Bank Competition, Information Choice and Inefficient Lending Booms

Silvio Petriconi*

Abstract

This paper studies the implications of a free-riding problem between competing banks: prospective borrowers can use loan offers of informed lenders to bargain for better terms of credit elsewhere. In anticipation of this problem, banks adopt inefficiently lax lending standards and reduce screening effort in order to deter borrower poaching. In a dynamic version of the model, the distortions from free-riding create inefficient boom-bust cycles in lending: credit is poorly screened and excessive in good times, and is inefficiently rationed during recessions. More bank competition exacerbates the problem and reduces welfare.

Keywords: free-riding, banking competition, poaching, credit booms
JEL-classification: G21, E44, D82

*Department of Finance and IGIER, Università Luigi Bocconi, Via Röntgen 1, 20136 Milan, Italy. Phone: +39 2 5836 5956 Fax: +39 2 5836 5920 e-mail: silvio.petriconi@unibocconi.it. This paper is based on the first chapter of my PhD dissertation. I am deeply indebted to my advisor, Jaume Ventura, for invaluable guidance and support. I thank Yasser Boualam, Ramon Caminal, Elena Carletti, Vasco Carvalho, Hans Degryse, Giovanni Dell'Arriccia, Andrew Ellul, Xavier Freixas, Mariassunta Giannetti, Hugo Hopenhayn, Vasso Ioannidou, José Liberti, Robert Marquez, Alberto Martin, Steven Ongena and Marco Pagano for helpful discussions and suggestions. I also thank conference participants at the CSEF-IGIER Symposium 2014 in Capri, the 2014 EFA Annual Meeting, the 2015 FIRS meeting in Reykjavik, and seminar participants at Bank of England, Banque de France, Banca d'Italia, Bocconi, Frankfurt School of Finance, ECB, HEC Paris, LSE, Sveriges Riksbank, University of Melbourne, UPF, University of Queensland and University of Vienna for their feedback. Financial support from the Generalitat de Catalunya via the AGAUR FI grant is gratefully acknowledged. All errors are my own.

1 Introduction

Over the past two decades, many countries worldwide have undertaken a process of deregulation[1] of their financial sectors that has turned tightly regulated bank oligopolies into much more competitive industries. It is widely believed that these reforms have provided credit-constrained firms and households with better access to bank credit[2]. However, the increasing occurrence of credit-driven boom-bust cycles[3] raises the question whether this increase in competition may have come at a cost: anecdotal evidence suggests that in episodes of strong economic outlook, credit may actually have become *too easy* to obtain. In good times, so the narrative goes, competitive pressure drives banks to reduce their screening effort and lower their lending standards, resulting in the rapid build-up of large positions of poorly screened assets in their balance sheets that lay the foundations for the next financial crisis.

In this paper, I develop a theory of inefficient lending cycles that are driven by a free-riding problem between competing lenders. In a static model of borrower screening, I obtain two important results: first, more competition can incentivize informed incumbent banks to knowingly take bad projects into their loan portfolio. This is optimal because it protects them against the entry of uninformed lenders who could poach their customers. Instead of raising welfare by reducing markups, more bank competition exerts detrimental downward pressure on lending standards. Since in equilibrium banks offer credit to some borrowers despite of a negative screening evaluation, they also fail to make best use of their information which leads to the second result: if banks choose their screening precision endogenously, I find that competition reduces borrower screening to inefficiently low levels. Extended to a dynamic setting, the combination of these two results yields a powerful theory of the credit cycle.

The key to these findings is to acknowledge that just like all other information centric industries, banks often face difficulties in fully protecting their private information while assessing credit. In particular, the loan offers of informed lenders reflect a considerable amount of private information, yet they can often be observed by competitors. This occurs for a variety of reasons. One reason is transparency regulation. Many countries have subjected especially the mortgage closing process to strict transparency rules. These rules attempt to protect borrowers from predatory lending terms by requiring that lenders must provide written loan estimates or even unilaterally binding loan offers to borrowers several days before a loan is closed[4]. However, written offers do create information spillovers:

[1] In the U.S. the 1994 Riegle-Neal Act eliminated previous interstate banking and branching restrictions, and the 1999 Gramm-Leach-Bliley Act repealed the separation between investment and commercial banking. For information on banking liberalization across countries, see Abiad et al. (2010).

[2] Jayaratne and Strahan (1996) provide evidence of better credit availability following deregulation.

[3] For stylized facts and more discussion of credit-driven boom-bust cycles, see Borio and Lowe (2002), Tornell and Westermann (2002), Mendoza and Terrones (2008, 2012), Hume and Sentance (2009) and Schularick and Taylor (2012).

[4] In the U.S. from October 3rd, 2015 onwards mortgage borrowers must be provided under the TILA-RESPA Integrated Disclosure rules not only with a good faith loan estimate, but also with a standardized closing disclosure of their actual mortgage terms at least three business days before a loan agreement

loan-approved borrowers will likely show their written offer to uninformed competing lenders as they shop for better terms on their mortgage[5]. These rival lenders can then free-ride on this information and attempt to poach approved borrowers from the informed lender. But banks' lending decisions can even become observable for rivals in the absence of written loan offers, for example when reputable mortgage brokers use an informed bank's quote to bargain with other lenders for better terms, or when borrowers refinance a recently made loan and present their existing loan contract to outside lenders.

When loan offers are observable by competitors, an informed incumbent bank must strike a careful balance between optimizing its portfolio quality and protecting itself from competition: the more wisely the bank chooses its loan portfolio, the more positive information will be conveyed by every loan approval, and the more profitable it becomes for uninformed outside lenders to enter the incumbent's market and poach loan-approved customers. If the informed incumbent "poisons the well" by making less prudent choices for its own loan portfolio, it will clearly suffer from more defaulting loans but may be rewarded with the successful deterrence of entry.

I show that the distortions in screening and lending decisions that arise from banks' optimal response to such free-riding problems reproduce the known stylized facts about credit procyclicality remarkably well. When the economy emerges from a recent recession, the composition of the borrower pool is sufficiently poor that competitive threats barely matter at all. Banks then screen very precisely to mitigate adverse selection, and the average quality of loans that are originated in such times is high. As economic conditions improve, competitive threats begin to distort banks' lending decisions: lending standards fall, and credit grows at an increasing pace because banks start to admit some negative net present value projects into their loan pool in order to keep competition away. At the same time, they reduce the precision of borrower screening because they can no longer appropriate the full returns to their costly information acquisition effort. In a booming economy, the average borrower becomes credit-worthy. The reduced level of screening precision then contributes further to the expansion of inefficient lending because the combination of high prior belief and imprecise screening information leaves many poor projects in the portfolio that is financed. In line with empirical evidence, the model predicts that the worst loans are made right at the peak of the boom, and that low policy rates can exacerbate inefficient lending. Once the boom goes bust, the situation reverses. If screening precision requires time to build, the bust phase will be characterized by a credit crunch and a flight to quality: as screening remains impaired from the effects of competition during the preceding boom phase, only exceptionally good borrowers succeed in generating a sufficiently positive signal to receive credit.

can be made. A similar regulation existed in Spain until 2012. It required banks to provide mortgage customers with a written loan offer *("oferta vinculante")* that was unilaterally binding for 10 days.

[5]There is plenty of anecdotal evidence that loan applicants frequently use written offers of other banks in the credit bargaining process to improve their terms. In fact, even the website of the U.S. Consumer Financial Protection Bureau recommends prospective mortgage borrowers to *"consider negotiating. [...] Your best bargaining chip is usually having Loan Estimates from other lenders in hand."* (Source: http://www.consumerfinance.gov/owning-a-home/process/compare/, accessed Oct 23rd, 2015)

Finally, the model also highlights the important role of project liquidation values for the lending cycle. In recessions, expected liquidation values are low. This makes banks hesitant to lend because the option of repossessing defaulted projects offers them little protection against risk. The opposite is true when liquidation values are high: not only will those high values reduce banks' incentives to screen thoroughly (as in Manove, Padilla, and Pagano, 2001), but in the presence of competition they can also greatly exacerbate the inefficiencies in bank lending due to free-riding: this is because diminishing risk encourages uninformed outside banks to compete more aggressively, and incumbents respond to this threat of competition by making more bad loans.

By establishing a link between free-riding problems, bank competition and inefficient lending cycles, this paper makes contributions to several strands of literature. It adds to a small existing literature which has (albeit in very different settings) considered the possibility that banks can extract information from the actions of their rivals. Following insights from the limit pricing literature, Gan and Riddiough (2008) show that monopolistic government-sponsored agencies like Fannie Mae optimally pool heterogenous borrowers in identically priced mortgage contracts in order not to reveal private information to retail banks who could enter the market via loan retention. I observe the same effect in my model: equilibrium loan interest rates under competition are totally *uninformative* of borrower types. The most fundamental difference between my model and theirs is that they fix the extensive margin of lending exogenously. Hence, information can only be revealed by interest rates but not by a positive loan decision itself, which leaves no scope for the harmful cross-subsidized loan approvals that are at the heart of my findings. Ogura (2006) presents a herding model in which banks infer borrower types from the previous period lending decisions of their rivals. However, lenders in his model are confined to financing at most one single customer each, which again rules out the strategies related to portfolio composition that I address in this paper. Hence his findings are the very opposite of mine: he concludes that increasing competition reduces the credit risk taken by every individual bank.

My result that more competition can trigger excess lending also speaks to the boader literature on bank competition, screening and lending standards. The vast majority of the banking literature[6] studies a setting in which banks can *not* observe each other's lending decisions. Under an imperfect screening technology, this leads to a winner's curse problem (Broecker, 1990; von Thadden, 2004): banks become hesitant to lend because more competition fills the applicant pool with borrowers that are rejected by other banks, which greatly increases the chances of mistakingly loan-approving bad borrowers. Adverse selection can even become so severe that entry is blockaded (Dell'Ariccia et al., 1999). Whilst the new arrival of large cohorts of fresh borrowers to such a market can significantly reduce this problem and make banks less reluctant to lend (Dell'Ariccia and Marquez, 2006), a recurrent finding in this literature is that more competition between banks does not lead to socially excessive lending. With observable actions, I obtain the opposite.

[6]see e.g. Broecker (1990), Marquez (2002), Hauswald and Marquez (2006), Direr (2008)

By establishing that more bank competition increases the riskiness of banks' portfolios, the paper also contributes to the debate whether competition leads to more fragility of banks[7] or potentially increases their stability[8]. A particularly influential line of thought has attributed higher fragility under competition to the fact that competition erodes banks' charter values (Keeley, 1990). This in turn gives bank shareholders incentive to let the bank take on excessive risk at the expense of other stakeholders. It is believed that sufficiently high bank capital standards could at least partially mitigate this problem (Hellmann, Murdock, and Stiglitz, 2000). I contribute to this debate by presenting a novel risk-augmenting channel which persists even if banks are sufficiently capitalized.

There are also close ties to a literature which has studied banks' optimal screening choices under competition[9]. Several authors have found that bank competition reduces screening incentives. However, virtually none discuss how screening varies over the business cycle. A notable exception is Ruckes (2004) who finds that screening follows an inverse-U curve: it is less valuable in very good (or very bad) times because there are so few borrowers for whom the screening process alters banks' lending decisions. In the second-best benchmark, my findings align perfectly with his results. What is new is the insight that competition creates a countercyclical distortion: in line with empirical evidence, I predict that screening is inefficiently low in good times, but high in recessions.

As a more technical contribution, I characterize banks' optimal loan portfolios for a continuum of borrower types and for a fairly general class of screening technologies. This deviation from the more common two-type assumption not only helps to obtain important insights regarding portfolio composition and cross-subsidization between different borrower types, but it also enables me to deliver meaningful comparative statics and to highlight an important connection between screening, the degree of dispersion in banks' posterior beliefs (as in Ganuza and Penalva, 2010) and bank lending standards.

Finally, there is a direct link to a larger macro-financial literature that has studied the interaction between financial frictions, collateral and the credit cycle (e.g. Kiyotaki and Moore, 1997; Gorton and Ordoñez, 2014). Much of this literature is particularly interested in the downturn of the credit cycle: falling collateral values amplify negative shocks as they constrain access to credit, which induces further liquidation. By offering a rational[10] explanation for the extreme[11] and inefficient expansion of collateralized risky credit during the preceding boom, my results help to set the scene for such downturn.

