A_i; \underline{A}, \bar{A})$. The success probability θ_i also (independently) differs across entrepreneurs. Some projects are "good" and have a high probability of success (θ_G) and others are "bad" with a low probability of success (θ_B). In the aggregate a proportion μ of projects are of the good type and this is the aggregate fundamental in the economy. The productivity parameter A_i is publicly observed by all agents but the success probability is not. In particular both the financiers and the entrepreneurs do not know the type of the projects they have. In this section only the aggregate proportion of good projects μ is known at the beginning of the period.

Both entrepreneurs and financiers have alternative uses for their time and resources - outside opportunities. Financiers have a savings technology which allows them to convert some or all of their endowments at the beginning of the period to more resources at the end of the period at the rate $1 + r_f$. This is the opportunity cost of financing in the model. On the other hand, if entrepreneurs do not run their project then they may use their time on an outside activity that yields a fixed output of w consumption goods at the end of the period. To abstract from potential distortions to the supply of credit, I assume that there are substantially more financiers than entrepreneurs and that there are sufficient endowments to fully finance all of the projects at their desired levels of investment.[7]

Finally, financiers have a screening technology which allows them to perfectly reveal a project's type at a cost of γ goods. In the credit market, financiers offer two types of loan contracts. They may provide credit without screening the borrower and thus the loan rate is conditioned on the average success probability of all entrepreneurs. Alternatively, they offer a screening contract where they first screen the borrower and then the entrepreneur may choose how much to borrow at the loan rate which is contingent on the screening outcome.[8]

In the market for loans each entrepreneur who wants to invest and borrow faces a menu of contracts from all financiers who will have to compete for the loan. I denote the screening contract and a no-screening contract with subscripts S and I respectively. Each contract details the (gross) rate of interest on the loan $R(\theta_i, K_i, S)$ and $R(\mu, K_i, I)$. Output from projects that are run are costlessly verifiable and ensures no strategic default in equilibrium. Given this menu, the entrepreneur chooses the loan type and size of the loan K_i and invests in the project. If financiers make identical offers, the entrepreneur is randomly matched to one of them. At the end of the period, projects that are run either succeed or fail, repayments are made and consumption takes place.

Equilibrium definition and derivation

Equilibrium is defined as Sub-game Perfect Nash. Given the state of the economy μ_t, equilibrium is given by the set of choices:

[7] These assumptions ensure that the participation constraint for financiers will bind and pin down the loan interest rate to the opportunity cost of financing adjusted for the probability of repayment.

[8] To rule out potential cross-sectional information spillovers as in Petriconi (2012), I assume that screening and lending are a packaged deal and a commitment to borrow from the same financier comes with screening.

1. A menu of contract offers consisting of screening loan rates $R_j(\theta_G, K_i, S)$, $R_j(\theta_B, K_i, S)$ for revealed good and bad types, and the no-screening interest rate $R_j(\theta_t, K_i, I)$ set by each each financier $j \in [1 : M]$ and for every potential match with the set of entrepreneurs $i \in [1 : N]$.
2. A set of participation, contract type, and loan size K_i choices for all entrepreneurs $i \in [1 : N]$

Here, θ_t reflects the average success probability given by the proportion μ_t of good projects. The time subscript t is used to denote an aggregate variable which agents will be learning about in the dynamic version of the model. These choices are made such that each financier and entrepreneur maximize expected end-of-period consumption.

B. *Credit market equilibrium*

Optimal contracts

The menu of screening (S) and no-screening (I) loan contracts set by each financier yield interest rates such that she is at least as well of as investing the loaned funds into her savings technology:

$$R(\theta_t, I) = \frac{1 + r_f}{\theta_t} \tag{1}$$

$$R(\theta_i, S) = R(\theta_i, I) + \frac{(1 + r_f)\gamma}{\theta_i K_i} \quad i \in \{G, B\} \tag{2}$$

Competition guarantees that this participation constraint holds with equality. Moreover, in the absence of information asymmetry and strategic default, the expected probability of repayment is equivalent to the expected success probability of the average entrepreneur. For the screening contract we have that the participation constraint for the financier, which now includes the cost of screening, must hold for both realizations.

Screening and participation choices

With this menu of interest rates, the entrepreneur may then decide on the optimal size of borrowing:

$$K_i^* = \left[\frac{\alpha \theta_i A_i}{1 + r_f}\right]^{\frac{1}{1-\alpha}} \tag{3}$$

where $\theta_i \in \{\theta_t, \theta_G, \theta_B\}$ depending on whether the entrepreneur chooses the screening or no-screening contract and the screening outcome.[9] In turn, expected profits from either the screening or the no-screening contracts are:

$$\mathbb{E}[\pi_i|\mu_t, I] = \theta_t^{\frac{1}{1-\alpha}} A_i^{\frac{1}{1-\alpha}} \Lambda \tag{4}$$

$$\mathbb{E}[\pi_i|\mu_t, S] = (\mu_t \theta_G^{\frac{1}{1-\alpha}} + (1-\mu_t)\theta_B^{\frac{1}{1-\alpha}}) A_i^{\frac{1}{1-\alpha}} \Lambda - \gamma(1+r_f) \tag{5}$$

where $\Lambda \equiv \left[\frac{\alpha}{(1+r_f)^\alpha}\right]^{\frac{1}{1-\alpha}} \left[\frac{1-\alpha}{\alpha}\right]$. Figure 1 plots expected profits under both contracts across different levels of productivities on the horizontal axis. The solid line (**I**) is for the no-screening contract whereas the dashed line (**S**) refers to the screening contract profits. Screening profits are initially lower due to the additional cost of screening but have a steeper incline as higher productivity implies a larger loan size to leverage the information gains.

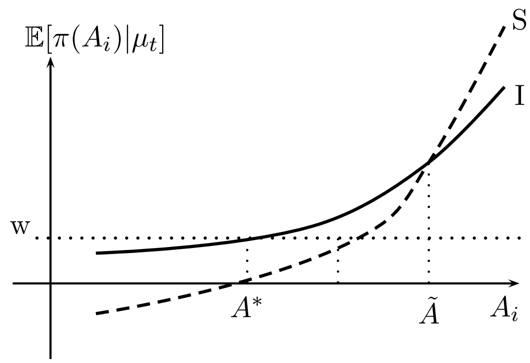

Figure 1: Profits over productivity levels

The point of intersection identifies a threshold productivity $\tilde{A}$ above which screening is preferred. Similarly, there is another threshold A^* such that investing in the project yields more profits than the outside opportunity w. Combining equations 4 and 5 yield the following:

$$\tilde{A}(\mu_t) = \left[\frac{\gamma(1+r_f)}{Z(\mu_t)\Lambda}\right]^{1-\alpha} \tag{6}$$

$$A^*(\mu_t) = \frac{1}{\theta_t \Lambda} min\{w, \frac{w+\gamma(1+r_f)}{\zeta(\mu_t)}\} \tag{7}$$

where $Z(\mu_t)$ and $\zeta(\mu_t)$ reflects the private value of information.[10] In this economy, the entrepreneurs

[9] In the case of the screening contract, expected profits are not always positive given the screening cost. In these cases, optimal loan sizes are zero.

[10] $Z(\mu_t)$ is given by $\mathbb{E}[\theta_i^{\frac{1}{1-\alpha}}|\mu_t] - \mathbb{E}[\theta_i|\mu_t]^{\frac{1}{1-\alpha}}$ and $\zeta(\mu_t) = \frac{\mathbb{E}[\theta_i^{\frac{1}{1-\alpha}}|\mu_t]}{\mathbb{E}[\theta_i|\mu_t]^{\frac{1}{1-\alpha}}}$. Note that $A^*(\mu_t) = A^*(\mu_t, I)$ whenever the screening threshold is above the participation threshold. This is the case whenever $\gamma \geq \zeta(\mu_t)\left(\frac{\Lambda}{1+r_f}\right)$

themselves do not know their own type. We can think of such information as market- or sector-relative characteristics which financiers, by interacting with multiple entrepreneurs, are better able to evaluate. Screening gains in this model is driven by the convexity of expected profits. Rather than investing the 'average' loan size, one can choose to be screened and thus condition the size of investment to their revealed type.[11] The model generates a hierarchy in the chosen activity given productivities. Productive entrepreneurs will engage in borrowing and the most productive can afford to acquire information while doing so. The proportion of agents who engage in these types of action determines the information revealed about the aggregate fundamental. Engaging in the outside activity and not running the project produces no information.

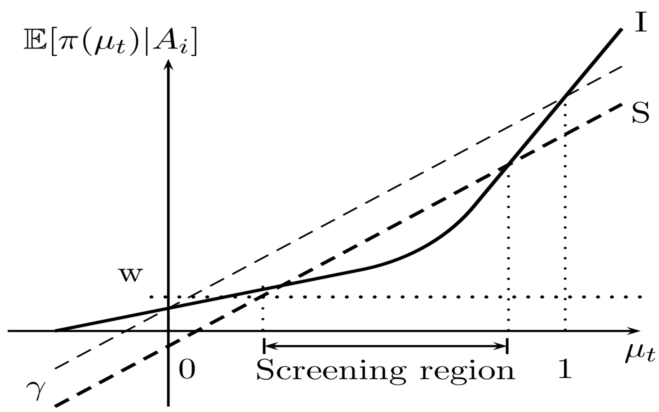

Figure 2: Profits over beliefs

How does the aggregate state affect the decision to be screened? Figure 2 plots expected profits for both the screening contract (equation 5 as thick dashed line) and the no-screening contract (equation 4 as solid line) over the range of μ_t on the horizontal axis for some productivity level A_i. When there is a large proportion of good projects, the value of screening is relatively low and does not merit the cost. The no-screening interest rate would be very similar to the interest rate that would be charged if one turns out to be of the good type. On the other hand, if the proportion is low then the likelihood of being the bad type is high and entrepreneurs are likely to get worse loan terms when screened.

To see how the proportion of entrepreneurs engaging in each of these activities vary over values of the fundamental, in Figure 3 I plot the screening and participation cutoffs over a range of states from μ_L to μ_H on the horizontal axis. On the vertical axis we have the range of observable pro-

[11] This is an extended version of the same mechanism found in (Gorton and Ordonez, 2014a). A key difference is that in our model screening changes the loan rate and allows for the investment size to optimally adjust to both better information about productivity and the new interest rate.

ductivities. The area above the dashed line (representing the cutoff productivity level to participate A^*) correspond to the measure of firms engaging in production and the area above the solid line (representing the cutoff productivity such that screening is optimal $\tilde{A}$) correspond to the measure of firms who would choose to be screened.

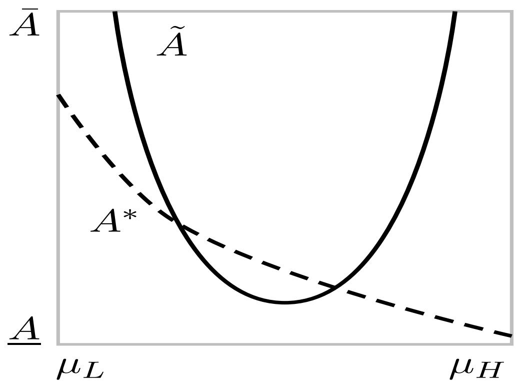

Figure 3: Relative values of cutoffs

In my economy, participation in credit markets is increasing in the state of the economy (the proportion of good projects). On the other hand, screening intensity, the proportion of screened projects, has a U-shaped pattern. Very few projects are screened when the aggregate fundamental is 'too' low or 'too' high. In the next section, the relative proportion of projects which are (i) not run, (ii) run and are not screened, and (iii) projects which are both run and screened, determine the precision of information about the aggregate fundamental.

3. Business cycle dynamics

We now move on to the dynamic version of the model and characterize the evolution of business cycles arising from endogenous persistence in beliefs. Consider now that the aggregate state of the economy follows a Hidden Markov Chain and agents may learn about it by observing aggregate credit market outcomes. In particular the proportion of good projects may either be high (μ_H) or low (μ_L). Further, the aggregate fundamental is persistent. With probability $\lambda > 0.5$, the proportion of good projects today will be the same as in the previous period. Equilibrium in credit markets for each period is as defined in the previous section and I now impose Bayesian learning on the process by which agents learn about the state of the economy. Equilibrium is defined as Sub-game Perfect Nash given a sequence of realizations of shocks for the state of the world, entrepreneur types, and project outcomes. For any period t, prior beliefs about the state of the economy $\mathbb{E}[\mu_t|\mathcal{I}_{t-1}]$ are formed given all past information.