The article is organized as follows. Section 2 presents the model. The planner's benchmark and equilibrium under competition are discussed in sections 3 and 4, respectively, followed by a dynamic model of credit cycles in section 5. Section 6 discusses robustness, section 7 provides policy implications and testable predictions, and section 8 concludes.

[7]see e.g. Keeley (1990), Besanko and Thakor (1993) and many others; Carletti and Hartmann (2002) and Carletti (2008) provide an excellent survey of this literature.

[8]Caminal and Matutes (2002), Boyd and De Nicoló (2005).

[9]See e.g. Riordan (1993), Gehrig (1998), Marquez (2002), Hauswald and Marquez (2003, 2006) and Direr (2008).

[10]Credit expansions due to overoptimistic irrational investors are considered by Thakor (2015).

[11]Different from Lorenzoni (2008), credit in my model can exceed even the first-best level.

2 Model

2.1 Setup

The economy in my model comprises of two islands, with a unit mass of entrepreneurs and a financial intermediary on each of these islands. Every entrepreneur $i \in [0, 1]$ is endowed with a risky project. The project requires one unit of investment, and may either succeed and yield a perfectly verifiable payoff of $R > 1$, or fail and yield its liquidation value, $r < 1$:

$$X_i = \begin{cases} R & \text{with probability } p_i \\ r & \text{with probability } 1 - p_i \end{cases} \tag{1}$$

The quality of projects is heterogeneous in the sense that some projects are more likely to succeed than others: the success probability p_i of entrepreneur i's project is drawn independently from a uniform probability distribution with mean $\bar{p}$:

$$p_i \sim U\left(\bar{p} - \frac{\varepsilon}{2}, \bar{p} + \frac{\varepsilon}{2}\right) \tag{2}$$

I assume that this distribution is the same for both islands and is publicly known whereas an individual project's success probability p_i is only known to the entrepreneur. Entrepreneurs have zero initial wealth, so they need to borrow an amount of 1 against the state-contingent promise of repayment of (D_i, d_i) from a bank in order to develop their project. I assume that all entrepreneurs apply for a loan irrespectively of their type[12], and that they do not have any signaling devices such as collateralization or self-financing at their disposal. Banks are risk-neutral and can access an unlimited amount of financing through the interbank market at a cost of ρ. I will interpret ρ directly as the monetary policy rate, and assume that $r < \rho < R$. Before coming to a decision on a loan, banks can screen every *domestic* project (i.e. every project on the same island) by using all soft and hard information available to them to generate an informative but imperfect private signal about its idiosyncratic probability of success.

To this end, they resort to an imperfect credit-worthiness test. The precision of this test depends on a parameter $\lambda \in [0, 1]$ which captures the extent to which the lender's institutional setup and business strategies are well-aligned with the purpose of generating reliable credit-relevant information and channeling it to the decision-making loan officers. In the case $\lambda = 0$ the test does not generate any useful information at all, whereas for $\lambda \to 1$ the test reveals every borrower's type perfectly. By making its choice of λ, a bank endogenously selects its optimal degree of exposure to asymmetric information problems in its lending activities. The cost associated with holding a given level λ of precision in credit testing are primarily fixed cost which are independent of the number of screened customers and are described by a strictly convex cost function $c(\lambda)$ that satisfies $c' > 0$, $c'' > 0$, $\lim_{\lambda \to 0} c(\lambda) = 0$ and $\lim_{\lambda \to 1} c(\lambda) = \infty$; I assume that once these fixed cost are paid, the screening of an individual domestic applicant is costless and yields an imperfect

[12]This could, for example, be ensured by postulating that entrepreneurs derive an additional non-verifiable rent from running their projects.

signal of his true type p_i. I refer to the signal's random variable as σ_i, and denote its realization as s_i. Active screening only works with domestic entrepreneurs; I assume that the screening of an entrepreneur from a different island always results in a completely uninformative signal.

Whilst the key results in this paper generalize to a wide class of screening technologies I postulate for now that the following specific test technology is in place: with probability λ, the credit-worthiness test generates a signal realization $s_i = p_i$ that is identical to the project's true success probability whereas with probability $1 - \lambda$ it yields a totally uninformative value s_i that is randomly drawn from p_i's prior distribution (2). In sharp contrast to the signal structure analyzed by Ruckes (2004), the bank does not know whether a given signal realization represents a "real" or an uninformative draw. I show in the appendix that Bayesian updating of beliefs given the observation of a signal realization of s_i results in a posterior expectation of

$$E[p_i|\sigma_i = s_i] = \lambda s_i + (1 - \lambda)\bar{p} \tag{3}$$

Note that the posterior expected value of p_i is simply a convex combination of the observed signal realization and the prior mean $\bar{p}$ whereby the test's precision determines the relative weight given to each of them. A more precise test will therefore move beliefs about p_i further away from the prior mean and create more dispersion in posterior expectations. As we shall see later, this is the first key ingredient for understanding the central properties of the model.

2.2 Competition

The second key ingredient to the model is competition between asymmetrically informed lenders where observability of actions in the market gives rise to informational spillovers. Specifically, I assume that legislation commands that any loan offer must be made in writing, and that banks cannot charge a fee for loan applications[13]. Entrepreneurs with a favorable loan evaluation by their domestic bank can then use the written offer to credibly signal their positive domestic evaluation to the uninformed outside lender on the other island. In this way, the uninformed bank on the other island can attempt to poach customers which the domestic bank considers credit-worthy. However, a cost disadvantage limits the ability of the outside bank to compete for customers that do not reside on its island: I assume that for every loan made to an off-shore customer, the lender incurs a cost of $\gamma > 0$. Whilst there are several possible interpretations[14] to this charge, I prefer to think of it as the extra cost from monitoring the execution of a project that does not reside on the same island. In my analysis, I use γ to parametrize changes in the strength

[13]The main results of the model are robust to positive loan application fees provided that these fees fail to fully compensate the bank for the value of screening.

[14] The model can also be reinterpreted as the reduced second period of a two-period game where in the first period, banks build customer relationships by providing non-credit banking services, e.g. cashless payment services. γ would then represent the switching cost of obtaining credit from a bank different from the one chosen for payment services in the first period.

of competition: $\gamma \to \infty$ will result in monopoly, whereas $\gamma \to 0$ generates the highest possible level of competition.

2.3 Timing

I now let the two banks compete with each other. In particular, I assume the following structure and timing of the game:

1. every bank $j \in \{1, 2\}$ chooses its publicly observable level of screening effort λ^j, pays screening cost $c(\lambda^j)$ and obtains private signals $\sigma_{i,\lambda}$ for all domestic projects $i \in [0, 1]$.

2. both banks then make their domestic loan offers: they choose a domestic *loan portfolio* comprising of a set $\mathcal{P}_j$ of projects to be offered a loan, and agreed repayment terms (D_i, d_i) for every project $i \in \mathcal{P}_j$ in case of success or failure, respectively.

3. each bank observes the domestic loan offers made on the other island $j' \neq j$ and decides whether and under which state-contingent repayment terms $(O_i^{j'}, o_i^{j'})$ it offers outside credit to the other islands' loan-approved entrepreneurs.[15]

4. entrepreneurs choose the loan offer with the lowest expected repayment terms; when two offers leave them indifferent, they stay with their domestic bank.

I solve the game by backward induction. Before doing so, I will however make a quick detour and analyze the information precision and credit allocation that a social planner who is constrained to using the same screening technology would choose.

3 The Social Planner's Solution

3.1 Constrained Optimal Portfolio Choice

Since I solve backwards, I first take λ as exogenously given. The constrained optimal portfolio is easily found by observing that the expected surplus π_i from a single project is monotonically increasing in its expected probability of success and reads

$$E[\pi_i|\sigma_{i,\lambda} = s_i] = E[p_i|s_i]R + (1 - E[p_i|s_i])r - \rho \tag{4}$$

Equating this expression to zero yields that a project with an expected success probability of

$$q \equiv \frac{\rho - r}{R - r} \tag{5}$$

[15]Note that only domestically loan-approved entrepreneurs have incentive to apply for a loan from the outside bank, and that the outside lender will never find it profitable to offer credit to entrepreneurs without domestic loan approval.

will contribute exactly zero surplus, and every project with a higher expected success probability will generate positive surplus. The constrained optimal portfolio must therefore include all projects that have an expected success probability above the cut-off threshold q, and deny financing to all those projects that fall below it. As we shall see, all important expressions in the paper can be written in terms of this cut-off threshold q, so it deserves a brief discussion at this point: holding R and r constant, it is obvious that q lies between 0 and 1 when the interbank rate ρ moves within its assumed boundaries, $r < \rho < R$. Taking R and ρ constant and varying r it is also easy to see that higher liquidation values r decrease the probability of success q that is required to break even.

With the cut-off threshold q at hand, it is straightforward to calculate the volume and average success probability of the constrained optimal portfolio. It is useful to first derive the cumulative distribution function of $E[p_i|\sigma_{i,\lambda}]$,

$$\mathcal{E}_\lambda(q) \equiv \text{Prob}\left(E[p_i|\sigma_{i,\lambda}] \leq q\right) \tag{6}$$

which can be obtained using equation (3):

$$\mathcal{E}_\lambda(q) = \text{Prob}\left(\sigma_{i,\lambda} \leq \frac{q-(1-\lambda)\bar{p}}{\lambda}\right) = \begin{cases} 0 & \text{if } q \leq \bar{p} - \frac{\lambda\varepsilon}{2} \\ \frac{q-\bar{p}}{\lambda\varepsilon} + \frac{1}{2} & \text{if } \bar{p} - \frac{\lambda\varepsilon}{2} < q < \bar{p} + \frac{\lambda\varepsilon}{2} \\ 1 & \text{if } q \geq \bar{p} + \frac{\lambda\varepsilon}{2} \end{cases} \tag{7}$$

The constrained efficient portfolio's mass of credit is then simply $m_\lambda^{SB} = 1 - \mathcal{E}_\lambda(q)$, whilst the portfolio's average success probability can be calculated as

$$\mathcal{A}_\lambda^{SB} = \frac{\int_q^1 p \, \mathrm{d}\mathcal{E}_\lambda(p)}{\int_q^1 \mathrm{d}\mathcal{E}_\lambda(p)} \tag{8}$$

The results are conveniently summarized in the following proposition:

Proposition 1. *The constrained efficient portfolio contains all projects with expected success probability above the cut-off* $q = \frac{\rho - r}{R - r}$ *and none below. The optimally financed mass of projects reads*

$$m_\lambda^{SB} = \begin{cases} 1 & \text{if } q \leq \bar{p} - \frac{\lambda\varepsilon}{2} \\ \frac{1}{2} - \frac{q-\bar{p}}{\lambda\varepsilon} & \text{if } \bar{p} - \frac{\lambda\varepsilon}{2} < q < \bar{p} + \frac{\lambda\varepsilon}{2} \\ 0 & \text{if } q \geq \bar{p} + \frac{\lambda\varepsilon}{2} \end{cases} \tag{9}$$

and the projects in the portfolio attain an average success probability of

$$\mathcal{A}_\lambda^{SB} = \bar{p} + \frac{\lambda\varepsilon(1 - m_\lambda^{SB})}{2} \tag{10}$$

Proof. see appendix. □

Remembering that the limit $\lambda \to 1$ yields the perfect information case, we can now directly compare the second-best choice with imperfect testing precision $\lambda < 1$ to the outcomes of a (clearly unattainable) first-best world in which project types are perfectly observable:

Corollary 1.1. *The second-best allocation when project types are noisily observed compares to the allocation when types are perfectly known as follows:*

- *If $\bar{p} < q$, strictly less projects are developed than in the first-best with perfect information. Moreover, the size of the constrained efficient portfolio is increasing in λ.*
- *If $\bar{p} > q$, the amount of projects that are developed exceeds the perfect information case. The size of the constrained efficient portfolio is decreasing in λ.*

In other words, imprecise information drives a wedge between the second- and the first-best amounts of financing whereby the sign of the wedge depends on whether the average project is credit-worthy: in exceptionally good times (i.e. $q < \bar{p}$), noisy information results in the financing of *more* projects than under perfect observability of types, whilst in normal times (i.e. $\bar{p} < q$), noisy information leads to *less* investment.

3.2 Constrained Optimal Screening Precision

Having determined the planner's optimal project portfolio decision, the next step is to ask how much screening precision λ the social planner would optimally choose to acquire. For this purpose I first calculate the gross surplus as a function of q and λ:

$$\begin{aligned} \Pi_\lambda^{SB} &= \int_q^1 pR + (1-p)r - \rho \, \mathrm{d}\mathcal{E}_\lambda(p) \\ &= (R-r) \int_q^1 \left(p - \tfrac{\rho - r}{R-r}\right) \mathrm{d}\mathcal{E}_\lambda(p) \\ &= m_\lambda^{SB} \, (R-r) \left(\mathcal{A}_\lambda^{SB} - q\right) \end{aligned} \tag{11}$$

Note the very intuitive structure of this expression: for every financed project, the planner obtains a surplus that is equal to the risky part $R-r$ of the project's payoffs multiplied by the margin by which the portfolio's average success probability exceeds the zero-surplus cut-off q. Substituting previous results leads to

$$\Pi_\lambda^{SB} = \begin{cases} (R-r)(\bar{p}-q) & \text{if } q \leq \bar{p} - \frac{\lambda\varepsilon}{2} \\ (R-r)\frac{(2\bar{p}-2q+\lambda\varepsilon)^2}{8\lambda\varepsilon} & \text{if } \bar{p} - \frac{\lambda\varepsilon}{2} < q < \bar{p} + \frac{\lambda\varepsilon}{2} \\ 0 & \text{if } q \geq \bar{p} + \frac{\lambda\varepsilon}{2} \end{cases} \tag{12}$$

The three regions in this equation are the same as for the constrained-efficient project mass in equation (9): the first region of the equation describes the case in which projects are so good and information is so imprecise that the size of the constrained optimal portfolio is 1. Region two stands for the intermediate case in which $0 < m_\lambda^{SB} < 1$; finally, the third region is relevant whenever screening precision is so low and average projects are so bad that it is impossible to identify any project with positive gross surplus at all.

The constrained efficient information choice λ^*_{SB} maximizes surplus net of information cost:

$$\begin{aligned} \max_{\lambda} \quad & \Pi^{SB}_{\lambda} - c(\lambda) \\ \text{s.t.} \quad & \lambda \geq 0 \end{aligned} \tag{13}$$

Although the exact shape of the solution to this problem depends on the specific functional form of $c(\lambda)$ about which I have not made any assumption so far, its main properties are independent of this choice:

Proposition 2. *If the planner's information choice attains a nonzero level of information* λ^*_{SB}*,*

- λ^*_{SB} *is strictly increasing in the risky part* $R - r$ *of the projects' payoffs, and* $\lim_{r \to R} \lambda^*_{SB} = 0$.
- λ^*_{SB} *as a function of* q *follows an inverse-U shape. It reaches its maximum when the cut-off quality* q *coincides with the average quality of the pool:* $q = \bar{p}$.

Proof. see appendix. □

These results are quite intuitive: screening is only useful in the presence of risk, and the acquisition of a very precise signal pays off most when it has the potential to alter the greatest amount of loan decisions. This corroborates the observation of Ruckes (2004) that there is low incentive to screen when the average quality of the project pool is either very good or very bad because in either case the signal obtained by screening will change lending decisions only for a very small percentage of the applicant pool.

I provide a graphical representation of the results in this section in Figure 1. Let me go over this figure in detail because it not only illustrates the planner's solution but also paves the way for the subsequent discussion of the competitive equilibrium. We have found that when the average borrower is credit-worthy and information is relatively imprecise (i.e., $\bar{p} - q \geq \frac{\lambda\varepsilon}{2}$), the volume of lending grows until every project is financed. Let me draw the set of all (q, λ) pairs for which this applies in the diagram and label it as area (1). Since within this parameter region every entrepreneur receives a loan, screening is useless there. We can therefore conclude that the curve of optimal information choice $\lambda^*_{SB}(q)$ will either remain outside this region or drop to zero wherever it overlaps with it. The same holds for the opposite case where information is relatively imprecise and the average project makes an expected loss: no projects will be financed, the mass of credit is 0 and there are no returns to information acquisition within this region either. I mark the corresponding area as (2).

Wherever the constrained-optimal screening precision $\lambda^*_{SB}(q)$ is not zero, its graph must thus lie inside the white triangular area: these are the only combinations of economic state q and information precision λ for which screening can deliver positive value. Whilst the findings of the previous propositions are independent of the functional form of the

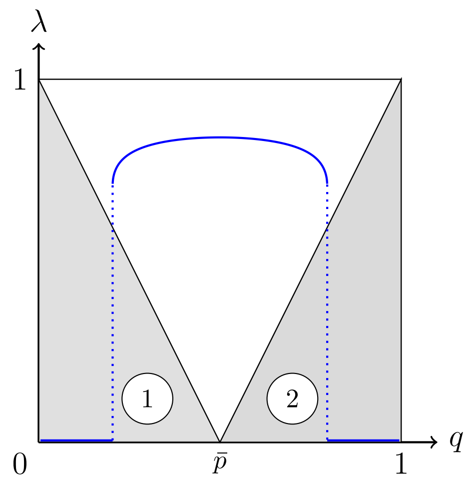

Figure 1: The planner's constrained optimal information choice.
The parameters of the plot are $\varepsilon = 1$, $\bar{p} = \frac{1}{2}$, $r = \frac{3}{4}$, $R = 2$ and $c(\lambda) = c_0 \frac{\lambda}{1-\lambda}$ with $c_0 = \frac{1}{250}$. Areas 1 and 2 which are shown in gray shading correspond to the cases handled in the first and third line of equation 9, respectively, where screening has no value because everybody, or nobody, is financed.

cost function $c(\lambda)$, we need to make such choice in order to draw a graph. I use here the specification $c(\lambda) = c_0 \frac{\lambda}{1-\lambda}$ which yields closed-form solutions[16] for both the planner's choice and the competitive case.[17]

Looking at the graph of $\lambda^*(q)$ we can see that for the chosen parameters the interior solution indeed covers a wide range of q, but as q moves further away from $\bar{p}$, the payoff to screening diminishes so much that it eventually becomes unprofitable to screen.

4 Equilibrium with Competition

4.1 Monopoly

Before discussing the full equilibrium under competition, it is instructive to look at the special case of monopoly. We can model this case within the existing setup by assuming that the remote monitoring cost γ are sufficiently high that no bank can ever profitably offer outside credit to projects outside its own island. This is the case for all possible values of q whenever $\gamma > (R - r)\varepsilon/2$.

It is easy to see that a profit-maximizing monopolistic lender will replicate the planner's choices perfectly: monopoly power enables the bank to extract the full surplus from all entrepreneurs by lending to them against a state-contingent repayment of (R, r). In order to maximize profits, the monopolist will choose the surplus-maximizing level λ^*_{SB} of

[16]See the appendix for details.

[17]Note that this specific cost function implies that marginal cost of information acquisition are strictly positive everywhere, even for $\lambda \to 0$: $c'(0) = c_0$. Thus, if c_0 is sufficiently large, holding any positive amount of information will be suboptimal and the surplus maximization problem (13) yields the corner solution $\lambda^*_{SB} = 0$ for all values of q. I avoid this situation by assuming that is c_0 sufficiently low, i.e. $c_0 < \frac{\varepsilon}{8}$, that there exists an interior solution $\lambda^*_{SB} > 0$ for some neighborhood of $q = \bar{p}$.

testing precision and (assuming that the lender observes the same signal realizations as the planner) give loans to exactly the same set of projects that the planner would choose to develop. Hence, the allocation under monopoly is constrained Pareto optimal. However, this message should clearly be taken with a grain of salt: the finding is driven by the fact that project size was assumed to be fixed. If we had allowed entrepreneurs to choose the size of their projects endogenously, monopolistic pricing would create deadweight losses and result in inefficiently small projects that are no longer constrained efficient.[18]

Inefficiencies would also arise in our model if a regulator would limit the monopolist's surplus extraction by curbing the maximum repayment on each unit of funds to some value $D_{\max} < R$: the resulting portfolio of financed projects would become inefficiently small since the corresponding cut-off $\hat{q} = \frac{\rho - r}{D_{\max} - r}$ up to which the monopolist provides funding would lie higher than q.

4.2 Portfolio Allocations under Competition

I now study the optimal portfolio choices of the two lenders when they compete against each other. Under competition, lenders must be careful in how they use the private information that they have obtained in the screening process because their decisions will be revealed to their uninformed competitor. If their loan approval conveys sufficiently good news about the quality of a borrower, the uninformed rival bank can enter the market as an outside lender, undercut the incumbent's loan offer and poach some or all of its loan-approved customers. However, the outside lender's cost disadvantage of γ when lending to the other island puts a limit to this poaching activity: entry is not profitable if a poached borrower earns the outside lender in expectation less than this extra cost γ. This motivates the following definition:

Definition Denote with $\Pi[\mathcal{P}]$ the gross profit that accrues to a domestic lender in the absence of competition from holding a given domestic loan portfolio $\mathcal{P}$, and denote the volume of loans in the portfolio as $|\mathcal{P}|$. Then, a loan portfolio $\mathcal{P}$ shall be called *noncontestable* if its gross surplus per loan is less or equal to γ: $\Pi[\mathcal{P}] \leq \gamma|\mathcal{P}|$.

In equilibrium, every bank will choose a noncontestable portfolio: otherwise, the competing bank could profitably poach the entire set of customers by undercutting the domestic bank's offer for every domestically loan-approved entrepreneur by a small $\delta > 0$: $(O_i^j, o_i^j) = (D_i - \delta, d_i)$. The domestic lender's profits would drop to zero and be strictly lower than if it had chosen some noncontestable portfolio which yields lower but positive gross profits.[19] It must be pointed out that noncontestability is a necessary, but not a sufficient condition to guarantee that a loan portfolio does not attract entry: it only secures that an entrant financing the *entire* loan portfolio will suffer losses. If the variation in repayment terms (D_i, d_i) of individual borrowers carries any information on borrower

[18] Unfortunately, a more complete model which could capture lending decisions both at the extensive and at the intensive margin presents major obstacles to tractability.

[19] We will see that such profitable noncontestable portfolio exists for every $\gamma > 0$.

quality, the entrant might still be able to profitably target a subset of projects that are identified as more lucrative than others. Such scenario is no concern if the incumbent's portfolio is by chance not only noncontestable but also *symmetric*, i.e. every loan offer in the portfolio has the same repayment terms $(D_i, d_i) = (D, d)$. Then there exists no profitable possibility of entry, and the incumbent wins the full surplus of the portfolio. As the following lemma shows, choosing a symmetric portfolio does not need to be inferior to choosing a non-symmetric one:

Lemma 3. *Let $\mathcal{P}$ be a (not necessarily symmetric) noncontestable loan portfolio. Then there always exists a symmetric noncontestable portfolio $\mathcal{Q}$ for which the incumbent's payoff in the competition game is at least as high as when choosing $\mathcal{P}$.*

Proof. see appendix. □

A direct consequence of the lemma is that if we manage to find within the class of all symmetric noncontestable portfolios some portfolio $\mathcal{Q}^*$ that is profit-maximizing in the sense that no other symmetric noncontestable portfolio generates higher surplus, it must be an equilibrium of the game: to see this, observe that if any arbitrary portfolio $\mathcal{R}$ could generate a strictly higher payoff for the incumbent, such portfolio would be noncontestable for sure (otherwise, as we know, payoff would be zero). But then the lemma assures us that a symmetric noncontestable portfolio that generates at least the same payoff as $\mathcal{R}$ exists, thus generating an immediate contradiction to the maximality of $\mathcal{Q}^*$. Therefore, $\mathcal{R}$ can not have existed in first place, and we have

Corollary 3.1. *Any symmetric portfolio $\mathcal{Q}^*$ that maximizes gross surplus subject to the constraint of noncontestability,*

$$\begin{aligned} \max_{\mathcal{Q}=(\mathcal{S},\,(D,d))} \quad & \Pi[\mathcal{Q}] \\ s.t. \quad & \Pi[\mathcal{Q}] \leq \gamma|\mathcal{Q}| \end{aligned} \tag{14}$$

is an equilibrium allocation of credit under competition.

The maximality of $\Pi[\mathcal{Q}^*]$ also makes it clear that even though the equilibrium portfolio $\mathcal{Q}^*$ is not necessarily unique, the equilibrium payoffs are always uniquely determined. The same is true for credit mass and average success probabilities: those two quantities are uniquely pinned down by the constraint whenever it is binding, whereas any possible indeterminacy that can arise if the constraint does not bind are eliminated by the previously made assumption that no project with zero expected surplus receives funding.