New information is produced at the end of each period in the form of aggregate statistics on credit market contracts and project outcomes. First, all agents observe the number of entrepreneurs who chose to be screened and the aggregate screening outcome. Second, they observe the number of projects which are run for each type of contract chosen and the number of projects which succeed within each category. For entrepreneurs that are screened, the relevant statistic is the proportion of those who were found to have θ_G. For the rest of the entrepreneurs that participate in credit markets, project successes are used to infer the state of the world. Denote the aggregate number of projects run and their composition into screened (S) and un-screened projects (I) as $n_t = n_t^S + n_t^I$. Define the number of successful projects in n_t^I as s_t^I and the number of screened projects (in n_t^S) with success probability θ_G as s_t^S. We then have two sets of signals which may be used to infer the state of the world at time t which we denote with $\Sigma_t \equiv \{\frac{s_t^S}{n_t^S}; \frac{s_t^I}{n_t^I}\}$.[12]

Beliefs about the current state are formed given the full history of past information. At the end of the period, these beliefs are updated with information generated at time t to form a posterior belief given the new information. That is, belief-formation has a dynastic flavor wherein agents born at time t have the information set $\mathcal{I}_{t-1}$ which is recursively updated with outcomes in each period $\mathcal{I}_t = \mathcal{I}_{t-1} \cup \Sigma_t$.

Given some prior probability that $\mu_t = \mu_H$ denoted by $p_{t|t-1}$, beliefs are updated using the set of signals from the unscreened and screened outcomes (Σ_t) to form posterior beliefs. The information content of current signals is quantified by the likelihood ratio between the high and low states. Let $\mathcal{L}(\mu_H|\Sigma_t)$ be the likelihood of a high state given period t signals and $\mathcal{L}(\mu_L|\Sigma_t)$ the corresponding likelihood of a low state. Then, posterior beliefs combine priors and period t signals using Bayes' theorem[13]:

$$p_{t|t} = \frac{\mathcal{L}(\mu_H|\Sigma_t)p_{t|t-1}}{\mathcal{L}(\mu_H|\Sigma_t)p_{t|t-1} + \mathcal{L}(\mu_L|\Sigma_t)(1 - p_{t|t-1})} \tag{8}$$

The numerator is the joint likelihood of the high state and the denominator normalizes the likelihood with the sum of both joint likelihoods. Finally the optimal forecast for the aggregate state of the world is given by the posterior belief and the persistence parameter:

$$p_{t+1|t} = \lambda\, p_{t|t} + (1 - \lambda)(1 - p_{t|t}) \tag{9}$$

[12]Both sets of signals are informative about the aggregate state since $s_t^S \sim Bin(\mu_t, n_t^s)$ and $s_t^I \sim Bin(\theta_B + \mu_t(\theta_G - \theta_B), n_t^I)$.

[13]For two competing hypotheses (H and L), evidence Σ, and some prior probability of one hypothesis $Pr(H) = p$, Bayes' theorem is $Pr(H|\Sigma, p) = \frac{Pr(\Sigma|H)p}{Pr(\Sigma|H)p + Pr(\Sigma|L)(1-p)}$

Equations 8 and 9 characterize the evolution of the state variable (prior beliefs) given a sequence of realizations $\{\Sigma_i\}_{i=1}^t$ and an initial prior $p_{1|0}$. My learning mechanism generates unbiased forecasts whose precision depend on endogenous information production.[14] In turn, the precision of information determine how much beliefs adjust with respect to period t shocks. In the next section I describe how the two margins to information production determine the precision of period t information.

A. Information Production

At any given period, the cutoffs $A^*(\mu_{t|t-1})$ and $\tilde{A}(\mu_{t|t-1})$ are sufficient to characterize equilibrium in credit markets. In turn, the cutoffs are given by the state variable $\mu_{t|t-1}$. Finally, the next generation's beliefs are going to be updated with new information Σ_t. We can then examine how beliefs about the state of the world affect the number and type of signals the economy generates. First, the quantity of information is monotonically increasing in beliefs.

Proposition 1 (The extensive margin to information production)**.** *Given a constant proportion of screening to undertaken projects, information production is non-decreasing in the expected proportion of good projects* $\mu_{t|t-1}$.

Proofs for all the propositions are in the Appendix. The extensive margin to information production generates a negative relationship between persistence and optimism. This makes business cycles asymmetric with slower recoveries than expansions as the quantity of information produced is pro-cyclical. These economies are characterized by asymmetry in persistence and would exhibit "*slow booms*" and "*sudden crashes*" (e.g. Veldkamp 2005). The key innovation of the paper is that the quality of information is also changing over time. In this economy, two types of signals may be produced and one is more informative about the state than the other. This is what I refer to as the intensive margin. Along this dimension, informatio production is hump-shaped over prior beliefs.

Proposition 2 (The intensive margin to information production)**.** *Given a fixed number of projects undertaken and whenever* $\underline{\gamma} < \gamma < \bar{\gamma}$, *information production is hump-shaped in the expected proportion of good projects* $\mu_{t|t-1}$.

Corollary 2.1. *When* $\gamma \geq \bar{\gamma}$, *screening never takes place and* $n_t = n_t^I \quad \forall \mu_{t|t-1}$. *When* $\gamma \leq \underline{\gamma}$ *then all credit market participants choose to be screened and* $n_t = n_t^S \quad \forall \mu_{t|t-1}$.

The intensive margin follows the literature on credit screening with hump-shaped incentives to screen. The value of screening and acquiring private information is inversely proportional to the

[14] Note that although the ratios $\frac{s_t^S}{n_t^S}$ and $\frac{s_t^I}{n_t^I}$ are exogenously driven by the true state of the world μ_t, the precision of period t information given by n_t and the ratio $\frac{n_t^S}{n_t}$ are endogenous and depend on beliefs $\mu_{t|t-1}$.

'strength' of prior beliefs about being in a particular state which in this case is when $\mu_{t|t-1}$ tends to either μ_H or μ_L. This allows for the possibility of rational exuberance episodes where information is seemingly abundant and yet appears to be discounted. As screening intensity is decreasing in γ, there exists an upper and lower bound to the cost of screening such that screening is either always preferred or never engaged in for any set of beliefs. That is, a corollary of proposition 2 is that there exists a $\bar{\gamma}$ such that no screening ever takes place. Conversely, there exists a $\underline{\gamma}$ such that all agents who participate in credit markets are always screened. For intermediate ranges of the screening cost, the intensive margin kicks in and the precision of date t information about the state is jointly determined by both the quantity and quality of signals. The next proposition outlines the overall evolution of information production in my economy depending on the relative cost to producing information.

Proposition 3 (Dynamics of belief persistence)**.** *The speed of learning, and hence the persistence of beliefs, is characterized by the following:*

1. *When $\gamma \leq \underline{\gamma}$, screening always occurs and the persistence of beliefs is monotonically decreasing in $\mu_{t|t-1}$. Similarly, when $\gamma \geq \bar{\gamma}$, no screening takes place and the persistence of beliefs is also monotonically decreasing in $\mu_{t|t-1}$. However, information production (persistence) is everywhere lower (higher) than in the previous case.*

2. *When $\underline{\gamma} < \gamma < \bar{\gamma}$, and under some parameter conditions on the relative informativeness of screening to no-screening signals, $\exists \mu^*$ for which persistence is decreasing in expectations within the range $\mu_{t|t-1} \in [1 - \lambda \quad \mu^*]$ and is increasing for the range $\mu_{t|t-1} \in [\mu^* \quad \lambda]$.*[15]

Persistence is inversely proportional to the precision of period t information which is jointly determined by the extensive and intensive margins. Depending on parameter values, my model allows for persistence to increase when beliefs become too optimistic giving rise to protracted booms where beliefs remain relatively optimistic even when negative shocks appear.

Before characterizing business cycles with endogenous learning, I first discuss some of the key assumptions behind my model of credit markets. In this economy, variations in the credit market equilibrium over time depend solely on differences in the expected proportion of good to bad projects. I have assumed constant other factors that may change the proportion of screening and participating agents. For instance, if the outside opportunity cost w were pro-cyclical then the extensive margin would be attenuated. The same would be true if the cost of funding $1+r_f$ were to be counter-cyclical.

[15]The parameter conditions require that the screening signals are sufficiently more informative than the no-screening signals such that a fall in the relative proportion of screening to total signals may generate a reduction in the overall precision of information despite the increase in the total number of signals. See the proof in the appendix for details.

One may also think that the screening cost γ varies over time and is likely to decline as the financial sector becomes more developed. Nevertheless, as the recent Financial Crisis has shown, financial innovation - through the introduction of new and more complex instruments and assets - may keep pace with financial development and keep the cost of acquiring further information relevant even in today's financial markets.

The inclusion of conventional financial frictions such as information asymmetry in the form of adverse selection or bankruptcy costs and costly state verification do not change the qualitative results. If borrowers knew their type, then Bad types would always prefer not to be screened and only the low productivity Good types who cannot afford the screening cost will join this pool of unscreened borrowers. When aggregate fundamentals improve, a larger proportion of the unscreened borrowers will be of the good type which also lowers the no-screening interest rate and may further increase the fraction of good types who choose not to be screened. This preserves the counter-cyclical nature of the intensive margin to information production although may attenuate its relative importance. On the other hand bankruptcy costs and costly state verification, by increasing the cost of financial intermediation, amplifies the extensive margin to information production and makes business cycles more asymmetric.

The assumption that financial intermediaries are in perfect competition and hence obtain zero profits is not crucial to my results. In my setup, the choices in the competitive equilibrium maximize the value of investing in projects and is thus invariant to the profit-sharing outcome implied by different market structures. Further, given that all intermediaries can offer the same loan contracts, they also have no strategic incentives to withhold the screening outcome as shown in Bolton et al. (2007).

B. The evolution of business cycles with endogenous learning

I focus on an economy satisfying case 2 of proposition 3. Under this setting, the model generates the following predictions. First, my economy tends to stay longer in periods of highly optimistic beliefs relative to moderately optimistic ones. This results in a relatively higher frequency of periods where beliefs are and remain at a higher threshold level of optimism. Second, when fundamentals deteriorate during these highly optimistic periods it takes a while before a recession appears. Further, uncertainty in the model would already have been rising prior to the start of the recession. Finally, these occur on top of the asymmetry in business cycles generated by the extensive margin.

I illustrate these main predictions by simulating my economy and examining the evolution of expansions and recessions.[16] To document how the two margins to information production affect the dynamics of business cycles, I compare the model simulation against two benchmarks, an economy *Extensive* which holds the proportion of screened to unscreened signals constant (the average in *Model*) but vary the total number of observed signals as per the extensive margin, and *Constant* where both are held constant. The simulations show that, relative to an economy with constant information production, business cycles are asymmetric with endogenous information production where interest rate changes are right skewed while investment growth is left-skewed. The asymmetry also appears in the frequency of periods where priors are below one half. Second, the intensive margin to information production generates persistence in expansions with sufficiently optimistic beliefs. This shows up as a higher frequency of periods with highly optimistic beliefs relative to the simulation with only the extensive margin to information production.

The consequences of optimism

We now turn to how expansions end in my economy. I collect all peaks in filtered output and compute the average evolution of participation, screening, and uncertainty in the simulations. In *Model* participation increases as we near the peak in economic activity while screening falls. This generates a U-shaped pattern in average uncertainty. In Figure 4 I plot the average evolution of uncertainty for *Model*, and *Extensive* relative to that in *Constant*. On the horizontal axis we have periods before the peak in trend economic activity and a value of zero on the vertical axis means that uncertainty would be the same as in *Constant*.[17]

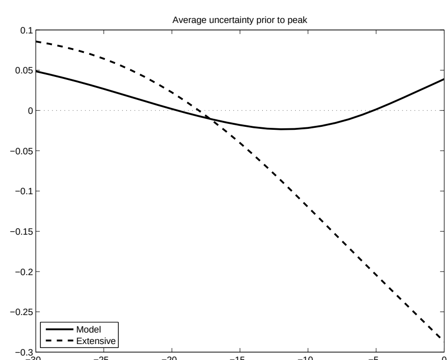

Figure 4: Average path of uncertainty

Here we see how the two margins contribute to macro-uncertainty. In *Extensive*, average uncer-

[16]See the appendix for details.