As a solution to the maximization problem for symmetric portfolios I find the following equilibrium allocations:

Proposition 4. *Let $\mathcal{F}$ denote the portfolio of the full unit measure of projects financed against state-contingent repayment promise of (R, r). Then, under competition the following portfolio allocations constitute an equilibrium:*

- *If the monopolistic portfolio is noncontestable, it is an equilibrium. This is the case if information is sufficiently imprecise, $\lambda \leq \frac{2(q-\bar{p})}{\varepsilon} + \frac{4\gamma}{\varepsilon(R-r)}$, and the threshold q is sufficiently high that $\mathcal{F}$ is noncontestable, $q > \bar{p} - \frac{\gamma}{R-r}$. The bank then acts as a monopolist and reproduces the constrained optimal allocation by lending to entrepreneurs whose expected success probability exceeds $q = \frac{\rho - r}{R-r}$ against state-contingent repayment of (R, r).*

- *If information is sufficiently precise that a monopolistic portfolio choice would attract competition, i.e. $\lambda > \frac{2(q-\bar{p})}{\varepsilon} + \frac{4\gamma}{\varepsilon(R-r)}$, but the full portfolio $\mathcal{F}$ remains noncontestable, $q > \bar{p} - \frac{\gamma}{R-r}$, it is an equilibrium to finance all positive net present value (NPV) projects and some projects with negative NPV by offering credit at terms (R, r) to projects whose expected success probability lies above $\hat{q} = \bar{p} - \frac{\lambda\varepsilon}{2} + 2\left(q - \bar{p} + \frac{\gamma}{R-r}\right)$, whereby $\hat{q} < q$.*

- *If both the monopolistic portfolio and the full portfolio $\mathcal{F}$ are contestable, i.e. $q \leq \bar{p} - \frac{\gamma}{R-r}$, it is an equilibrium to offer credit to every domestic entrepreneur against a state-contingent repayment of (D, r), with $D = \frac{\gamma + \rho - r(1-\bar{p})}{\bar{p}}$.*

Proof. see appendix. □

This important result deserves several comments:

First, the surprising finding is that more competition has virtually zero impact on the cost of borrowing until every available project receives a loan. Before this point, an increase in competition (i.e. fall in γ) only lowers banks' lending standards and prompts them to take projects with negative net present value into their loan portfolios. The central force behind this result is that it is more profitable for the bank to deter entry by reinforcing the entrant's adverse selection problem than to do so by lowering its terms of repayment: imagine for a moment that the bank had instead reduced its repayment terms for its mass m of borrowers to some (D, r) with $D < R$ but had not lowered its lending standards. Its portfolio must then satisfy the noncontestability constraint with equality which bounds profits to $\gamma|m|$. This is no equilibrium because the bank can do better: it can extract the full surplus (R, r) of those m projects and use the proceeds to finance exactly as many additional negative NPV projects n as to restore noncontestability, $\Pi[m \cup n] \leq \gamma(|m| + |n|)$. The larger size of the project portfolio relaxes the noncontestability constraint and thereby allows the bank to raise its profits by $\gamma|n|$. This mechanism works until the bank runs out of bad borrowers that could be used to further poison its pool: only then, it optimally reacts to competition by offering lower repayment terms. Note that my assumption of fixed refinancing cost contributes to the *complete* absence of any price response: if we had considered a richer model in which careless lenders incur higher refinancing cost, banks might choose an optimal mix of more aggressive pricing and lower lending standards in order to defend themselves against the entry of competitors.

Another important observation is that the game's competitive equilibrium is essentially a contestable market: the incumbent's informational advantage and the cost disadvantage of the entrant make it impossible for the entrant to actually ever poach any customers from the incumbent. It is the mere threat of entry that drives all the changes in allocations although in equilibrium entry never occurs.

Finally, the fact that the game has an equilibrium in pure strategies stands in sharp contrast to most credit screening games in the literature for which the nonexistence of pure strategy equilibria has been established (see e.g. Broecker, 1990; von Thadden, 2004). This is, however, not really unexpected given my substantially different setup: the sequential nature of bidding together with the observability of actions ensure that the entrant can correctly infer the incumbent's true valuation for the pool of loan-approved borrowers and hence does not face any winner's curse problem when submitting a bid on this pool.

I now proceed to discuss the equilibrium credit volume which can be calculated from the results of proposition 4:

Corollary 4.1. *In equilibrium, the volume of credit is the following:*

$$m_\lambda^E(q,\gamma) = \begin{cases} 1 & \textit{if } 0 \le \lambda \le \frac{2(\bar{p}-q)}{\varepsilon} \textit{ and } \bar{p} - \frac{\gamma}{R-r} < q < \bar{p} \\ 0 & \textit{if } 0 \le \lambda \le \frac{2(q-\bar{p})}{\varepsilon} \\ \frac{1}{2} - \frac{q-\bar{p}}{\lambda\varepsilon} & \textit{if } \frac{2|q-\bar{p}|}{\varepsilon} < \lambda \le \frac{2(q-\bar{p})}{\varepsilon} + \frac{4\gamma}{\varepsilon(R-r)} \\ 1 - \frac{2\left(q-\bar{p}+\frac{\gamma}{R-r}\right)}{\lambda\varepsilon} & \textit{if } \frac{2(q-\bar{p})}{\varepsilon} + \frac{4\gamma}{\varepsilon(R-r)} < \lambda < 1 \textit{ and } q > \bar{p} - \frac{\gamma}{R-r} \\ 1 & \textit{for all } \lambda \in [0,1) \textit{ if } q \le \bar{p} - \frac{\gamma}{R-r} \end{cases} \tag{15}$$

Whilst this expression looks rather complex at first glance, it is actually quite easy to understand. The first three lines represent the absence of competition: they are practically the same expressions that we had found for the planner's benchmark and the monopolistic case. The only difference is that the domain where the monopolistic case applies has shrunken, and there is a new domain of (q, λ) values where threat of entry is relevant. The new area is represented by the ultimate two lines: line four describes the case in which the bank cross-subsidizes some negative NPV loans in order to deter entry. Line five finally stands for the case in which the bank cross-subsidizes *all* negative NPV projects and additionally reduces repayments in order to attain a noncontestable portfolio.

To illustrate in which situations banks are exposed to competition, it is useful to make a similar graphical representation of the (q, λ) plane as in the planner's solution. Figure 2 plots the five different domains of the above function, numbered by the corresponding line number. Areas (1) and (2) are the same as in Figure 1. We can see that threat of entry (as indicated by the dark shaded areas (4) and (5)) affects banks that have very precise information and / or operate under very favorable conditions such that the cut-off q is very low. As one can see from the expressions in lines 4 and 5 of equation (15), these areas grow as competition becomes stronger: in the limiting case $\gamma \to 0$, they cover almost the entire (q, λ) plane with the exception of area (2).

How do the comparative statics of credit allocations under threat of entry of a competitor differ from the second-best benchmark? The following proposition holds the answer:

Proposition 5. *Let q be such that in contestable market equilibrium some but not all projects receive credit, i.e. $\bar{p} - \frac{\gamma}{R-r} < q < \bar{p} + \frac{\lambda\varepsilon}{2}$, and let competition be strong enough to potentially impact lenders within this regime, i.e. $\frac{\gamma}{R-r} < \frac{\lambda\varepsilon}{2}$. Then,*

- *the lower the chosen level λ of information acquisition, the more sensitive is the volume of lending $m_E(q,\gamma)$ to changes in both monetary policy rate ρ and project values (R,r).*
- *holding constant the level of λ, the sensitivity $\frac{\partial m_E}{\partial q}$ of credit volume to changes in monetary policy rate and project values is twice as high under threat of competition than in the second-best (monopoly).*
- *the average default rate $\mathcal{D}_\lambda = 1 - \mathcal{A}_\lambda$ in a lender's portfolio increases as monetary policy rate falls and expected liquidation values rise. The sensitivity $\frac{\partial \mathcal{D}_\lambda}{\partial q}$ to such changes is independent of λ, but is twice as high under threat of competition than in the second-best (monopoly).*

Proof. see appendix. □

In other words, the presence of competition makes credit excessively volatile. An improvement in economic conditions will lead to both faster credit growth and faster deterioration of portfolio quality.

4.3 Information Choice under Competition

As the final step in solving the competition game backwards, I now find the equilibrium choices of screening precision that maximize total profits in a competitive environment. The gross profit function $\Pi^E_\lambda(q,\gamma)$ that is needed for this purpose follows immediately

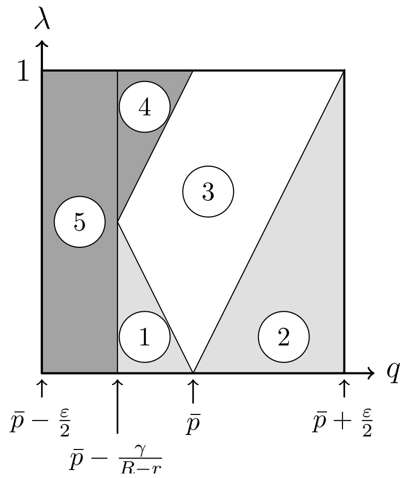

Figure 2: Competitive and monopolistic domains of lending.

from the results in the last section: for all those (q, λ) combinations for which there is no threat of entry, gross profits are exactly the same as under monopoly. In the remaining parameter ranges, the threat of competition limits equilibrium gross profits to $\gamma \cdot m_E$.

The equilibrium screening intensity λ_E^* then solves the problem

$$\begin{aligned} \max_{\lambda} \quad & \Pi_\lambda^E - c(\lambda) \\ \text{s.t.} \quad & \lambda \geq 0 \end{aligned} \tag{16}$$

Even without a specific cost function, one can infer the impact of competition on screening directly from an inspection of marginal returns:

Proposition 6. *The equilibrium screening intensity* λ_E^*

- *is equal to the constrained efficient screening intensity* λ_{SB}^* *whenever the monopolistic portfolio at this screening level does not attract competition, i.e. for all* $q > \bar{p} - \frac{\gamma}{R-r}$ *for which* $\lambda_{SB}^*(q) \leq \frac{2(q-\bar{p})}{\varepsilon} + \frac{4\gamma}{\varepsilon(R-r)}$.
- *falls below the constrained efficient level when competition is sufficiently strong to pose a threat of entry, i.e.* $q > \bar{p} - \frac{\gamma}{R-r}$ *and* $\lambda_{SB}^*(q) > \frac{2(q-\bar{p})}{\varepsilon} + \frac{4\gamma}{\varepsilon(R-r)}$.
- *is zero if competitive threats result in the financing of all projects regardless of their type, i.e. for all* $q \leq \bar{p} - \frac{\gamma}{R-r}$.

Proof. see appendix. □

This underinvestment in screening is my second key result. The intuition is clear: Whenever threat of entry prompts banks to "poison" their loan portfolios with some negative net present value loans, there is less incentive to acquire costly screening precision ex-ante. After all, banks disregard some of the information that is obtained by screening when they intentionally make bad loans. This is most apparent in the extreme case in which q is so low that banks finance all projects regardless of their type: under such conditions, screening is entirely useless.

I illustrate the result graphically in Figure 3 with a plot of λ_E^* over q for two different levels of competition. The cost function is the same as in the planner's case, $c = c_0 \frac{\lambda}{1-\lambda}$. In the graph on the left-hand side, competition is weak and generates little impact. Borrower poaching is only profitable under the best possible economic conditions, i.e. when the cut-off q is exceptionally low. Only in such exceptionally good economic states, the equilibrium choice of screening precision (shown as the solid line) will fall below the constrained-optimal level (dashed line). In all other times, the screening and lending choices of the bank and the social planner coincide. As the graph on the right-hand side of Figure 3 shows, the advent of more competition changes the situation dramatically: screening incentives are eroded over a wide range of economic states q, and for nearly all except the worst states of the economy, banks will choose a screening precision far below the constrained efficient level.