[17]Here it is important to evaluate uncertainty relative to *Constant* as the two-state assumption in the model necessarily implies that uncertainty has a hump-shaped pattern over beliefs.

tainty is monotonically decreasing as we approach the peak in economic activity. In $Model$, where both margins to information production are active, we get a U-shaped pattern.

Next, I simulate an episode of rational exuberance. I start the simulation from the most optimistic belief and then simulate a fall in fundamentals by hitting the economy with shocks from the Low state. I do this 1,000 times and report the average evolution of beliefs and entrepreneurial profits in the top left and right panel of Figure 5. I also report the actual and expected default rates in the bottom right panel and average uncertainty in the bottom left panel.

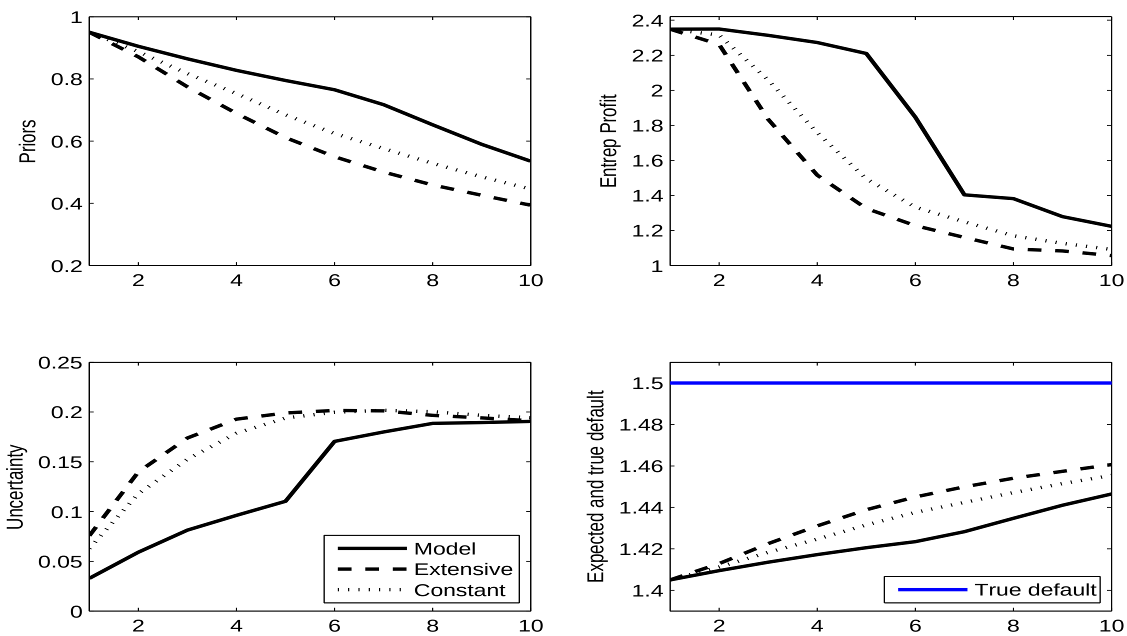

Figure 5: Simulated rational exuberance

For *Extensive*, high optimism leads to a lot of information production and learning is quick. On the other hand, optimistic beliefs slow down learning and induce persistence in our model and this implies two things. First, as the bottom right panel shows, on average financiers experience persistent and sizable surprises in the expected and actual default rates. Nevertheless, optimism also implies that a wider range of projects get financed and output does not fall significantly until about five periods into the simulation for $Model$. Relative to *Constant* or *Extensive*, the recession would have been dated much later in our model and in this intermediate period, uncertainty would be rising, default rates are larger than expected, and yet the fall in output is not too large.

To an econometrician who observes and treats data for each period as being equally informative, our model generates an economy where agents appear to disregard warning signs and are *irrationally* *exuberant*. Who pays for this over-optimism? First, entrepreneurs who are screened get to know their types which makes prior beliefs irrelevant for their investment decisions. Thus optimism, by reducing the proportion of agents who are screened, also reduce the proportion of investments insulated from informational inefficiency. What about those who are not screened? The first implication of over-optimism is that the participation threshold is low. That is, a certain mass of entrepreneurs who would have taken the outside opportunity are instead investing in their projects. Nevertheless, the no-screening interest rate is also low. This leads to larger investment sizes for all unscreened borrowing. Further, as repayment is contingent on production being successful, it turns out that entrepreneurs do not suffer from overly optimistic beliefs. Instead, those who succeed in production would be making more profits than they would otherwise have. It is the financiers who shoulder the costs of being overly optimistic in our economy. The low interest rate regime brought about by optimistic beliefs effectively transfers wealth from financiers to successful entrepreneurs.[18] The opposite would be true in the recovery, when beliefs are pessimistic relative to the true state of the fundamental.

C. Financial development

I now evaluate the model's predictions on how business cycles evolve under financial development. I approximate financial development with either a decrease in the cost of producing private information (γ) or a fall in the opportunity cost of funding $(1+r_f)$. In the former, a fall in γ increases information production primarily through the intensive margin and thus the precision of information improves during booms and optimistic periods. This induces more asymmetric cycles where the threshold level of optimism which induces rational exuberance episodes increases. This suggests that less financially developed economies are more likely to experience rational exuberance booms (lower threshold level of optimism) whereas more financially advanced economies have more asymmetric business cycles and a lower frequency of such booms. Nevertheless, when a rational exuberance boom occurs for these economies, they do so at high levels of optimism and economic activity. Rational exuberance booms in developed economies are larger though rare.

On the other hand, a fall in the risk free rate improves the production of information during pessimistic periods or recessions when economic activity is low. It reduces asymmetry by speeding up recoveries. Further, a fall in the cost of funding has a relatively negligible effect on information production during booms. This is akin to the results from Ordonez (2013) where lower levels of

[18] In the context of an open economy where financing comes from external sources, this would imply that the rest of the world is subsidizing the excesses of optimism in my economy. This temporarily keeps the economy in a boom until such a time that a sufficient set of negative surprises triggers information production and financing dries up leading to a large crash and a sudden stop or reversal in capital flows.

financial development, in the form of higher monitoring or bankruptcy costs, raises the cost of financing for all borrowers. This result also hints at the what could change in the model predictions once we allow for endogenous income and savings. Under the assumption that periods of low output and hence low savings also induces a rise in the cost of funding, then the counter-cyclical cost of funding will make business cycles even more asymmetric. Second, this also suggests that policies which raise the cost of funding during booms is unlikely to increase information production.

D. Socially optimal information production

One question that emerges is whether these types of fluctuations are inefficient. The production of private information generates spillovers to public signals (market outcomes) that become available to succeeding generations. In my economy, efficiency is in part[19] constrained by how precisely market outcomes reveal the true state of the world. In the competitive equilibrium, agents take this precision as given not internalizing the fact that more participation and screening activity generates more precise prior beliefs for the next period. Instead, the cutoffs that arise in the competitive equilibrium are the ones that maximize only the current period's expected profits. A free-rider problem is present and, even in the presence of a market for information, inter-temporal trade is unlikely to resolve this inefficiency.

In the appendix, I consider the case where a constrained social planner maximizes the expected stream of current and (discounted) future profits by choosing the participation and screening thresholds. The social planner cannot influence belief-formation in any other way nor is she allowed to change the optimal loan contracts I have earlier derived for the economy. In my economy, information about the aggregate fundamental is increasing in participation and screening activity. However, the incentives to do either only depend on the private benefits from doing so. The information generated about aggregate fundamentals is a positive externality in my economy. I show that the constrained social planner would choose lower thresholds than in the competitive equilibrium. Intuitively, increasing information production today increases the allocative efficiency of financial markets tomorrow. In the model this manifests in a convex value function and where more precise information induces a mean preserving spread in the distribution of prior beliefs in the next period.

In my economy, there are no avenues by which resources can be transferred through agents across time and an inter-temporal market for information does not exist. Nevertheless, since information is a public good, even in the presence of such a market a free-rider problem is present and there are no individual incentives to participate in such an exchange. This creates space for a policy to

[19] Uncertainty and costly screening at the individual level also reduces the efficiency of the competitive allocation.

improve on the competitive allocation by providing subsidies on information production and may be financed by a lump-sum tax on all agents. In particular, a policy which subsidizes investment and screening can implement the constrained social planner's solution. In particular, given the results presented earlier on the effects of changes in the cost of screening and cost of funding, a policy which subsidizes both investment during pessimistic periods and screening during optimistic ones can potentially implement the constrained social planner's solution.

This result suggests that current macro-prudential policies which stimulate credit and economic risk-taking during recoveries and limit financial risk-taking by financial intermediaries, especially at the heights of optimistic credit booms, may generate informational gains that are currently not considered in the policy debate. Stimulating credit during recoveries increases the precision of information through the extensive margin at a time when financial intermediaries are already likely to be screening borrowers but where credit provision in the aggregate is limited. On the other hand, through the lens of the model, macro-prudential policies which limit the expected volatility of the performance of financial intermediaries' loan portfolios (or their profits) especially during periods of high credit growth induces screening and private information production. This would reduce the likelihood of crises following from rational exuberance episodes I describe in this paper.

4. Supporting Evidence

In this section I document several features of uncertainty over the business cycle using quarterly U.S. data. I find that both the beginning and the end of expansions are preceded by periods of rising macro-uncertainty. These facts are corroborated by evidence on business cycles and crises episodes documented elsewhere. With regard to asymmetric business cycles for example, Van Nieuwerburgh and Veldkamp (2006) and Ordonez (2013), and Jurado et al. (2013) document asymmetries in investment, lending rates, and real activity. For crises episodes, Gorton and Ordonez (2014b) show that credit booms that end in crises feature a larger initial productivity shock and a faster fall in total factor productivity over the boom. Further, excessive optimism seems to appear in many facets of the recent Financial Crisis. In their analysis of the 2006 housing bubble in the U.S., Cheng et al. (2014) find that misguided optimism was an important factor in the run-up to the crises over alternative explanations such as *bad incentives* or *bad luck*. Piazzesi and Schneider (2009) document an increase in a *momentum cluster* of households believing that house prices will continue to rise towards the end of the housing boom. Dell'Ariccia et al. (2012) link declining lending standards in the sub-prime market to the housing boom which led to an increase in delinquency rates. Similarly, Loutskina and Strahan (2011) show that the share of informed lending[20] in mortgage markets fell during the housing boom and such a fall in information production may have been an important factor in the crash that followed. Griffin and Tang (2012) look at credit ratings of collateralized debt obligations where they find subjective positive adjustments to model-implied ratings which predict future downgrades.

Macro-uncertainty is quite difficult to measure and various proxies are present in the literature.[21] Two of the most common are survey forecast disagreement and the option-implied expected volatility of the *S&P 500* index (VIX). In Figure 6 I plot the evolution of these two over the last four decades.

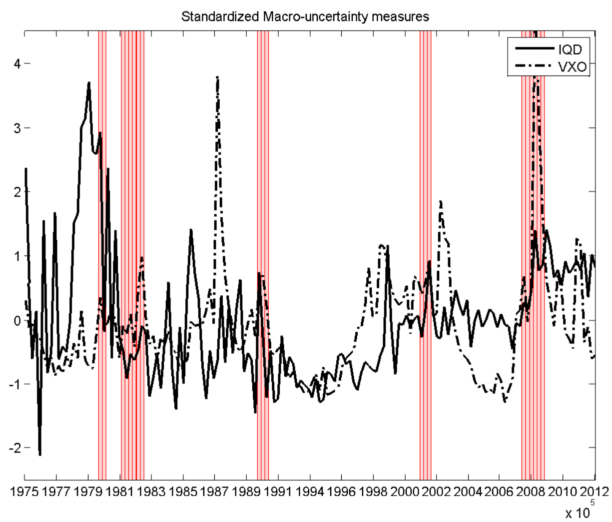

Figure 6: U.S. Macro-uncertainty proxies over time

IQD is the 75th less 25th percentile of four-quarter-ahead quarter-on-quarter real GDP growth forecasts from the Survey of Professional Forecasters. VXO is the quarter average of daily options-implied volatility of the S&P 500. Prior to 1986 I use realized volatility of the log difference of the S&P500 index. Between 1986 and up to 1989 I use the old definition of the VIX (VXO) and from 1990 onwards I use the current definition of the VIX. All measures have been standardized and a linear trend was taken out of IQD.