4.4 Excessive Lending with Endogenous Information

What are the consequences of inefficiently low screening for the total amount of lending? To answer this question, I evaluate the credit mass $m^E_\lambda(q,\gamma)$ at the equilibrium level $\lambda^*_E(q)$ of screening precision. Let me move the discussion immediately to the most interesting case:

Imagine that average project characteristics are good enough as to render the average project of the pool credit-worthy, i.e. $\bar{p} - \frac{\gamma}{R-r} < q < \bar{p}$. Then, as we have seen in corollary 1.1, the second-best amount of investment already exceeds the first-best benchmark of perfect information. Moreover, banks that hold *less* precise information than the planner will lend even *more* because their signal is too imprecise to actually push many bad projects below the zero expected surplus cut-off q. To make things worse, this is not even where lending under competition[20] actually ends! The equilibrium financing cut-off lies below q because (as shown in proposition 4) banks add additional loans of negative net present value to their portfolio in order to protect themselves against poaching of their clients. The overall amount of credit in this situation is therefore excessive relative to both second-best and first-best levels and indeed deserves to be called an "inefficient lending boom":

$$m^E_{\lambda^*_E}(q,\gamma) > m^{SB}_{\lambda^*_E}(q) > m^{SB}_{\lambda^*_{SB}}(q) > m^{FB}_{\lambda=1}(q) \tag{17}$$

Figure 4 illustrates the equilibrium credit mass as a function of the economic conditions q using the same equilibrium screening levels that were already shown in Figure 3. We can see in the left-hand side picture that for a moderate amount of competition, credit becomes excessive only when economic conditions are particularly strong, i.e. q is very low. The right-hand side graph displays the behavior of credit as a function of q when there is more banking competition. We can observe that credit is excessive over a much wider range of economic conditions q. The lending boom is most pronounced for very low values of q, which are attained whenever the monetary policy rate ρ is low and the liquidation value r of failed projects is high.

But the most important factor that determines the extent of an inefficient boom is the amount of banking competition. In fact, it is possible to show that independently of the chosen screening cost function, the size of the lending boom is always greater when there is more competition:

Proposition 7. *Let the average project be credit-worthy, i.e.* $q \in (\bar{p} - \frac{\gamma}{R-r}, \bar{p})$*, and let competition be strong enough to pose threat of entry, i.e.* $\gamma < \frac{R-r}{2}\left(\bar{p} - q + \frac{\varepsilon\lambda^*_{SB}(q)}{2}\right)$*. Then, the size* $m^E_{\lambda^*_E}$ *of the inefficient lending boom is increasing in the level of bank competition:*

$$\frac{\mathrm{d}}{\mathrm{d}\gamma} m^E_{\lambda^*_E}(q,\gamma) < 0. \tag{18}$$

Proof. see appendix. □

[20] i.e. for $\gamma < \frac{R-r}{2}\left(\bar{p} - q + \frac{\varepsilon\lambda^*_{SB}(q)}{2}\right)$

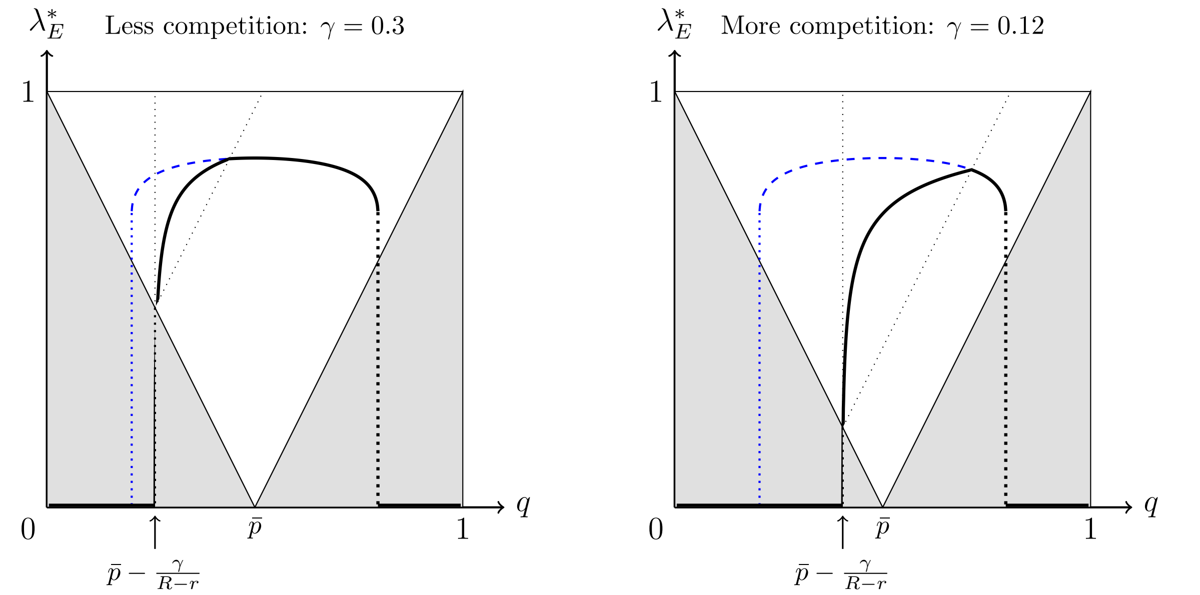

Figure 3: Screening precision λ_E^* as a function of q for two different levels of competition. The constrained efficient choice is indicated as a dashed line.

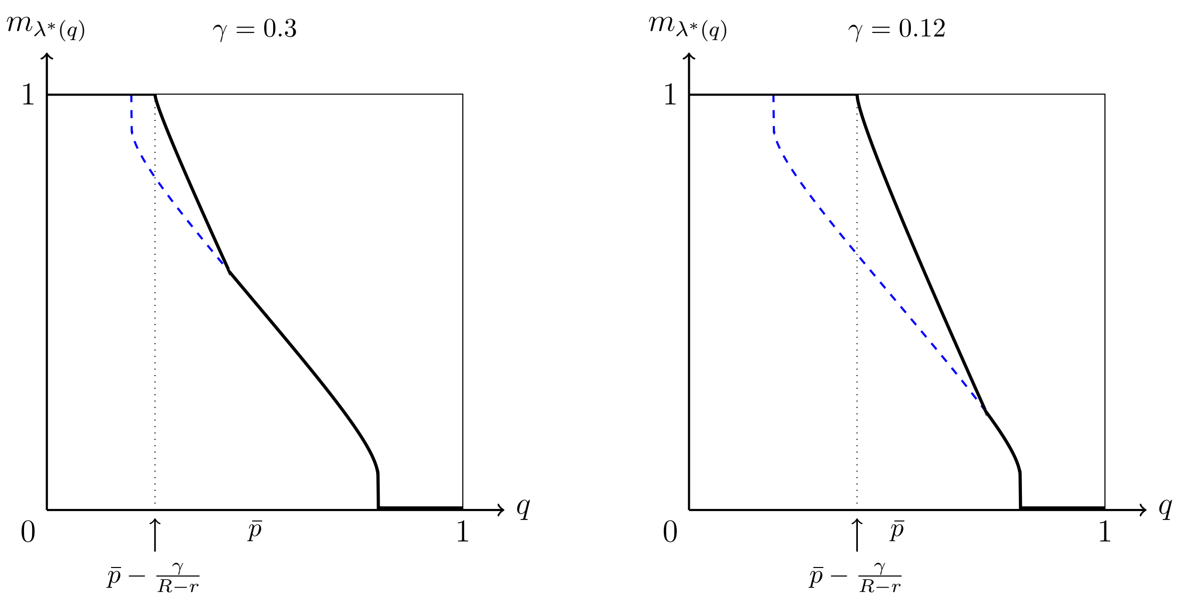

Figure 4: Credit mass $m_{\lambda^*}^E$ as a function of economic state q for two different levels of competition. The dashed line marks the constrained efficient amount.

5 Credit Cycles

So far, we have only been considering an essentially static setting which has shown that credit can become excessive in good times. Can free-riding also contribute to the unusually severe credit rationing that is often observed once a lending boom goes bust? To obtain a better understanding of the dynamics of credit over the cycle that is implied by the model, I now develop a dynamic version of the baseline model.

The main advantage over a static setting is that we can study the intertemporal allocation of screening precision. This is important because there are substantial rigidities that prevent instant adjustments to screening: banks' screening skills are determined by their organizational structure, by their access to accumulated data, and by the tacit skills embodied in their human capital. Improvements to any of these variables are costly and take time to show effect. Hence, we will model screening precision as a stock variable: it accumulates or depreciates over time, depending on how much the bank invests.

Time is discrete. The setup of banks and the timing of actions within each period is identical to the static model; the only differences are that λ_t is now an endogenous state variable, and the economic state q_t follows an exogenous stochastic Markov process with transition operator $\mathcal{M}$. I only consider Markov strategies. Moreover, to abstract from the intertemporal impact of banks' rejections on future applicant quality, I assume that all applicants are removed from the market at the end of every period, and a pristine loan applicant population replaces all previous clients. In equilibrium, banks will choose the sequence of their investments C_t in screening as to maximize the discounted sum of expected profits,

$$\max_{\{C_t\}_{t=0}^{\infty}} \quad E\left\{\sum_{t=0}^{\infty} \beta^t \left(\Pi^E_{\lambda_t}(q_t,\gamma) - C_t\right)\right\} \tag{19}$$

subject to

$$\lambda_{t+1} = \lambda_t(1-\delta) + f(C_t) \tag{20}$$

$$\text{Prob}(q_{t+1} = z | q_t = q) = \mathcal{M}(z,q) \tag{21}$$

$$C_t \geq 0 \text{ and } 0 \leq \lambda_t < 1 \tag{22}$$

where $\delta \in (0,1]$ is the depreciation rate of screening, $\beta \in [0,1)$ is the discount factor, and $f(\cdot)$ is a concave function which describes the production of screening skill as a function of invested resources.

In order to build intuition for the key properties of this model, we will look at a particularly simple (and intentionally quite stylized) parametrization: I assume full depreciation ($\delta = 1$) and a screening production function of the form $f(C_t) = C_t/(\beta c_0 + C_t)$. This creates a direct link to our previous discussion because it implies that the screening precision λ_{t+1} in the forthcoming period has the same cost (when discounted to that period) as in the static model:

$$c(\lambda_{t+1}) = c_0 \cdot \frac{\lambda_{t+1}}{1-\lambda_{t+1}} \tag{23}$$

In fact, if q_t was constant forever, equilibrium allocations would be exactly the same as our previous results. We will make a related but slightly less extreme assumption by choosing the Markov process such that the macroeconomic state remains constant with large probability $\phi \gg 1/2$ but there also is a small chance of $(1-\phi)$ of a radical change to a new state:

$$q_{t+1} = \begin{cases} q_t & \text{with probability } \phi \\ z_{t+1} & \text{with probability } 1-\phi, \text{ where } z_{t+1} \sim \mathcal{U}(\bar{p}-\varepsilon/2,\, \bar{p}+\varepsilon/2) \end{cases} \tag{24}$$

Because we have assumed full depreciation, banks' decisions regarding their screening investments C_t in period t determine the available screening precision λ_{t+1} in period $t+1$ without affecting future screening choices. As a consequence, the dynamic model essentially becomes a sequence of one-shot games where in every period banks choose next-period screening λ_{t+1} according to their expectations about the future state q_{t+1}:

$$\begin{aligned} \max_{\lambda_{t+1}} \quad & \phi \left[\Pi^E_{\lambda_{t+1}}(q_t, \gamma) - c(\lambda_{t+1}) \right] + (1-\phi) \left[\int_{\bar{p}-\frac{\varepsilon}{2}}^{\bar{p}+\frac{\varepsilon}{2}} \Pi^E_{\lambda_{t+1}}(q_{t+1}, \gamma)\, \varepsilon^{-1} \mathrm{d}q_{t+1} - c(\lambda_{t+1}) \right] \\ \text{s.t.} \quad & 0 \leq \lambda_{t+1} < 1 \end{aligned} \tag{25}$$

As we can see, this objective function is a convex combination of two elements: the first element is exactly the objective of the static model and captures the benefit of investing in screening precision if the economy persists in the current state q_t, whereas the second element represents the expected gains from screening if the economy shifts to a new state. Unsurprisingly, when ϕ is large there is much macroeconomic persistence and thus the solution to eq. (25) bears much resemblance to the static case[21]. In particular, if times are sufficiently good (i.e. $q_t < \bar{p}$) and competition is strong enough that there is a lending boom today, tomorrow's *ex-ante* profit-maximizing screening precision λ_{t+1} is rather low. This is because the probability of a regime change that could move q_{t+1} to some new value is small. Moreover, even if q_{t+1} would turn out different from q_t, there is quite a chance to again end up in states of the economy in which the threat of free-riding competitors diminishes the usefulness of screening precision. Thus, there is no incentive ex-ante for building large stock of precautionary screening precision in good times.