Though largely counter-cyclical, these two measures were rising well before the end of the last

[20]These are mortgage lenders that concentrate in a few markets and thus invest in more information about their borrowers.

[21]See Baker et al. (2013) for a measure of economic policy uncertainty based on news reports; Bloom (2009) and Bloom (2014) for uncertainty measures based on stock market volatility and micro-level dispersion and a comparison of various measures respectively; Jurado et al. (2013) for a factor-based approach using a host of macro time series; Orlik and Veldkamp (2014) focusing on uncertainty measures allowing for parameter uncertainty in forecast models; and Scotti (2013) for a higher frequency measure based on the size of surprises in real-time macro variables. More recently Rossi and Sekhoposyan (2015) constructs an uncertainty index based on the probability of observing a realized forecast error given the historical distribution of forecast errors.

two expansions. The data appears to be noisier in the previous cycles and perhaps other factors played a larger role in generating the observed fluctuations. Nevertheless, one concern is that these are noisy measures of uncertainty and may not reflect the type of uncertainty consistent with the concept driving information production in the model. I introduce another measure of uncertainty which identifies forecast uncertainty at the individual level to augment these existing measures. In particular, I use the average dispersions of individual density forecasts (as against the dispersion of mean forecasts *across* forecasts) of annual average real GDP growth from the Survey of Professional Forecasters provided by the Federal Reserve Bank of Philadelphia from the first quarter of 1992 to the second quarter of 2013.[22] In a panel regression framework, I compute averages over time taking into account individual and forecast horizon differences. Further, I propose a simple way to correct for a potential bias in the measurement of uncertainty due to the truncation of survey responses.

These survey responses encode a coarse measure of the density of individual predictions about annual real GDP growth. Respondents are asked to provide probability values to specific ranges of outcomes for the target variable. I compute the entropy of a forecast $ENT_{i,t,h}$ as a measure of the diffusion of a forecast made by individual i at time t with a forecast horizon h.[23] A more dispersed distribution for the forecast yields a higher entropy which I interpret as forecast uncertainty. To obtain average forecast uncertainty over time, I run a regression with the following specification:

$$y_{i,t,h} = \alpha_i + \gamma_h + \delta_t + \epsilon_{i,t,h}$$

The coefficients δ_t reflect the average individual forecast uncertainty for each quarter in the sample after controlling for individual and forecast-horizon average effects. I also estimate a specification controlling for a potential downward bias to the entropy measure when the survey responses place significant probabilities to the outer bins. In Figure 7 I plot the estimated time fixed effects for the entropy measure. My measure appears to co-move with the other two earlier shown and tend to be higher during recessions. Second, we also observe a U-shaped pattern over expansions. That is, macro-uncertainty begins to rise well before the end of an expansion from 1997 to 2001 and from 2006 to 2009.

My hypothesis for this pattern is that the rate of information production is not simply procyclical as the current literature would suggest. A fall in private information production at the

[22] In the Appendix I also include estimates using forecast of the GDP price index growth. Other works derive a similar measure are Zarnowitz and Lambros (1987),Rich and Tracy (2010), and Bloom (2014) for the U.S. survey and Boero et al. (2008), Abel et al. (2015), and Boero et al. (2014) using the Bank of England and ECB surveys of professional forecasters. Of these, only Bloom (2014) ask how this measure of macro-uncertainty evolves over the business cycle.

[23] See the Appendix for the data description. In contrast, Bloom (2014) compute the implied standard deviation of forecasts using the midpoints of bins and averages standard deviations per year.

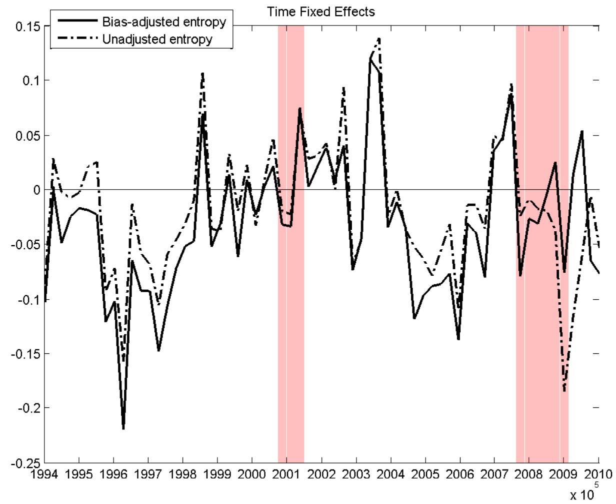

Figure 7: Average forecast uncertainty over time

The values reflect difference from the average level for the omitted time dummies for 1992. The adjusted series includes a bias-adjustment factor which depends on the median probability bin for each survey response. When the median probability bin is closer to the outer edges, the adjustment factor is larger.

heights of optimism in conjunction with pro-cyclical abundance of information may account for the U-shaped pattern of macro-uncertainty.

5. Conclusion

I have outlined a theory of learning and information production over the business cycle which regularly generates sharp recessions and gradual recoveries and produces the occasional boom that is sustained by optimistic beliefs even in the presence of warning signs that fundamentals have already began to deteriorate. In my theory, there is nothing irrational about these episodes. Instead, they arise because individuals have invested little in private information production. There is not much that can be learned from the actions of others in these booms and markets are content with being spared the details. These rational exuberance episodes endogenously arise in the model when beliefs become highly optimistic during peaks in economic activity. I have also documented suggestive evidence on measures of macro-uncertainty in the U.S. consistent with the proposed mechanisms.

My theory has several implications regarding the role of financial innovation and development on financial crises. Economies and periods in time with very high (or low) levels of financial development have a limited role for the intensive margin to information production and reduces the likelihood of rational exuberance episodes. On the other hand this also suggests that financial innovation, by generating complex and opaque assets, contributed to the fall in information production in the boom preceding the recent Financial Crisis. Furthermore, information is under-produced in the competitive equilibrium and one policy implication is that a subsidy on screening and lending may attain the constrained social planner's allocation. In the model, deviations of beliefs from the true state of fundamentals manifest in cyclical fluctuations of financier profits. This suggests that current proposals on macro-prudential policies that limit bank risk-taking, and hence induce private information production, and those that encourage credit and economic risk-taking during recoveries may generate additional information gains. In the model I abstract from several features of financial markets which we think are important drivers of crises and credit cycles such as information asymmetries and competition among creditors, the positive feedback between asset prices and credit, and leverage. Taking these into account is an area for future research.

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A. Model Derivations

All aggregate variables which are subject to the learning mechanisms I propose have the time subscript $t|t-1$ denoting expectation of its value at time t given information up to time $t-1$.

A. Optimal contracts

Given a prior belief $p_{t|t-1}$ we then have the average expectation for borrower quality $\theta_{t|t-1}$ which we use to solve for credit market equilibrium where:

$$\theta_{t|t-1} = \theta_B + \mu_{t|t-1}(\theta_G - \theta_B)$$

First, we solve for loan rates. Given that there are no information asymmetries in the model, the probability of repayment is equal to the success probability of a project. If the borrower asks for the no-screening contract (I), then the participation constraint for each financier is given by:

$$\begin{aligned} \theta_{t|t-1} R_i(\theta_{t|t-1}, I) K_{i,\theta_{t|t-1}} &\geq (1+r_f) K_{i,\theta_{t|t-1}} \\ R_i(\theta_{t|t-1}, I) = R(\theta_{t|t-1}, I) &\geq \frac{1+r_f}{\theta_{t|t-1}} \qquad (10) \end{aligned}$$

That is, without screening, the rate of interest must be such that the financier is at least as well of as investing the loaned funds into her savings technology. On the other hand, for the screening contract we have that the participation constraint for the financier must hold for both realizations of screening and thus the participation constraints of financiers are given by:

with Probability $\mu_{t|t-1}$:

$$\begin{aligned} \theta_G R_i(\theta_G, S) K_{i,\theta_G} &\geq (1+r_f)(K_{i,\theta_G} + \gamma) \\ R_i(\theta_G, S) &\geq \frac{1}{\theta_G}[(1+r_f)(1+\frac{\gamma}{K_{i,\theta_G}})] \\ &\geq R(\theta_G, I) + \frac{(1+r_f)\gamma}{\theta_G K_{i,\theta_G}} \qquad (11) \end{aligned}$$

with Probability $1-\mu_{t|t-1}$:

$$R_i(\theta_B, S \geq R(\theta_B, I) + \frac{(1+r_f)\gamma}{\theta_B K_{i,\theta_B}} \qquad (12)$$

Perfect competition among financiers ensure that these constraints bind and pins down interest rates.

B. *Loan sizes and expected profits*

With these interest rates, I solve for the optimal borrowing size. The entrepreneur will want to borrow the amount that maximizes his expected profits from running the project given by:

$$\mathbb{E}[\pi_i|\mu_{t|t-1}] = \theta_{t|t-1}(A_i K_i^{\alpha} - R(\theta_{t|t-1})K_i) \tag{13}$$

$$K_i^*(\mu_{t|t-1}) = \left[\frac{\alpha A_i}{R(\theta_{t|t-1})}\right]^{\frac{1}{1-\alpha}} \tag{14}$$

Given the optimal investment[24] size, expected profits from the no-screening contracts is given by:

$$\begin{aligned}\mathbb{E}[\pi_i|\mu_{t|t-1}, I] &= \left[\theta_{t|t-1}\frac{\alpha\, A_i}{(1+r_f)^{\alpha}}\right]^{\frac{1}{1-\alpha}}\left[\frac{1-\alpha}{\alpha}\right] \\ &= (\theta_{t|t-1}A_i)^{\frac{1}{1-\alpha}}\Lambda \end{aligned}\tag{15}$$

where $\Lambda \equiv \left[\frac{\alpha}{(1+r_f)^{\alpha}}\right]^{\frac{1}{1-\alpha}}\left[\frac{1-\alpha}{\alpha}\right]$. Similarly, we can solve for expected profits from a screening contract:

$$\mathbb{E}[\pi_i|\mu_{t|t-1}, S] = (\mu_{t|t-1}\theta_G^{\frac{1}{1-\alpha}} + (1-\mu_{t|t-1})\theta_B^{\frac{1}{1-\alpha}})A_i^{\frac{1}{1-\alpha}}\Lambda - \gamma(1+r_f) \tag{16}$$

C. *Screening threshold*

A given borrower with productivity A_i will choose the screening contract whenever expected screening profits are higher. Then screening is chosen when:

$$Z(\mu_{t|t-1}) \geq \left[\frac{\gamma(1+r_f)}{\Lambda}\right] A_i^{\frac{-1}{1-\alpha}} \tag{17}$$

where

$$Z(\mu_{t|t-1}) \equiv \mu_{t|t-1}\theta_G^{\frac{1}{1-\alpha}} + (1-\mu_{t|t-1})\theta_B^{\frac{1}{1-\alpha}} - (\mu_{t|t-1}\theta_G + (1-\mu_{t|t-1})\theta_B)^{\frac{1}{1-\alpha}}$$

The right-hand side of the above equation is decreasing in A_i and the left-hand side is concave in $\mu_{t|t-1}$ whose minimum is zero when $\mu_{t|t-1} \in \{0,1\}$. $Z(\mu_{t|t-1})$ captures the value of information to the borrower arising from prior beliefs about the state of the world.

Further, when γ is zero, the inequality always holds, and screening is always preferred. We can then define a cutoff level of productivity $\tilde{A}(\mu_{t|t-1})$ given expectations about the state of the world

[24] In the case of the screening contract, expected profits are not always positive given the screening cost. In these cases, optimal loan sizes are zero.

such that an entrepreneur with such a level of productivity is indifferent between either contract. For any A_i greater than this cutoff, the equation will hold with strict inequality and an entrepreneur would choose the screening contract. In equilibrium, financiers will also offer the screening contract to these agents and the no-screening contract to the rest. This guarantees that entrepreneurs who asked to be screened and turn out to be the Bad type have no incentive to go to a different financier and ask for the unscreened contract. For this reason, financiers offer a particular contract to each entrepreneur given their observed productivity.

$$\tilde{A}(\mu_{t|t-1}) = \left[\frac{\gamma(1+r_f)}{Z(\mu_{t|t-1})\Lambda}\right]^{1-\alpha} \tag{18}$$

D. Participation threshold

Given the optimal loan contract, an entrepreneur would like to borrow and invest whenever profits from this activity, exceed the outside option w. Since expected profits from production are increasing in A_i, define $A^*(\mu_{t|t-1})$ as the level of productivity such that an entrepreneur would be indifferent:

$$\begin{aligned} A^*(\mu_{t|t-1}) &= min\{A^*(\mu_{t|t-1}, S), A^*(\mu_{t|t-1}, I)\} \\ &\text{where:} \\ A^*(\mu_{t|t-1}, S) &= \left[\frac{w+\gamma(1+r_f)}{(\mu_{t|t-1}\theta_G^{\frac{1}{1-\alpha}} + (1-\mu_{t|t-1})\theta_B^{\frac{1}{1-\alpha}})\Lambda}\right]^{1-\alpha} \quad (19) \\ A^*(\mu_{t|t-1}, I) &= \left[\frac{w}{(\mu_{t|t-1}\theta_G + (1-\mu_{t|t-1})\theta_B)^{\frac{1}{1-\alpha}}\Lambda}\right]^{1-\alpha} \quad (20) \end{aligned}$$

The equations above simply equate expected profits from the screening and no-screening contract with the outside opportunity compensation w. Thus, a borrower finds it optimal to invest in her project $iff \quad A_i > A^*(\mu_{t|t-1})$.

Note that when $\gamma = 0$ then $A^*(\mu_{t|t-1}) = A^*(\mu_{t|t-1}, S)$ and the screening threshold is below the participation threshold whereas when $\gamma = \infty$ then $A^*(\mu_{t|t-1}) = A^*(\mu_{t|t-1}, I)$. In particular, this is the case whenever

$$\gamma(1+r_f) \geq \zeta(\mu_{t|t-1})\Lambda \tag{21}$$

where $\zeta(\mu_{t|t-1}) \equiv \left[\frac{\mu_{t|t-1}\theta_G^{\frac{1}{1-\alpha}}+(1-\mu_{t|t-1})\theta_B^{\frac{1}{1-\alpha}}}{(\mu_{t|t-1}\theta_G+(1-\mu_{t|t-1})\theta_B)^{\frac{1}{1-\alpha}}}\right] \geq 1.$

E. *Optimal updating*

Beliefs about the current state today are formed given the full history of past information. This is a summarized in a recursive setup in which prior beliefs at any time t encapsulates all prior information and is updated with information at time t (Σ_t) to form a posterior belief given the new information. Denote the aggregate number of projects run and their composition into screened (S) and unscreened projects (I) as $n_t = n_t^S + n_t^I$. Define the number of successful projects in n_t^I as s_t^I and the number of screened projects (in n_t^S) with success probability θ_G as s_t^S. Define $\Sigma_t \equiv \{\frac{s_t^S}{n_t^S}; \frac{s_t^I}{n_t^I}\}$ as new information generated at time t. Thus, agents born at time t have the information set $\mathcal{I}_{t-1}$ which is recursively updated with outcomes (Σ_t) in each period $\mathcal{I}_t = \mathcal{I}_{t-1} \cup \Sigma_t$.

The proportion of successes among the number of projects run that were not screened is informative about the state of the world since they map into aggregate success rates.

$$\begin{aligned} \theta_H &= \theta_B + \mu_H(\theta_G - \theta_B) \\ \theta_L &= \theta_B + \mu_L(\theta_G - \theta_B) \end{aligned}$$

On the other hand, the proportion of screened projects with success probability equal to θ_G is also a direct statistic that may be used to infer μ_t.

Given some prior probability that $\mu_t = \mu_H$ denoted by $p_{t|t-1}$, we can use the set of signals from the unscreened outcomes to form posterior beliefs using Bayes' Law:

$$p_{t|t}^I = \frac{\theta_H^{s_t^I}(1-\theta_H)^{n_t^I - s_t^I} p_{t|t-1}}{\theta_H^{s_t^I}(1-\theta_H)^{n_t^I - s_t^I} p_{t|t-1} + \theta_L^{s_t^I}(1-\theta_L)^{n_t^I - s_t^I}(1-p_{t|t-1})}$$

The numerator is simply the likelihood of being in the high state given th signal $\frac{s_t^I}{n_t^I}$ weighted by the prior probability. The denominator normalizes the likelihood with the sum over the likelihood of both states. Similarly, we can use the second set of signals from the screened projects using the posterior from the first set of signals as a prior:

$$p_{t|t} = \frac{\mu_H^{s_t^S}(1-\mu_H)^{n_t^S - s_t^S} p_{t|t}^I}{\mu_H^{s_t^S}(1-\mu_H)^{n_t^S - s_t^S} p_{t|t}^I + \mu_L^{s_t^S}(1-\mu_L)^{n_t^S - s_t^S}(1-p_{t|t}^I)}$$

Combining the two steps produce the following updating equation:

$$\begin{aligned} p_{t|t} &= \left[1+(\frac{\mu_L(1-\mu_H)}{\mu_H(1-\mu_L)})^{s_t^S}(\frac{(1-\mu_L)}{(1-\mu_H)})^{n_t^S}(\frac{\theta_L(1-\theta_H)}{\theta_H(1-\theta_L)})^{s_t^I}(\frac{(1-\theta_L)}{(1-\theta_H)})^{n_t^I}(\frac{1-p_{t|t-1}}{p_{t|t-1}})\right]^{-1} \\ &= \left[1+LR^{-1}(\Theta,\Sigma_t)\frac{1-p_{t|t-1}}{p_{t|t-1}}\right]^{-1} \end{aligned} \tag{22}$$

and

$$\mu_{t|t} = \mu_L + p_{t|t}(\mu_H - \mu_L) \tag{23}$$

$LR(\Theta,\Sigma_t)$ is the likelihood ratio between the two states given parameters $\Theta = \{\mu_L, \mu_H, \theta_L, \theta_H\}$ and the signals $\{n_t^S, s_t^S, n_t^I, s_t^I\}$. Finally the optimal forecast for the aggregate state of the world is given by the posterior belief and the persistence parameter:

$$\begin{aligned} p_{t+1|t} &= \lambda p_{t|t} + (1-\lambda)(1-p_{t|t}) \\ &= (1-\lambda) + (2\lambda - 1)p_{t|t} \end{aligned} \tag{24}$$

$$\mu_{t+1|t} = \mu_L + p_{t+1|t}(\mu_H - \mu_L) \tag{25}$$

Information production

The sensitivity of posterior beliefs to period t information depends on the informativeness of period t signals. These are characterized by their quantity and quality. As a measure for how much information is produced consider the likelihood of being in the high or low state given signals Σ_t:

$$\begin{aligned} \mathcal{L}(\mu_H|\Sigma_t) &= \mu_H^{s_t^S}(1-\mu_H)^{n_t^S - s_t^S}\theta_H^{s_t^I}(1-\theta_H)^{n_t^I - s_t^I} \\ \mathcal{L}(\mu_L|\Sigma_t) &= \mu_L^{s_t^S}(1-\mu_L)^{n_t^S - s_t^S}\theta_L^{s_t^I}(1-\theta_L)^{n_t^I - s_t^I} \end{aligned}$$

The above equations are the conditional likelihood of either states given period t information. The likelihood ratio $LR(\Theta,\Sigma_t)$ is just the ratio of these two equations. As a measure of information, the

Kullback-Leibler divergence D_{KL} between these two likelihoods is[25]:

$$
\begin{aligned}
D_{KL}(\mu_H||\mu_L) &= s_t^S log(\frac{\mu_H}{\mu_L}) + (n_t^S - s_t^S) log(\frac{1-\mu_H}{1-\mu_L}) + \ldots & (26)\\
& \quad s_t^I log(\frac{\theta_H}{\theta_L}) + (n_t^I - s_t^I) log(\frac{1-\theta_H}{1-\theta_L}) & (27)\\
&= n_t \left[\frac{n_t^S}{n_t} \left(\mu_H log(\frac{\mu_H}{\mu_L}) + (1-\mu_H) log(\frac{1-\mu_H}{1-\mu_L}) \right) + \ldots \right. & (28)\\
& \quad \left. \frac{n_t^I}{n_t} \left(\theta_H log(\frac{\theta_H}{\theta_L}) + (1-\theta_H) log(\frac{1-\theta_H}{1-\theta_L}) \right) \right] & (29)\\
D_{KL}(\mu_L||\mu_H) &= n_t \left[\frac{n_t^S}{n_t} \left(\mu_L log(\frac{\mu_L}{\mu_H}) + (1-\mu_L) log(\frac{1-\mu_L}{1-\mu_H}) \right) + \ldots \right. & (30)\\
& \quad \left. \frac{n_t^I}{n_t} \left(\theta_L log(\frac{\theta_L}{\theta_H}) + (1-\theta_L) log(\frac{1-\theta_L}{1-\theta_H}) \right) \right] & (31)
\end{aligned}
$$

The first equation is conditional on μ_H being the true state, and thus $\mathbb{E}[s_t^S] = \mu_H n_t^S$ and $\mathbb{E}[s_t^I] = \theta_H n_t^I$, whereas the second is with respect to the low state μ_L.

F. The extensive margin to information production

To construct the proof first we show that the quantity of signals is increasing in beliefs. Denote participation with the variable $\mathbb{1}_{w,i}$ if entrepreneur i decides to participate in credit markets and invest.

Lemma 1. *The number of signals $n_t \equiv \sum_{i \in N} \mathbb{1}_{w,i}$ is non-decreasing in beliefs about the state of the world $\mu_{t|t-1}$.*

[25] The Kullback-Leibler divergence is a weighted average *distance* between two probability density functions evaluated at one of the measures taken to be the correct one. Note that this implies that this implies that this implies that this measure of divergence between two distributions is not symmetric.

Proof.

$$
\begin{aligned}
\frac{n_t}{N} &= 1 - F(A^*(\mu_{t|t-1})) \\
& \frac{\partial\, A^*(\mu_{t|t-1})}{\partial\, \mu_{t|t-1}} < 0 \\
\text{since} & \\
& \frac{\partial\, A^*(\mu_{t|t-1}, S)}{\partial\, \mu_{t|t-1}} < 0 \\
& \frac{\partial\, A^*(\mu_{t|t-1}, I)}{\partial\, \mu_{t|t-1}} < 0 \\
\text{Thus} & \\
\frac{\partial\, n_t}{\partial\, \mu_{t|t-1}} &\geq 0
\end{aligned}
$$

The last equation holds with strict inequality whenever $F'(A^*) \neq 0$. □

Proof of Proposition 1: The extensive margin to information production. The amount of information in Σ_t about the state of the world is characterized by $D_{KL}(\mu_L||\mu_H)$ and $D_{KL}(\mu_H||\mu_L)$. Assuming a constant proportion of screened projects, more optimistic beliefs yield a lower A^* and, by the previous lemma, increases n_t. Then, given the constant screening proportion:

$$
\begin{aligned}
\frac{\partial D_{KL}(\mu_L||\mu_H)}{\partial n_t} &= \left[\frac{n_t^S}{n_t}\left(\mu_L log(\frac{\mu_L}{\mu_H}) + (1-\mu_L) log(\frac{1-\mu_L}{1-\mu_H})\right) + \ldots \right. \\
& \left. \frac{n_t^I}{n_t}\left(\theta_L log(\frac{\theta_L}{\theta_H}) + (1-\theta_L) log(\frac{1-\theta_L}{1-\theta_H})\right)\right] \\
&> 0 \\
\frac{\partial D_{KL}(\mu_H||\mu_L)}{\partial n_t} &= \left[\frac{n_t^S}{n_t}\left(\mu_H log(\frac{\mu_H}{\mu_L}) + (1-\mu_H) log(\frac{1-\mu_H}{1-\mu_L})\right) + \ldots \right. \\
& \left. \frac{n_t^I}{n_t}\left(\theta_H log(\frac{\theta_H}{\theta_L}) + (1-\theta_H) log(\frac{1-\theta_H}{1-\theta_L})\right)\right] \\
&> 0
\end{aligned}
$$

The inequality arises since $\mu_H \neq \mu_L$ and $\theta_H \neq \theta_L$. If this were the case, then the two likelihoods are the same and the Kullback-Leibler divergence is always zero. Thus information production, or the information contained in period t signals, is non-decreasing in beliefs through the extensive margin. □

G. The intensive margin to information production

As before, we first show that the proportion of screened projects is weakly concave (inverse-U shaped) in beliefs.