But *ex-post*, there can be a very different story: let us think what happens if a macroeconomic regime change actually occurs and pushes the cut-off q_{t+1} to some relatively high value, i.e. $q_{t+1} > \bar{p} + \frac{\lambda_{t+1}\varepsilon}{2} - \frac{2\gamma}{R-r} > \bar{p}$. Asset values are poor and refinancing cost are high enough that no competitor can profitably enter the market as an outside lender. In other words, the ex-ante threat of competition turns out to be irrelevant ex-post. One of the preemptive measures taken by the bank ex-ante to optimally respond to this threat remains in place, however, and impedes its lending activities: the bank's chosen screening precision λ_{t+1} is inefficiently low due to the ex-ante expectation of competition. Since

[21] In appendix A.4 I plot numerical solutions to this problem for $\phi = 0.8$ which show that this is indeed the case.

the average project is not credit-worthy, we already know from corollary 4.1 that the imprecise information will prevent the bank from lending to as many borrowers as in the second-best benchmark.

In fact, due to the low precision of the screening signal, only borrowers of excellent quality will generate a signal that is sufficiently positive that they get funded. The lack of precise information thus manifests empirically as a flight to quality combined with a sharp contraction in lending. This shows that one single cause – free-riding – has the potential to consistently explain two key pathologies that trouble most modern economies these days: the rise of inefficient credit booms, and the severe credit rationing that follows when such booms go bust.

6 Discussion

6.1 Information Spillovers

If information spillovers have such harmful effect on the banking system, then why have so many countries adopted regulations (e.g. disclosure requirements) or encouraged the presence of market intermediaries (e.g. mortgage brokers) which almost seem *designed* as to create spillovers?

The surprisingly simple answer to this question is that most of these institutions have one and the same raison d'être: they limit the bargaining power of informed banks over their prospective borrowers. In their absence, informed lenders would move last in the loan bargaining process, and they could fully use their ex-post monopoly over the informationally captured borrower to appropriate borrower surplus by making a take-it-or-leave-it offer. In addition, the lack of outside options may render borrowers more vulnerable to accepting predatory terms of credit. By giving borrowers the possibility to seek other offers before the loan is closed, the aforementioned institutions create an opportunity for other banks to move after the informed lender. Whilst this provides borrowers with some protection against predatory lending practices, it generates all of the spillover-related problems that we have studied in the model.

It is also important to point out that the problem of information spillovers in credit markets is fairly general and is not at all confined to mortgage markets with disclosure requirements. For example, information spillovers occur just as well in small business relationship lending, albeit more ex-post than ex-ante: in a banking relationship firms become informationally captured. These firms obtain relatively unfavorable terms of credit from their informed lender (Schenone, 2010) and thus have all incentive to refinance early by obtaining credit from an uninformed competitor. When refinancing, firms will show their current loan contract. Thus, uninformed rivals can learn about the terms of the informed bank's offer which, if sufficiently informative, enables them to poach the most profitable borrowers. Informed banks will therefore find it optimal to dilute the informativeness of their loan contracts by resorting to the very same strategy of cross-subsidized excess lending that we have already discussed.

6.2 Credit Registers and Information Sharing

In many countries, banks share information among each other on a voluntary or even mandatory basis via credit registers. In the light of our previous findings, this raises the question which effect credit registers have on the allocation of credit, and whether they reduce or exacerbate the tendency towards unhealthy excesses in lending. The answer is that both outcomes are possible, and which one is attained depends considerably on the type of information being shared. If banks share information on their *actions*, they will likely adopt the detrimental signal-jamming mechanism of excessive lending that we have already studied[22]. In contrast, if they share hard information on borrower quality or if they provide information on *outcomes*, the result can be a more positive one.

To illustrate this point, consider our model in a situation in which borrowers' success probabilities are drawn iid from a uniform $\mathcal{U}(0,1)$ distribution. Assume now that a joint credit register is in place which provides a public signal $\chi_i^j \in \{1,2,3\}$ on every applicant i on all islands j. This signal truthfully reveals whether a prospective borrower's type lies in the upper, middle or lowest tercile of the applicant population. Since the signal is observed by all lenders, it partitions lending into three distinct markets. In each of these markets, domestic banks retain their potential information advantage over outsiders and thus competition is structured as in our original model. One obtains three separate instances of the baseline model, each with a mass of 1/3 of borrowers, $\varepsilon = 1/3$, and $\bar{p}$ adjusted such that *stellar* applicants ($\chi_i = 1$) have a success probability $p_i \in [2/3, 1]$ whereas prime applicants ($\chi_i = 2$) have $p_i \in [1/3,\ 2/3]$ and *subprime* ($\chi_i = 3$) ones have $p_i \in [0,\ 1/3]$.

How will banks choose their loan portfolios and screening intensities in each of these three markets? Our first observation is that in only one of these three markets, namely the one containing the marginal borrower, banks may engage in additional private information collection. Take for example the situation in which the marginal borrower lies somewhere in the subprime field ($q < 1/3$). Banks will then lend to *all* stellar and to *all* prime applicants[23], so screening them is useless. Loan approvals and offered interest rates in these markets are based on credit score only: since competition prevents banks from extracting on average more than γ per loan on any of these markets, borrowers with better credit scores obtain lower rates. More bank competition would just reduce markups and would not affect credit supply or credit quality in prime markets. Only for one market, namely the subprime market which contains the marginal borrower of type q, the worrisome picture of our baseline model emerges: in the subprime market, banks charge the maximal repayment R, choose positive (but inefficiently low) screening precision, deny credit to some borrowers and respond to stronger competition by making more loans of poor quality. This shows that credit scoring based on reliable shared information confines harmful distortions from free-riding to the credit market with the lowest borrower quality.

[22] If shared information is not verifiable, banks have incentive to manipulate such information before sharing it. Giannetti, Liberti, and Sturgess (2015) present evidence from the Argentinian public credit registry that banks intentionally misreport information to prevent poaching of high-quality borrowers.

[23] Formally, these markets satisfy the conditions of the fifth case of equation 15.

6.3 The Nature of Bank Competition in the Model

Another point that deserves to be given more detailed consideration is the nature of bank competition in the model, which is captured by the "extra monitoring cost" parameter γ. I think of γ as a parameter that has a lot of economic meaning because it captures several distinct effects:

First, γ can indeed reflect the additional cost of monitoring a borrower who is more difficult to observe for the bank. For example, this could be the case if the bank has no further service relationship with this customer (such as checking services) that could generate relevant information for monitoring the borrower's actions.[24] A reduction in γ could thus reflect improvements in the ability of lenders to access information about remote customers, for example due to advances in information technology (Hauswald and Marquez, 2003).

In an alternative interpretation of the model, γ can be considered a switching cost: in fact, one can think of my model as the second stage of a two-period game where in the first period, banks build customer relationships by providing banking services. Banks might initially compete for extending a loan to the customer, or for handling the customer's main checking and payroll account. The exact nature of this first-period service competition remains irrelevant as long as it gives the chosen "inside" bank the exclusive opportunity to collect additional private information about the customer that can be used in the second period. In period two, the "inside" bank then competes with outside lenders for winning the customer as a borrower. In this interpretation of the model, it is more natural to think of γ as a switching cost (due to the loss of the original bank relationship, or the cost of initiating a new business relationship with another lender) that any customer incurs who chooses to obtain his second period loan from a different lender. The existence of such switching cost are empirically well documented (e.g. Barone et al., 2011). An increase in competition in the model would be equivalent to a reduction in switching cost, which could for example occur due to changes in the regulatory environment.

Another important dimension of competition between banks is comparative advantage due to specialization. One could think of an extension of the model in which one of the two banks (which I will refer to as the *money center bank* or M) has a comparative advantage relative to the other (which I will call the *local bank* or L) because of its specialization as a large transnational lender which gives it cheaper access to wholesale funding, i.e. $\rho_M < \rho_L$. On the other hand, the *local bank* might benefit from its geographic specialization in the form of lower marginal cost of screening, i.e. $c'_L(\lambda) < c'_M(\lambda)$. What would the corresponding equilibrium allocations under competition be? Without having to solve the model all over again, it is possible to see the answer directly by careful inspection of the symmetric model. I approach this issue in several steps:

Let us first think of a world in which both banks have identical cost of screening but the money center bank has access to cheaper wholesale funding, $\rho_M = \rho_L - \Delta\rho$. This cost advantage enables the money center bank to compete more aggressively for

[24] Mester et al. (2007) provide evidence that transaction account data help banks monitor borrowers.

customers of the local lender: it could earn a strictly positive profit by poaching any loan portfolio on which the local lender earns more than $\gamma - \Delta\rho$ per loan. The local bank will anticipate this and respond to the threat of poaching by taking on more excessive credit and reducing its screening precision λ_L^*. In fact, it is easy to see that the local bank will act exactly *as if* in a symmetric model the value of γ had decreased to $\gamma - \Delta\rho$. The money center bank, on the other hand, will act in the opposite way: first of all, the lower refinancing cost translate into a lower required probability of success for a project to break even: $q_M = q_L - \frac{\Delta\rho}{R-r}$. Thus, the bank is able to extend its lending to more risky borrowers. To the extent that the resulting portfolio remains noncontestable, this expansion of credit will also be efficient. But more interestingly, the new loan portfolio is also more easily kept noncontestable since the local lender incurs higher cost on every loan-approved customer that it poaches from the money center bank: the local lender can only engage in profitable poaching of customers if the money center bank's profits per loan exceed $\gamma + \Delta\rho$. The comparative advantage of lower refinancing cost therefore translates into lower competitive pressure: in equilibrium, the money center bank will behave exactly as if it was playing the symmetric game where $q = q_L - \frac{\Delta\rho}{R-r}$ and the "extra monitoring cost" parameter γ was increased to $\gamma + \Delta\rho$.

We can now complete the picture and ask what happens once we bring the local bank's advantage in screening cost back into play. Because of free-riding, the local bank's greatest gift – generating precise information at lower cost – actually turns into a curse: since in equilibrium the local lender holds more precise private information, its loan portfolio is particularly attractive for the money center bank whose entry threshold moreover is lowered by its cost advantage in refinancing. In order to protect itself from poaching, the local bank must therefore respond by approving a substantially larger mass of negative NPV borrowers than a lender with higher information acquisition cost (see eq. 15). This not only severely limits its ability to benefit from its specialization but also renders it more fragile.

Finally, we may ask what happens in the limit of perfect competition, which should be somehow related to the model's equilibrium in the limiting case $\gamma \to 0$. Unfortunately, in the limit $\gamma \to 0$ the fact that each bank earns zero profit also implies that there will be zero information collection. Lending would be all-or-nothing, depending only on how q stands relative to $\bar{p}$. More meaningful conclusions about the perfect competition limit can only be attained if we assume that screening is costless and banks choose the maximal screening of $\lambda = 1$. In this case, the model produces exactly the same allocations as the well-known paper of de Meza and Webb (1987): in the limit of perfect competition, all profits from lending to positive NPV borrowers are dissipated into additional negative NPV loans.

6.4 Robustness: Generalizing the Screening Technology

We may also wonder to which extent the main result of the model – i.e. the finding of cross-subsidized lending under competition – depends on the chosen screening technology.

Not much, as I will show: the driving force behind most results is the fact that credit-worthiness testing creates dispersion in posterior expectations – the more precise the test, the more of it (see Ganuza and Penalva, 2010).

Let me define a completely general credit-worthiness test as follows: for a given level of test precision λ, the test comprises of a family of cumulative distribution functions $\{S_\lambda(s|p_i)\}_{p_i\in[0,1]}$ which indicate for every possible realization of a project's true type p_i the probability of obtaining a signal less or equal to s. Together with the prior distribution $B(p)$, this induces a joint distribution from which one can calculate by Bayes' Law the posterior distribution of p conditional on observing a signal realization $\sigma_{i,\lambda} = s_i$. From this posterior distribution, one can then finally calculate the expected probability conditional on the observed signal, $E[p_i|s_i]$. Just as before, I denote the cumulative density function of the random variable $E[p_i|\sigma_i]$ under test precision λ as $\mathcal{E}_\lambda(p)$.

For any test specification that satisfies the following single-crossing assumption regarding $\mathcal{E}_\lambda(p)$, the model yields similar qualitative results:

Assumption 1. *Let $\lambda \in [0,1)$ and $\mu \in [0,1)$ with $\lambda > \mu$. Then, a credit-worthiness test with higher precision λ disperses posterior expectations further away from the prior $\bar{p}$ than a test with lower precision μ in the sense that*

$$\begin{aligned} \mathcal{E}_\lambda(p) &> \mathcal{E}_\mu(p) \text{ for all } p \in (0,\bar{p}), \text{ and} \\ \mathcal{E}_\lambda(p) &< \mathcal{E}_\mu(p) \text{ for all } p \in (\bar{p},1). \end{aligned} \tag{26}$$

The results of the second-best benchmark as in proposition 1 then follow trivially from $m_\lambda^{SB}(q) = 1-\mathcal{E}_\lambda(q)$: for exogenous λ, the constrained optimal amount of lending is higher than under perfect information if $q < \bar{p}$, and is lower than under perfect information if $q > \bar{p}$.

With a minor twist in order to accommodate discrete posterior distributions I can also solve for the optimal portfolio under competition: remember that we defined the average success probability of the set of all projects that lie above some cut-off z as $\mathcal{A}_\lambda(z) = \int_z^1 p\,\mathrm{d}\mathcal{E}_\lambda(p)/\int_z^1 \mathrm{d}\mathcal{E}_\lambda(p)$. This definition can cause problems when the posterior distribution is discrete since $\mathcal{A}_\lambda(z)$ would become a discontinuous function. By a change of variables, this problem is easily circumvented: I simply rewrite the average success probability as a function of credit mass[25] m rather than cut-off probability z via the transformation $m = \mathcal{E}_\lambda(p)$ and define it as

$$\hat{\mathcal{A}}_\lambda(m) = \frac{1}{m}\int_{1-m}^{1} \mathcal{E}_\lambda^{-1}(\mu)\,\mathrm{d}\mu \tag{27}$$

which makes it a continuous and decreasing function in m. Lemma 3 and corollary 3.1 continue to hold for this more general case, and one obtains an equilibrium portfolio under competition that bears much resemblance in its structure to what we have found before:

[25] It is understood that m stands for a mass of m projects selected in the order from best towards worse quality.

- If $\hat{\mathcal{A}}_\lambda(m_\lambda^{SB}) \leq q + \frac{\gamma}{R-r}$, the earnings per loan do not exceed γ and the monopolistic portfolio is noncontestable. In this case, the allocation will reproduce the second-best, and a state-contingent repayment terms for loans are (R, r).

- Under threat of entry $\hat{\mathcal{A}}_\lambda(m_\lambda^{SB}) > q + \frac{\gamma}{R-r}$, not every project will be financed as long as the full portfolio remains noncontestable, i.e. $q > \bar{p} - \frac{\gamma}{R-r}$. The financed mass of projects in this regime will be

$$m_\lambda^E(q) = \hat{\mathcal{A}}_\lambda^{-1}\left(q + \frac{\gamma}{R-r}\right) \tag{28}$$

  where $\hat{\mathcal{A}}_\lambda^{-1}(a) \equiv \sup\{m \in [0,1] : \hat{\mathcal{A}}_\lambda(m) = a\}$. Due to financing of negative-NPV projects, credit mass is excessive in this range, $m_\lambda^E(q) > m_\lambda^{SB}(q)$. Equilibrium repayment terms remain at (R, r), and gross profits amount to $\gamma \cdot m_\lambda^E(q)$.

- Finally, for $q \leq \bar{p} - \frac{\gamma}{R-r}$, every project is financed at reduced repayment terms such that total gross profit equals γ.

In other words, an equilibrium with cross-subsidized loans and excessive lending is attained for a wide class of possible screening technologies.

7 Policy Implications and Testable Predictions

7.1 Regulating Loan Disclosures and Information Sharing

One immediate policy implication of the model is that regulators should be concerned about potential information spillovers when designing lending transparency rules.

In the U.S., disclosure rules for mortgage lenders have changed recently. The Dodd-Frank Act has given the U.S. Bureau of Consumer Financial Protection the mandate to design a single, integrated TILA-RESPA disclosure process *"to aid the borrower or lessee in understanding the transaction by utilizing readily understandable language to simplify the technical nature of the disclosures"*[26]. Under the new TILA-RESPA regulations which have come into force on October 3rd 2015, consumers have the right to receive written loan estimates on standardized forms within three business days of their loan application, and they must be given a final standardized loan disclosure at least three days before they enter a binding agreement. A clear goal of these regulations was not only to make credit offers more comprehensible for consumers, but also to facilitate shopping for loans. In fact, Richard Cordray, director of the Consumer Financial Protection Bureau, stated at the 2013 Boston "Know Before You Owe" Mortgage Field Hearing:

> *"Our second major goal is to improve the opportunities for comparison shopping. Consumers will first get the Loan Estimate within three days after they apply for a loan. They can take this form, apply for another loan elsewhere, and then make a direct comparison between the two forms."*

[26] Dodd-Frank Act Sec. 1098, 1100A.

Whilst the Consumer Financial Protection Bureau expects these improved bargaining opportunities to have zero impact on credit availability and lending standards, this will clearly not be true if banks react strategically to the observable loan offers of other informed lenders. The resulting harmful deterioration of credit standards will likely remain small for prime mortgage markets where borrower quality is almost exclusively determined by widely available hard information and credit scores and information differences between lenders are small; it could, however, become very significant in subprime mortgage markets where borrower quality is more opaque and the differences in private information between banks are far more pronounced. Potential remedies here could include subjecting disclosed offers to strict confidentiality agreements.

For other countries whose regulations require that banks provide unilaterally binding loan offers for an extended period of time[27], a policy recommendation would be to dramatically shorten the timespan for which such commitment must remain valid, and to ensure that mandatory information sharing (for example via a credit registry) diminishes private information differentials between lenders. Since all these measures reduce the strategic value of loan offers, they curb the potential for harmful booms.

7.2 Harmful Regulation of Credit Screening Standards

A second policy implication of the model relates to screening standards. Given that the model predicts socially suboptimal levels of screening in equilibrium, we may want to think about what would happen if a regulator who is unaware of the actual origin of the problem would attempt to increase banks' screening levels by means of some intervention (for example, via a subsidy to screening, or by some minimum due diligence requirements).

By looking at the mechanics of the model, it is easy to see that such regulatory action would yield an unpleasant surprise: assume that the inefficiently low screening level of banks was forced to some higher level λ_{RG} by means of regulatory intervention such that $\lambda^*_{SB}(q) \geq \lambda_{RG} > \lambda^*_E(q, \gamma)$. This elevated screening precision enables banks to make better portfolio choices than if they had retained the less precise equilibrium level of screening. But for this very same reason banks will also need to take more aggressive countermeasures against outside lenders who could poach their customers. They do so by adding further negative NPV clients to their borrower pool: an inspection of the fourth line in equation (15) reveals immediately that whenever banks operate in the competitive regime, more information precision will translate into larger credit mass. Thus, as long as regulatory intervention fails to reduce information spillovers between lenders and instead only restores information acquisition, the outcome will be just a further expansion in credit which will be associated with further welfare losses.

[27]For example, banks in Mexico are currently required to provide a unilaterally binding loan commitment, the "oferta vinculante", that is valid for at least 20 days.

7.3 Testable Predictions

How can one empirically detect the booms that we have discussed and distinguish them from other economic mechanisms that create excess credit? In this section, I present the key predictions of the model and contrast them with available evidence in the literature.

Bad times, good loans: Screening skills are countercyclical

One key prediction which differentiates the model from most theories of the credit cycle is that credit quality is most compromised by asymmetric information problems in exceptionally *good* times whereas credit quality is highest towards the end of recessions. This is well in line with empirical findings of Berger and Udell (2004) who document that loan officers' skill to identify bad borrowers deteriorates the more the further the economy moves away from the last recession. More recently, Becker, Bos, and Rozbach (2015) have analyzed the internal ratings of a large Swedish bank. They observe that the internal ratings of corporate borrowers are least informative of actual performance during booms, and most precise in business cycle downturns; interestingly, they find that the effect persists even when the sample is restricted only to the borrower population that is initially known to the bank. This observation is compatible with my hypothesis of lending booms due to free-riding but contradicts theories in which lending expansions are driven by the arrival of new borrowers of unknown type, as in Dell'Ariccia and Marquez (2006).

Small informed banks are the most reckless lenders during lending booms

Another prediction of the model is that lenders with a comparative advantage in screening will be the most reckless lenders during a boom if they face tough competition. Recent evidence from U.S. HMDA mortgage application data points exactly in this direction: Feng (2014) observes that during the 2000-2005 run-up to the financial crisis, small local mortgage lenders lowered their lending standards much more than large national lenders. Moreover, he finds that extensive lending to risky borrowers was most pronounced in markets in which bank competition was strongest and where house prices responded the most. This expansion was at the expense of credit quality: after 2007, foreclosure rates were particularly high in those markets.

All these observations are in line with the predictions of my model, but they are also compatible with excessive risk-taking due to diminished bank charter values. The next prediction however offers a possibility to distinguish free-riding frictions from risk-taking or other conflicts of incentives between banks' stakeholders:

Borrowers with different internal ratings get identical loan contracts

A sharp and to the best of my knowledge untested prediction of the free-riding theory presented in this paper is that banks give credit at identical terms to very heterogenous borrowers in order to minimize the information that is revealed. This does not mean that all borrowers receive unconditionally the exactly same rates: differences in available public or shared information about borrowers will still lead to variation in interest rates. However, borrowers who look identical in terms of public information but who are actually of very heterogenous quality according to a bank's internal rating should be pooled in identical contracts. We should expect the strength of this effect to vary over the cycle: it should be most pronounced when strong competition meets with favorable economic outlook, high collateral liquidation values and low monetary policy rates.

Lower policy rates and stronger creditor rights result in riskier loan portfolios

Lower policy rates ρ and stronger creditor rights (which increase r) are predicted to lead to riskier bank loan portfolios and to result in more bad loans. For both of these parameters, empirical studies have indeed revealed such a "dark side": the fact that banks make worse loans after an exogenous decrease in the monetary policy rate has been observed in loan-level data from Spanish and Bolivian credit registries (Jiménez, Ongena, Peydró, and Saurina (2014); Ioannidou, Ongena, and Peydró (2015)).

Using a sample of 2,400 banks across 69 countries, Houston, Lin, Lin, and Ma (2010) show that stronger creditor rights prompt banks to lend more and to take on more risk, increasing the likelihood of financial crisis. Interestingly, they also find a strong interaction between information sharing and creditor rights: more information sharing reduces the risk-augmenting effect of stronger creditor rights. Whilst one can also think of competing explanations for this finding, our free-riding model naturally leads us to expect the existence of such interaction term and correctly predicts its sign.

Institutional differences across countries explain propensity for lending booms

The final observation is that a country's lending-related institutions determine both the dispersion of information across lenders and the extent of possible information spillovers in the lending process. I thus predict a greater propensity for lending booms in countries in which the following two conditions coincide: first, there must be considerable differences in private information across lenders, either due to opaque borrowers or due to a strong relationship lending culture. Second, some institutions must undermine the secrecy of banks' lending decisions. Variables that would be particularly suitable to capture potential information deficiencies in the lending process include the scope of a country's loan disclosure regulations; the existence of regulation that protects early refinancing (e.g., penalty cap); the percentage of loans made through brokers; or the presence of ill-designed mandatory information sharing rules that provide information on actions via a credit register. We should expect these variables to have significant explanatory power for the severity of lending booms across countries.

8 Conclusions

In this paper, I have constructed a model of bank lending and bank competition that gives a free-riding perspective on lending booms: when banks' loan offers are observable, excessive lending can be an optimal signal-jamming strategy that is used by informed banks to deter the poaching of loan-approved borrowers by uninformed rivals.

The potential implications of free-riding frictions for banking industry go substantially beyond what I could explore in this paper. In particular, the business model of most banks has shifted dramatically over the past two decades from originate-to-hold to originate-to-distribute. Whilst the harmful impact of this change on screening is increasingly well understood (Purnanandam, 2011), convincing reasons that would explain why banks intentionally chose a business model that severely diminished the usefulness of their core competency are harder to come by. If lenders had suffered from some fundamental friction that increasingly prevented them from appropriating the benefits of their information production, we could readily understand why they would eventually prefer alternative business models over the more screening-intensive originate-to-hold model.