Lemma 2. *The proportion of screening $n_t^S \equiv \sum_{i \in N} \mathbb{1}_{S,i}$ to total n_t signals in each period is weakly concave in beliefs $\mu_{t|t-1}$. In particular, it is inverse-U shaped whenever the screening cost γ is within a particular range.*

Proof. The measure of entrepreneurs who choose to be screened are given by:

$$n_t^S \propto 1 - \max\{F(A^*(\mu_{t|t-1})), F(\tilde{A}(\mu_{t|t-1}))\}$$

On the other hand, the measure of unscreened entrepreneurs is:

$$n_t^I \propto [F(\tilde{A}(\mu_{t|t-1})) - F(A^*(\mu_{t|t-1}))]^+$$

Then:

$$\frac{n_t^S}{n_t} \equiv \frac{n_t^S}{n_t^S + n_t^I} \begin{cases} = 1 & \text{if } A^*(\mu_{t|t-1}) \geq \tilde{A}(\mu_{t|t-1}) \\ \propto \frac{1-F(\tilde{A}(\mu_{t|t-1}))}{1-F(A^*(\mu_{t|t-1}))} & \text{if } A^*(\mu_{t|t-1}) < \tilde{A}(\mu_{t|t-1}) \end{cases}$$

Thus, it is sufficient to show that the ratio $\frac{A^*(\mu_{t|t-1})}{\tilde{A}(\mu_{t|t-1})}$ is inverse-U shaped. We use equations 6 and 7 to get:

$$\begin{aligned} \frac{A^*(\mu_{t|t-1})}{\tilde{A}(\mu_{t|t-1})} \quad = \quad \min\Big\{ & (1 - \zeta(\mu_{t|t-1})^{-1})^{1-\alpha}(1 + \frac{w}{\gamma(1+r_f)})^{1-\alpha}, \; \ldots \\ & (\zeta(\mu_{t|t-1}) - 1)^{1-\alpha}(\frac{w}{\gamma(1+r_f)})^{1-\alpha} \Big\} \end{aligned}$$

where $\zeta(\mu_{t|t-1}) > 1$ and is concave in $\mu_{t|t-1} \in (0,1)$. In turn, both arguments in the minimization function are concave (inverse-U shaped) in $\mu_{t|t-1}$. $\square$

Proof of Proposition 2: The intensive margin to information production. Keeping the total number of signals constant, and under the previous lemma, the change in informativeness of period t signals given an increase in the proportion of screened projects is given by:

$$\begin{aligned}
\frac{\partial D_{KL}(\mu_L||\mu_H)}{\partial n_t^S} - \frac{\partial D_{KL}(\mu_L||\mu_H)}{\partial n_t^I} &= \left(\mu_L log(\frac{\mu_L}{\mu_H}) + (1-\mu_L)log(\frac{1-\mu_L}{1-\mu_H})\right) - \dots \\
&\quad \left(\theta_L log(\frac{\theta_L}{\theta_H}) + (1-\theta_L)log(\frac{1-\theta_L}{1-\theta_H})\right) \\
&> 0 \\
\frac{\partial D_{KL}(\mu_H||\mu_L)}{\partial n_t^S} - \frac{\partial D_{KL}(\mu_H||\mu_L)}{\partial n_t^I} &= \left(\mu_H log(\frac{\mu_H}{\mu_L}) + (1-\mu_H)log(\frac{1-\mu_H}{1-\mu_L})\right) - \dots \\
&\quad \left(\theta_H log(\frac{\theta_H}{\theta_L}) + (1-\theta_H)log(\frac{1-\theta_H}{1-\theta_L})\right) \\
&> 0
\end{aligned}$$

Both differences are positive in that $\theta_H - \theta_L = (\mu_H - \mu_L)(\theta_G - \theta_B) < \mu_H - \mu_L$ which guarantees that the first term in both equations are larger than the second. Intuitively, the larger difference in parameters of the binomial likelihoods given the screening signals relative to the no-screening signals makes the screening signals more informative as these signals would be sampled from relatively more different distributions. □

The following corollary identifies special cases of the proposition.

Corollary. *When $\gamma \geq \bar{\gamma}$, no screening ever takes place and $n_t = n_t^I \quad \forall \mu_{t|t-1}$. When $\gamma \leq \underline{\gamma}$ then all credit market participants choose to be screened and $n_t = n_t^S \quad \forall \mu_{t|t-1}$.*

$$\begin{aligned}
\bar{\gamma} &\equiv Z(\mu^*)\bar{A}^{\frac{1}{1-\alpha}}\frac{\Lambda}{1+r_f} \\
\underline{\gamma} &\equiv [\zeta(\mu^{**}) - 1]\left(\frac{w}{1+r_f}\right)
\end{aligned}$$

The screening cost $\bar{\gamma}$ is the smallest value such that $min(\tilde{A}(\mu_{t|t-1})) = \bar{A}$. This is $\tilde{A}(\mu^*) = \bar{A}$ where μ^* is the level of beliefs which maximizes the gains from screening:

$$\mu^* \equiv \frac{1}{\theta_G - \theta_B}\left[\frac{(1-\alpha)(\theta_G^{\frac{1}{1-\alpha}} - \theta_B^{\frac{1}{1-\alpha}})}{\theta_G - \theta_B}\right]^{\frac{1-\alpha}{\alpha}} - \theta_B$$

On the other hand, $\underline{\gamma}$ is the largest screening cost such that $\tilde{A} \leq A^* \quad \forall \mu_{t|t-1} \in [\mu_L, \mu_H]$ where $\mu^{**} \in \{\mu_L, \mu_H\}$ is the level of beliefs which minimizes the gains from screening[26].

[26] That is, μ^{**} minimizes $Z(\mu_{t|t-1})$ which will be at one of the boundaries, depending on parameter values.

H. *Persistence*

Proof of Proposition 3: Dynamics of belief persistence. Define a change in beliefs given market outcomes as $\Delta p_{t|t} \equiv log(\frac{p_{t|t}}{p_{t|t-1}})$ and endogenous persistence as the degree by which this change in beliefs is small arising from the information content of date t signals. Then,

$$\Delta p_{t|t} = -log(\left[p_{t|t-1} + LR^{-1}(\Theta, \Sigma_t)(1 - p_{t|t-1})\right])$$

Clearly $\Delta p_{t|t} \neq 0$ when $LR^{-1}(\Theta, \Sigma_t) \neq 1$ and the extent by which posterior beliefs deviate from priors is proportional to the extent by which the likelihood ratio differs from one - the amount of information contained in signals at date t. To illustrate the two channels clearly, we rewrite the likelihood ratio as follows:

$$LR^{-1}(\Theta, \Sigma_t) = \left(\left[\left(\frac{\mu_L(1-\mu_H)}{\mu_H(1-\mu_L)}\right)^{\frac{s_t^S}{n_t^S}} \left(\frac{1-\mu_L}{1-\mu_H}\right) \right]^{\frac{n_t^S}{n_t}} \left[\left(\frac{\theta_L(1-\theta_H)}{\theta_H(1-\theta_L)}\right)^{\frac{s_t^I}{n_t^I}} \left(\frac{1-\theta_L}{1-\theta_H}\right) \right]^{\frac{n_t^I}{n_t}} \right)^{n_t}$$

$\frac{s_t^S}{n_t^S}$ and $\frac{s_t^I}{n_t^I}$ are date t shocks, $\frac{n_t^S}{n_t}$ and $\frac{n_t^I}{n_t}$ are the relative shares of each type of signal, and n_t is the aggregate quantity of signals. The deviation of $LR^{-1}(\Theta, \Sigma_t)$ from one represents the total information content of all signals generated at time t. Thus, the object of interest is how priors affect the sensitivity of the likelihood ratio to date t shocks.

Suppose $\frac{s_t^S}{n_t^S}$ and $\frac{s_t^I}{n_t^I}$ are equal to ϵ. We evaluate the sensitivity of posteriors to a small change to such realizations $\Delta\epsilon$.

$$\begin{aligned}
\frac{\partial \Delta p_{t|t}}{\partial \Delta\epsilon} &= \frac{\partial \Delta p_{t|t}}{\partial LR^{-1}(\Theta, \Sigma_t)} \frac{\partial LR^{-1}(\Theta, \Sigma_t)}{\partial \Delta\epsilon} \\
&= -\left[\frac{LR^{-1}(\Theta, \Sigma_t)}{\frac{p_{t|t-1}}{1-p_{t|t-1}} + LR^{-1}(\Theta, \Sigma_t)} \right] \left[n_t \left(\frac{n_t^S}{n_t} log(\frac{\mu_L(1-\mu_H)}{\mu_H(1-\mu_L)}) + \frac{n_t^I}{n_t} log(\frac{\theta_L(1-\theta_H)}{\theta_H(1-\theta_L)}) \right) \right]
\end{aligned}$$

The first term reflects the sensitivity of posterior beliefs to current information while the second reflects the information content of shocks to date t signals. We are interested in the second component of the above equation[27].

First, the extensive margin reduces persistence in that sensitivity is increasing in n_t which in turn

[27] The first component reflects persistence generated from how extreme priors are. Further, its functional form is sensitive to the assumption of a bivariate state. In this two-state economy, the ratio reflects both how extreme beliefs are (mean of the prior) and how precise these beliefs are thought to be (variance of the prior).

is non-decreasing in priors $\mu_{t|t-1}$ as shown in proposition 1. Second, sensitivity is increasing in $\frac{n_t^S}{n_t}$ given that signals from the screening outcomes are more precise: $log(\frac{\mu_L(1-\mu_H)}{\mu_H(1-\mu_L)}) < log(\frac{\theta_L(1-\theta_H)}{\theta_H(1-\theta_L)}) < 0$. Thus, the intensive margin generates an inverse-U shaped component to persistence as shown in proposition 2.

Depending on the relative values of the parameters $\{\mu_H, \mu_L\}$ and $\{\theta_H, \theta_L\}$, the contribution of the intensive margin to persistence in beliefs may either be amplified or attenuated. These, together with the sensitivity of the cutoffs A^* and $\tilde{A}$ to $\mu_{t|t-1}$ (also a function of the other parameters r_f, α, w) determine whether there exists a threshold μ^* as defined in the proposition for a given level of γ. Finally case one in the proposition refer to the special cases such that $n_t^S = n_t$ or $n_t^I = n_t$ corresponding to threshold levels of the screening cost identified in the corollary to the previous proposition. In this case, the intensive margin does not apply and through the extensive margin, persistence of beliefs is monotonically decreasing in $\mu_{t|t-1}$ $\square$

B. Socially Optimal Information Production

I compare the competitive equilibrium allocation in Section 2 to that chosen by a constrained social planner. To facilitate our analysis, define aggregate expected profits in period t as given by the sum of all expected end-of-period returns to entrepreneurs:

$$\begin{aligned}\mathbb{E}[\pi_t|p_{t|t-1}] &= Nw + \sum_{A_i\in(A^*,\bar{A})}(\mathbb{E}[\pi_i|p_{t|t-1,I}]-w)f(A_i)+...\\ &\sum_{A_i\in(max\{A^*,\tilde{A}\},\bar{A})}(Z(p_{t|t-1})A_i^{\frac{1}{1-\alpha}}\Lambda-\gamma(1+r_f))f(A_i)\end{aligned} \tag{32}$$

Aggregate expected profits is the sum of the outside opportunity return for all entrepreneurs plus the gains from participation given by the no-screening contract for all entrepreneurs above the participation threshold and finally the gains from screening for all entrepreneurs above the screening threshold. This expression is increasing and convex in beliefs about the state ($p_{t|t-1}$) and is concave in the two thresholds A^* and $\tilde{A}$.

The cutoffs that maximize aggregate expected profits are given by the lowest values of A_i that give positive values for the second and third terms. This is exactly the conditions satisfied by the competitive equilibrium (equations 6 and 7). Thus, the competitive equilibrium yields the same allocation as a constrained social planner with this objective. This is what is done in Van Nieuwerburgh and Veldkamp (2006).

I consider an alternative objective for my social planner who internalizes the impact of these thresholds on the distribution of next period beliefs. Define a social welfare function as the discounted sum of all expected profits conditional on prior beliefs.

$$\max_{\{\tilde{A}_t,A_t^*\}_{t=1}^{\infty}}\mathcal{W} = \sum_{t=1}^{\infty}\beta^{t-1}\mathbb{E}[\pi_t|p_{t|t-1}]$$

The constrained social planner chooses a sequence of cutoffs that maximizes social welfare taking into account the intertemporal information spillover externality. I do not allow our social planner to deviate from the loan contracts specified in Section 2. Instead, the social planner only chooses the thresholds A_t^{*CSP} and $\tilde{A}_t^{CSP}$ which determine the set of participating and screened entrepreneurs. As in the competitive equilibrium, these cutoffs must be measurable with respect to period t information.

The constrained social planners problem yields the following Bellman equation and first order conditions

$$\begin{aligned}
V(p_{t|t-1}) &= \max_{\{\tilde{A}_t, A_t^*\}} \mathbb{E}[\pi_t|p_{t|t-1}] + \beta \mathbb{E}[V(p_{t+1|t})|p_{t|t-1}] \\
\frac{\partial \mathbb{E}[\pi_t|p_{t|t-1}]}{\partial A_t^*} &= -\beta \frac{\partial \mathbb{E}[V(p_{t+1|t})|p_{t|t-1}]}{\partial A_t^*} \\
\frac{\partial \mathbb{E}[\pi_t|p_{t|t-1}]}{\partial \tilde{A}_t} &= -\beta \frac{\partial \mathbb{E}[V(p_{t+1|t})|p_{t|t-1}]}{\partial \tilde{A}_t}
\end{aligned}$$

Proposition 4 (Cutoffs under optimal learning)**.** *The solution to the constrained social planner's problem yields cutoffs* $\tilde{A}^{CSP}(p_{t|t-1})$ *and* $A^{*CSP}(p_{t|t-1})$ *which are lower than the cutoffs in the competitive equilibrium.*

The proof rests on two features of the model. First, the expected value function tomorrow is increasing and convex in the expected state of the economy $p_{t+1|t}$. As in the individual profit functions, the average of aggregate profits in the high and low states are higher than aggregate profits at the average state. Second, increasing the precision of information, by reducing either cutoff, induces a mean-preserving spread in the distribution of $p_{t+1|t}$. The next two lemmas derive these properties and the proof of the proposition follows.

Lemma 3. *The value function* $V(p_{t+1|t})$ *is increasing and convex in* $p_{t+1|t}$

Proof. Expected period $t+1$ profits $\mathbb{E}[\pi_{t+1}|t]$ is increasing and convex in $p_{t+1|t}$. This is straightforward from equation 32 which is just the aggregation of increasing and convex individual profit functions (equations 15 and 16). Further, the sequence of expected aggregate states of the economy $\{p_{t+1+s|t}\}_{s=1}^{\infty}$ are a linear and increasing function of $p_{t+1|t}$. Recall that

$$\begin{aligned}
p_{t+s|t} - \frac{1}{2} &= (2\lambda - 1)(p_{t+s-1|t} - \frac{1}{2}) \\
&= (2\lambda - 1)^{s-1}(p_{t+1|t} - \frac{1}{2})
\end{aligned}$$

This then implies that $V(p_{t+1|t})$ is just the discounted sum of expected future profits which are increasing and convex in $p_{t+1|t}$ thus completing the proof.[28] □

Lemma 4. *A reduction in the cutoffs* A_t^* *and* $\tilde{A}_t$ *induce a mean-preserving spread in the distribution of* $p_{t+1|t}$.

[28]Note that as $s \to \infty$ the sensitivity of expected $t+s$ profits to current priors goes to zero.

Proof. This lemma is implied by proposition 3. For any given period t shocks, lowering the cutoffs A_t^* and $\tilde{A}_t$ increases the precision of information but preserves the mean as the ratios $\frac{s_t^S}{n_t^S}$ and $\frac{s_t^I}{n_t^I}$ are independent random variables which only depend on μ_t. On the other hand, as persistence falls with the precision of period t information, the expected variance of posterior beliefs increases.

To show that a reduction in the cutoffs preserve the mean forecast, note that

$$\begin{aligned}
\mathbb{E}[p_{t+1|t}|p_{t|t-1}] &\equiv p_{t+1|t-1} \\
&= \mathbb{E}[(2\lambda-1)(p_{t|t}-\frac{1}{2})|p_{t|t-1}] \\
&= (2\lambda-1)(p_{t|t-1}-\frac{1}{2})
\end{aligned}$$

To show that the forecast variance increases I use the result from proposition 3 which shows a negative relationship between the participation and screening thresholds and the resulting distance between the likelihood ratio of period t signals from one.

$$\begin{aligned}
\mathbb{E}[(p_{t+1|t}-p_{t+1|t-1})^2|p_{t|t-1}] &= (2\lambda-1)^2\mathbb{E}[(p_{t|t}-p_{t|t-1})^2|p_{t|t-1}] \\
&= \left[(2\lambda-1)(\frac{1}{4}-(p_{t|t-1})^2)\right]^2 \dots \\
&\quad \mathbb{E}[\left(\frac{LR(\Sigma_t)-1}{1+p_{t|t-1}(LR(\Sigma_t)-1)}\right)^2|p_{t|t-1}]
\end{aligned}$$

The first term in the above equation captures the persistence of the state and thus the usefulness of past information. The second term captures the strength of prior beliefs (i.e., if priors are close to one or zero then posteriors are unlikely to move far away from priors). The last term reflects the variation in posteriors due to the precision of period t information as captured by the expected deviation of the likelihood ratio between the High and Low states ($LR(\Sigma_t)$) from one.

By proposition 3 we have that for any realization of the random variables s_t^S and s_t^I

$$\begin{aligned}
\frac{\partial |LR(\Sigma_t) - 1|}{\partial A_t^*} &< 0 \\
\frac{\partial |LR(\Sigma_t) - 1|}{\partial \tilde{A}_t} &< 0 \\
\text{then} & \\
\frac{\partial \left(\frac{LR(\Sigma_t)-1}{1+p_{t|t-1}(LR(\Sigma_t)-1)} \right)^2}{\partial A_t^*} &< 0 \\
\frac{\partial \left(\frac{LR(\Sigma_t)-1}{1+p_{t|t-1}(LR(\Sigma_t)-1)} \right)^2}{\partial \tilde{A}_t} &< 0
\end{aligned}$$

Thus a reduction in either cutoff will also yield an increase in the expected squared deviation of the likelihood ratio from one which implies that

$$\begin{aligned}
\frac{\partial \mathbb{E}[(p_{t+1|t} - p_{t+1|t-1})^2 | p_{t|t-1}]}{\partial A_t^*} &< 0 \\
\frac{\partial \mathbb{E}[(p_{t+1|t} - p_{t+1|t-1})^2 | p_{t|t-1}]}{\partial \tilde{A}_t} &< 0
\end{aligned}$$

Thus we have that a fall in either cutoff A_t^* or $\tilde{A}_t$ induces a mean-preserving spread on the distribution of posterior forecasts and next-period priors. □

We can now complete the proof of the proposition.

Proof of Proposition 4: Cutoffs under optimal learning. For the social planner cutoffs $\tilde{A}_t^{CSP}$ and A_t^{*CSP} to be lower than the cutoffs chosen in the competitive equilibrium, it is sufficient to show that:

$$\begin{aligned}
\beta \frac{\partial \mathbb{E}[V(p_{t+1}) | p_{t|t-1}]}{\partial A_t^*} &< 0 \\
\beta \frac{\partial \mathbb{E}[V(p_{t+1}) | p_{t|t-1}]}{\partial \tilde{A}_t} &< 0
\end{aligned}$$

Using the previous two lemmas, a reduction in the thresholds induce a mean-preserving spread in the distribution of next-period priors $p_{t+1|t}$. In turn, since the value function is increasing and convex in next-period priors, such a mean-preserving spread implies an increase in the expected value of the value function and completes the proof. □

C. Model Simulation

A. Simulation Parameters

The simulations uses the parameter values reported in the following table.

Table 1: Simulation Parameters

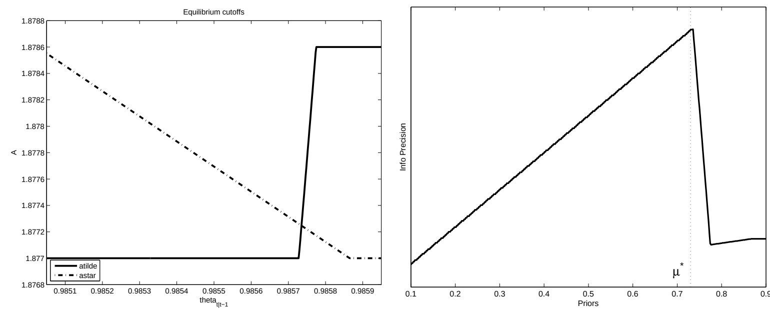
Variable	Symbol	Value
Number of Agents	N	20
Productivity lower bound	$\underline{A}$	1.877
Productivity upper bound	$\bar{A}$	1.879
Returns to scale	α	0.7
Good type probability of success	θ_G	0.99
Bad type probability of success	θ_B	0.98
High state proportion of good	μ_H	0.60
Low state proportion of good	μ_L	0.50
Cost of funds	r_f	0.001
Outside opportunity return	w	1.013
Screening cost	γ	1e-4
Persistence of state	λ	0.95

Although the parameters were chosen so as not to be too unrealistic, the simulations are not meant to provide a quantitatively accurate representation of what we observe in the data. Rather, they are chosen so as to highlight some features of the model. The number of agents is sufficiently large so as to minimize the impact of idiosyncratic shocks to aggregate outcomes and small enough that the state is not always fully inferred from market outcomes. The upper and lower bounds to observable productivity and the outside opportunity return where chosen so as to minimize the proportion of agents whose choices do not vary over time[29]. The relatively small difference between the high and low state proportions were chosen so as to allow for a sufficiently large number of agents N in the simulation while still generating variations in the precision of signals across ranges of prior beliefs[30]. The state persistence parameter is consistent with an average duration of a state equal to 20 periods. Finally, given the other parameter values the outside opportunity cost w and screening cost γ were chosen to generate the screening and participation thresholds in Figure 8a. The relative precision

[29] We assume a uniform distribution of A_i over 20 equally spaced values in between (and including) $\underline{A}$ and $\bar{A}$.

[30] See for example the calibration of the endogenous learning model in Veldkamp (2005) where U.S. speculative bond default rates in recession and non-recession years of five and three percent yield success probabilities of 95 and 97 percent respectively where $N = 25$ and a period is one year. Similarly, the calibration of the partial equilibrium model of endogenous information production with bankruptcy and monitoring costs in Ordonez (2013) with a monthly frequency yield default probabilities for the two states as 99.65 and 99.15 percent respectively.

of information, as well as the threshold level of optimism identified in proposition 3, are plotted in Figure 8b.



(a) Participation and Screening Thresholds over Beliefs

(b) Relative precision of information

B. Simulated business cycles

I simulate for 50,000 periods with an initial prior of one half and estimate business cycle turning points by filtering out high frequency fluctuations[31]. Given the filtered output I define a peak (or the start of a recession) as a point in time with the local maximum of filtered output. A trough (end of the recession) is identified similarly. This gives us between 992 to 1,104 full cycles across simulations. In Table 2 I first report the skewness of the growth rate of investment and changes in the no-screening interest rate.

Table 2: Skewness estimates

	Investment	**Loan rates**
Model	-0.48	0.25
Extensive	-0.49	0.48
Constant	0.04	0.06

First, constant information production generates symmetric changes in these variables whereas in simulations *Extensive* and *Model*, interest rate changes are right-skewed and investment growth is negatively skewed. These are features of asymmetric business cycles consistent with slow recoveries generated by the extensive margin to information production. This asymmetry also appears in the frequency of pessimistic periods relative to optimistic ones. In Figure 9, I report the frequency (in percent) of periods with beliefs given on the horizontal axis.

[31]This was done using a Hodrick-Prescott filter set to 14400.

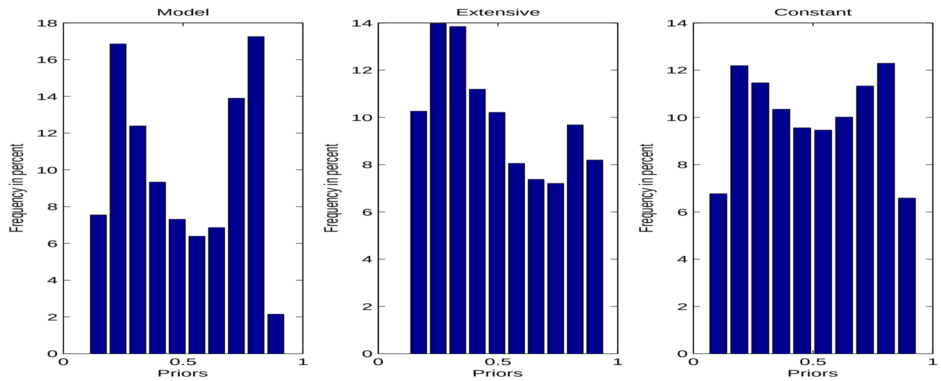
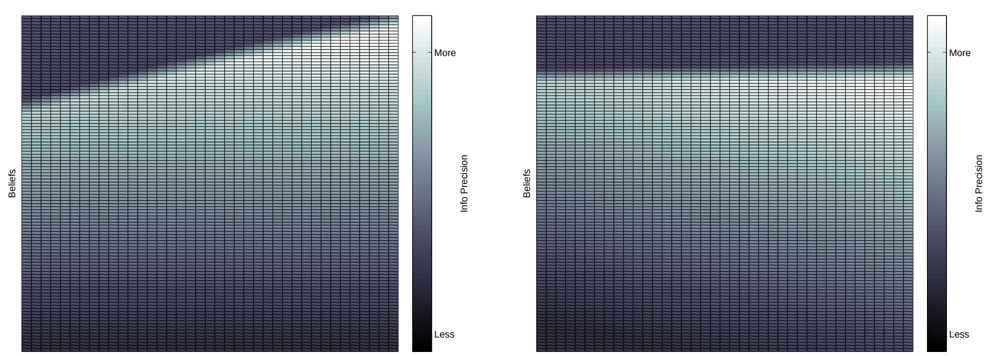


Figure 9: Frequency of pessimistic and highly optimistic beliefs

The distribution of beliefs for *Constant* is symmetric whereas pessimistic beliefs ($p_{t|t-1} < 0.5$) occur two to five percent more often in *Model* and *Extensive*. On the other hand, through the intensive margin, highly optimistic beliefs also occur more frequently in *Model* relative to *Extensive*. Beliefs higher than 75 percent probability of the High state occur four percent more often in *Model* relative to *Extensive*.

C. Financial development

The following figures plot the relative precision of information from both margins over the range of prior beliefs (vertical axes) and different values for the cost of screening and cost of funding.



(a) Information precision over screening cost (b) Information precision over funding cost

D. Macro Uncertainty

A. Data description

Uncertainty:

We are interested in measuring macro-uncertainty arising from information flows about aggregate fundamentals over time. Survey forecasts provide a rich dataset for this purpose in that we have available individual forecasts over probability ranges of the same target variable (e.g. annual average real GDP growth for the year 2009) for several forecast horizons. Given the probability range forecasts, we can compute the relative dispersion of each forecast with an entropy measure as detailed below. The variable is defined as the average entropy of individual probability range forecasts.

I make use of probability range forecasts of current and following year *annual average over annual average* change in real GDP. Survey respondents are asked to detail the probability that GDP growth will fall under a certain range. We use survey responses from the first quarter of 1992 to the fourth quarter of 2012 where the GDP growth ranges are binned into < -2,-2 to -1.1, and so on until > 6 percent for a total of ten bins of one percent width each except for the extremes.[32]. Sample responses are provided in the table below:

Table 3: Sample Survey Responses

year	quarter	id	industry	Cur > 6	Cur 5 to 5.9	Cur 4 to 4.9	Cur 3 to 3.9	Cur 2 to 2.9	Cur 1 to 1.9	Cur 0 to 0.9	Cur -1 to -0.1	Cur -2 to -1.1	Cur < -2
1992	1	30	3	0	0	10	60	30	0	0	0	0	0
1992	1	35	2	0	0	10	10	20	50	10	0	0	0
year	quarter	id	industry	Fol > 6	Fol 5 to 5.9	Fol 4 to 4.9	Fol 3 to 3.9	Fol 2 to 2.9	Fol 1 to 1.9	Fol 0 to 0.9	Fol -1 to -0.1	Fol -2 to -1.1	Fol < -2
1992	1	30	3	0	0	30	50	20	0	0	0	0	0
1992	1	35	2	0	10	20	20	40	10	0	0	0	0

Table 3 reproduces the responses of two participants (identified as 30 and 35). The first two columns report the date of the survey and the fourth column reflects the industry to which the respondent belongs two (financial, non-financial or unknown). Categories $Cur > 6$ to $Cur < -2$ reflect the 10 annual average growth rate bins for real GDP growth for the current year 1992. Given that these responses were obtained in the first quarter of 1992, we have coded these as 4-quarter ahead forecasts. The categories $Fol > 6$ to $Fol < -2$ are the same growth rate bins for the following year (1993) and are coded as 8-quarter ahead forecasts. The values in these categories reflect the

[32] From the second quarter of 2009 onwards, the lowest bin has been split into < -3 and -3 *to* -2.1. I have aggregated the responses for these two bins. Further, I only use data beginning on the first quarter of 1992 as the survey question from the third quarter of 1981 to the fourth quarter of 1992 corresponds to forecasts of real GNP and only has 6 bins. Prior to this period the survey asks for forecasts of nominal GNP.

probabilities (in percent) that the respondents attach to real GDP growth rate falling within these bins. Our variable of interest is the diffusion of these forecasts. In the table above, forecaster 35 has a more diffuse forecast than forecaster 30 for the current and following year real GDP growth. We may interpret this as higher forecast uncertainty. I do a similar exercise using probability range forecasts for the GDP price index from the same survey (annual average over annual average percent change in the GDP price index) with similar results and are omitted from this paper.

I compute an entropy measure for each individual respondent i in date t defined as[33]:

$$ENT_{i,t,h} \equiv -\sum_{b=1}^{10} p_{i,t,h,b} log(p_{i,t,h,b})$$

where $p_{t,i,b}$ is the probability value for the bin b given by respondent i in date t for real GDP or the GDP Price index growth in year y where each annual average growth rate is forecasted for eight periods (for each period h may refer to either the current year or the following year and t is quarterly). For the sample period (86 quarters), each forecaster makes two predictions per quarter (current and following year) where there are 162 unique forecasters for the real GDP growth series[34]. Within the sample, there is a minimum of 23 (fourth quarter of 2001) and a maximum of 50 respondents (third quarter of 2005) for any given quarter.

This measure is bounded between zero and $log(10)$ and reflects the dispersion of a respondent's forecast. The forecast horizon ranges from 8 quarters ahead (for a forecast of the following year's annual average GDP growth made in the first quarter of the current year) to 1 quarter ahead (a forecast made for the current year annual average GDP growth in the fourth quarter of the current year)[35]. In the following table, I report some summary statistics.

Table 4: Entropy measure statistics

	Individuals	Non-zero lowest bin	Non-zero highest bin	Mean	Median	Standard deviation	Min	Max	Obs
GDP Growth	162	326	188	1.0821	1.0627	0.4571	0.0000	2.2804	6120

I observe a total of 6,120 forecasts and about eight percent of these have probabilities on the extreme bins. Note that the entropy measures are biased downwards when the location of the reported

[33] Rich and Tracy (2010) conduct a similar exercise. We have also computed a sample standard deviation of the forecast using midpoints of the bins and obtained similar time series.

[34] Note that the FRB Philadelphia's caveat on the identifiers apply. That is sometimes the identifier is associated with a firm rather than an individual.

[35] That is, for the first quarter of each year we have two average entropy measures corresponding to the forecast of the current year with horizon 4 and the forecast of the following year with horizon 8. In the second quarter of each year we would have the same forecast targets but with corresponding horizons of 7 and 3. Similarly, the horizons for measures in the third quarter are 6 and 2 and in the fourth quarter they are 5 and 1

probability distributions are close to either of the extreme bins as all the probability weights for growth less than two percent (or greater than 6 percent) are lumped into one bin. In the data, this problem is negligible for most of the sample with less than one percent of respondents placing non-zero probabilities at either extreme bins. However, more than a third of responses for the 2009 surveys had non-zero probabilities on the smallest bin. This suggests that our entropy measure is likely to be biased downwards in 2009.

To get a sense of the potential size of this bias in 2009 I conduct the following exercise for real GDP growth forecasts. First I use the responses in the fourth quarter of 2007 to generate a representative distribution. The fourth quarter of 2007 was chosen since it is relatively close to the second quarter of 2009 and the average responses reflect a median probability located centrally in the two to three percent bin. The following figure plots the averaged responses for the fourth quarter of 2007 and the second quarter of 2009. Note that by averaging responses, the measured entropy from this average distribution will also reflect the disagreement across forecasters. The right panel in Figure 11 is quite informative over the source of disagreement and lower uncertainty for the second quarter of 2009. We have that 21 of the 90 current and following year forecasts in this period put all probability mass at the bottom two bins (less than one percent growth) generating a second mode in the average distribution and low individual entropy measures. The rest of the respondents were more optimistic and were forecasting growth to be in the one to three percent bin on average. To estimate average forecast uncertainty over time, we need to introduce controls for this potential downward bias at the individual level.

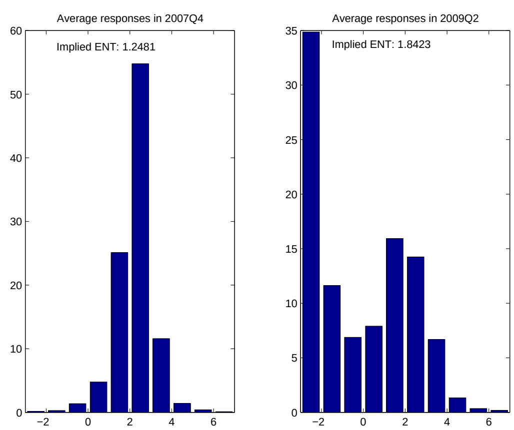


Figure 11: Average responses in 2007Q4 and 2009Q2

B. Entropy measure regression

This measure may be subject to horizon effects where uncertainty is expected to be increasing in the forecast horizon (see Patton and Timmerman, 2010 for horizon effects on forecast dispersion and Patton and Timmerman, 2011 for mean squared errors). To account for this, I estimate a panel regression with both individual and forecast horizon fixed effects. I include time fixed effects to capture the average value of entropy for each period. I then derive a bias-adjusted measure of individual entropy for real GDP growth forecasts. First, I calculate the average distribution of probabilities for the responses where the median bin is at two to three percent. This distribution is then shifted either to the right or to the left where probabilities at the outermost bins are truncated. I then compute the estimated entropy measure for each case and compute the difference with respect to the original distribution with no truncation. The next table reports the bias-adjustment factor equivalent to the difference in measured entropy using the transformed responses relative to the original response.

Table 5: Relative reduction in measured entropy

Median Bin	< -2	-2 to -1.1	-1 to -0.1	0 to 0.9	1 to 1.9	2 to 2.9	3 to 3.9	4 to 4.9	5 to 5.9	> 6
Relative Entropy	-1.113	-0.604	-0.159	-0.038	-0.008	0.000	-0.002	-0.007	-0.028	-0.1467

The final regression specification is as follows¿

$$ENT_{i,t}(h) = \alpha_i + \gamma_h + \delta_t + \beta\, bf_{i,t} + \epsilon_{i,t,h}$$

where $bf_{i,t}$ is the bias factor given by Table 5 and the median bin of the forecast for each respondent. Figure 7 reports the time fixed effects of these regression with and without the bias adjustment control. The figure suggests that the fall in uncertainty in 2009 is not robust to adjustment for potential bias due to truncation of responses. As with forecast error and forecast dispersion, I also find that uncertainty appears to increase in the forecast horizon. Finally, an alternative measure of dispersion based on the estimated standard deviation of probability forecasts yield similar results.

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