As I have shown in this paper, free-riding frictions can generate exactly such effect: they curb the benefits to information production. The question which of today's loan markets are particularly plagued by free-riding distortions is therefore not only of fundamental importance for our understanding of the lending cycle. It could as well hold an answer to our question about the recent reorganization of banking industry. This underscores the high relevance of quantifying free-riding distortions in future empirical research.

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A Appendix

A.1 Derivation of Posterior Beliefs after Screening

From the definition of the test, it is immediate that the cumulative density function of σ_i conditional on the project's actual quality p_i being p is given by a weighted combination of the cumulative of the random distribution and a step function,

$$P(\sigma_i \leq s | p_i = p) = (1-\lambda)\left(\frac{1}{2} + \frac{s-\bar{p}}{\varepsilon}\right) + \lambda \mathcal{H}(s-p) \tag{29}$$

where $\mathcal{H}(\cdot)$ is the Heaviside step function that evaluates to zero if the argument is negative, and to one otherwise. The corresponding probability density function[28] then reads

$$P(\sigma_i = s | p_i = p) = (1-\lambda)\frac{1}{\varepsilon} + \lambda \delta(s-p) \tag{30}$$

where $\delta(x)$ denotes the Dirac delta distribution that satisfies

$$\int_{-\infty}^{\infty} \delta(x) = 1 \text{ and } \delta(x) = \begin{cases} 0 & \text{for } x \neq 0 \\ +\infty & \text{for } x = 0 \end{cases}$$

By Bayes' Law,

$$P(p_i = p | \sigma_i = s) = \frac{P(\sigma_i = s | p_i = p) P(p_i = p)}{P(\sigma_i = s)} = (1-\lambda)\varepsilon^{-1} + \lambda \delta(s-p) \tag{31}$$

and the conditional expectation becomes

$$\begin{aligned} E[p_i | \sigma_i = s] &= \int p \left[(1-\lambda)\varepsilon^{-1} + \lambda \delta(s-p)\right] \mathrm{d}p \\ &= \int (1-\lambda)\varepsilon^{-1} p \, \mathrm{d}p + \lambda s \\ &= (1-\lambda)E[p] + \lambda s \end{aligned} \tag{32}$$

A.2 Proofs

Proof of Proposition 1:

The result for m_λ^{SB} follows trivially from $m_\lambda^{SB} = 1 - \mathcal{E}_\lambda(q)$. To verify the indicated average success probability $\mathcal{A}_\lambda^{SB}$, observe that the statement is true for $m_\lambda^{SB} \in \{0, 1\}$. Thus, we

[28] strictly, this is not a function, but a distribution in the Schwartz sense

can assume $0 < m_\lambda^{SB} < 1$. Then,

$$\begin{aligned}
\mathcal{A}_\lambda^{SB} &= \frac{1}{m_\lambda^{SB}} \int_q^1 p \, \mathrm{d}\mathcal{E}_\lambda(p) = \frac{1}{m_\lambda^{SB}} \int_q^{\bar{p}+\frac{\lambda\varepsilon}{2}} (\lambda\varepsilon)^{-1} p \, \mathrm{d}p \\
&= \frac{1}{m_\lambda^{SB}\lambda\varepsilon} \left[\frac{(\bar{p}+\frac{\lambda\varepsilon}{2})^2}{2} - \frac{q^2}{2} \right] \\
&= \frac{\lambda\varepsilon}{2m_\lambda^{SB}} \left(\frac{\bar{p}-q}{\lambda\varepsilon} + \frac{1}{2} \right) \left(\bar{p} + q + \frac{\lambda\varepsilon}{2} \right) = \frac{\bar{p}+q+\frac{\lambda\varepsilon}{2}}{2} \\
&= \bar{p} + \frac{\lambda\varepsilon}{2} \left(\frac{q-\bar{p}}{\lambda\varepsilon} + \frac{1}{2} \right) = \bar{p} + \frac{\lambda\varepsilon}{2}(1 - m_\lambda^{SB})
\end{aligned}$$

□

Proof of Proposition 2:

Marginal gross returns from information are

$$\frac{\partial}{\partial\lambda}(R-r)\frac{(2\bar{p}-2q+\lambda\varepsilon)^2}{8\lambda\varepsilon} = (R-r)\left[\frac{\varepsilon}{8} - \frac{(\bar{p}-q)^2}{2\lambda^2\varepsilon}\right]$$

which is always non-negative and attains a maximal value of $(R-r)\varepsilon/8$ when $q = \bar{p}$. Note that for $R \to r$ or $\varepsilon \to 0$ this goes to zero which proves that there will be no screening in the limit of disappearing risk or diminishing applicant heterogeneity. □

Proof of Lemma 3:

Define the *gross repayment* of any portfolio $\mathcal{P}$ of loans as $G[\mathcal{P}] \equiv \int_{\mathcal{P}} p_i(D_i - d_i) + d_i \, \mathrm{d}i$. Furthermore, as in the main text denote the *gross surplus* of a portfolio $\mathcal{P}$ as $\Pi[\mathcal{P}] \equiv G[\mathcal{P}] - \rho \cdot |\mathcal{P}|$ and the *expected gross surplus per loan* as $\pi[\mathcal{P}] = \Pi[\mathcal{P}]/|P|$. With these notations in place, I prove the lemma in three steps:

1. *In equilibrium, the incumbent's payoff from choosing any noncontestable symmetric portfolio $\mathcal{Q}$ is equal to its surplus $\Pi[\mathcal{Q}] = G[\mathcal{Q}] - \rho \cdot |\mathcal{Q}|$.*

   Noncontestability and symmetry of the portfolio implies that for any subset $\mathcal{R} \subset Q$ of positive measure, $\pi[R] \leq \gamma$. Thus an entrant's expected profit from poaching a nonzero measure of borrowers is always negative. The entrant thus does strictly better by staying out of the market and leaving $\Pi[\mathcal{Q}]$ to the incumbent.

2. *If $\mathcal{P}$ is a (not necessarily symmetric) noncontestable portfolio, and $\mathcal{Q}$ is a symmetric noncontestable portfolio with $\Pi[\mathcal{Q}] \geq \Pi[\mathcal{P}]$, then in equilibrium the incumbent obtains at least the same payoff by choosing the symmetric portfolio $\mathcal{Q}$ instead of $\mathcal{P}$.*

   As shown in step 1, playing $\mathcal{Q}$ yields a game payoff of $\Pi[\mathcal{Q}] \geq \Pi[\mathcal{P}]$ for the incumbent. Assume the incumbent could do better by playing $\mathcal{P}$ and obtain a payoff greater than $\Pi[\mathcal{P}]$. Since every loan in the loan portfolio $\mathcal{P}$ will be financed either by the incumbent or by the entrant, the sum of the payoffs to the incumbent and entrant is bounded from above and is at most as large as the total surplus of the entire portfolio $\Pi[\mathcal{P}]$. Hence, in order for the incumbent to obtain even higher payoff, the entrant would have to play a strategy that results in a negative payoff for the entrant, which is clearly no equilibrium strategy.

3. *If $\mathcal{P}$ is a (not necessarily symmetric) noncontestable portfolio, then there always exists a symmetric noncontestable portfolio $\mathcal{Q}$ with weakly higher gross surplus* $\Pi[\mathcal{Q}] \geq \Pi[\mathcal{P}]$.

   Define $D_{\max} = \sup_{i \in \mathcal{P}}\{D_i\}$, and denote the portfolio that is constructed by financing every project $i \in \mathcal{P}$ at repayment rates $(D_{\max}, r)$ as $\hat{\mathcal{P}}$. If $\pi[\hat{\mathcal{P}}] \leq \gamma$, then $\hat{\mathcal{P}}$ is already such symmetric noncontestable portfolio and we are done.

   Let thus be $\pi[\hat{\mathcal{P}}] > \gamma$. We will now restore noncontestability of the symmetric portfolio $\hat{\mathcal{P}}$ by adding more loans and, if further necessary, by lowering repayments.

   There are two subcases. The first subcase is the one in which the *full* portfolio $\hat{F}$ comprising of the entire measure 1 of *all* projects financed at repayment rates $(D_{\max}, r)$ is noncontestable, $\Pi[\hat{F}] \leq \gamma$: For this case, denote the measure of projects *not* in $\mathcal{P}$ as N, index them arbitrarily with j (where $0 \leq j \leq |N|$), and denote as N_k the portfolio constructed from all projects in N whose index is no higher than k, financed at $(D_{\max}, r)$. Then, the function $k \mapsto \pi[\hat{\mathcal{P}} \cup N_k]$ is continuous and satisfies by construction $\pi[\hat{\mathcal{P}} \cup N_0] > \gamma$, and $\pi[\hat{\mathcal{P}} \cup N_{|N|}] \leq \gamma$. By the intermediate value theorem there exists some l with $0 < l \leq |N|$ such that $\pi[\hat{\mathcal{P}} \cup N_l] = \gamma$. Since $|\hat{\mathcal{P}} \cup N_l| \geq |\mathcal{P}|$, the symmetric noncontestable portfolio $\mathcal{Q} \equiv \hat{\mathcal{P}} \cup N_l$ must yield weakly higher surplus than $\mathcal{P}$.

   In the second subcase, $\Pi[\hat{F}] > \gamma$. Then, portfolio $\hat{F}$ can be made noncontestable by lowering repayment rates symmetrically to yield profits exactly equal to γ. The resulting surplus is weakly higher than $\Pi[\mathcal{P}]$ since $\gamma \cdot 1 \geq \gamma|\mathcal{P}|$.

Thus, let $\mathcal{P}$ be an arbitrary noncontestable portfolio. Then by the last step we can construct a noncontestable symmetric $\mathcal{Q}$ with the same or higher surplus, and due to the first two steps we know that the game payoff attained by playing $\mathcal{Q}$ is at least the same as the payoff from playing $\mathcal{P}$. □

Proof of Proposition 4:

To prove the statement, I solve the maximization problem in corollary 3.1 for which I have already shown that every solution is an equilibrium portfolio choice in the game with competition. There are three cases:

1. If the solution to the unconstrained profit maximization problem is noncontestable, it is obvious that the monopolistic allocation maximizes eq (14). All projects with

expected success probability above $q = \frac{\rho - r}{R - r}$ are financed at terms (R, r). This occurs whenever the success probability of the monopolistic portfolio satisfies

$$\begin{aligned} \mathcal{A}_\lambda^{SB} &\leq q + \frac{\gamma}{R-r} \\ \frac{\bar{p}+q}{2} + \frac{\lambda\varepsilon}{4} &\leq q + \frac{\gamma}{R-r} \\ \Rightarrow \lambda &\leq \frac{2(q-\bar{p})}{\varepsilon} + \frac{4\gamma}{\varepsilon(R-r)} \end{aligned} \tag{33}$$

2. If the noncontestability constraint in equation (14) binds (i.e. $\lambda > \frac{2(q-\bar{p})}{\varepsilon} + \frac{4\gamma}{\varepsilon(R-r)}$), it must hold with equality:

$$\begin{aligned} \max_{\mathcal{Q}=(\mathcal{S},(D,d))} \quad & \Pi[\mathcal{Q}] \\ \text{s.t.} \quad & \Pi[\mathcal{Q}] = \gamma|\mathcal{Q}| \end{aligned} \tag{34}$$

Thus, any equilibrium has to maximize the size $|\mathcal{Q}|$ of the portfolio whilst maintaining an average profit per loan of exactly γ. We now first handle the case in which q is such that the *full* portfolio $\mathcal{F}$ which comprises of all projects financed at (R, r) remains noncontestable (i.e. $q \geq \bar{p} - \frac{\gamma}{R-r}$).

To solve this problem, I first characterize what the largest possible portfolio $\mathcal{Q}$ is that satisfies $\Pi[\mathcal{Q}] = \gamma|\mathcal{Q}|$ when repayment terms are exogenously fixed at some (D, d), where $D \leq R$ and $d \leq r$. To yield exactly γ per loan, the average probability of success in the portfolio must be equal to

$$\mathcal{A}_\lambda[\mathcal{Q}] = \frac{\int_{\mathcal{S}\in\mathcal{Q}} p \, \mathrm{d}\mathcal{E}_\lambda(p)}{\int_{\mathcal{S}\in\mathcal{Q}} \mathrm{d}\mathcal{E}_\lambda(p)} = \frac{\rho - d + \gamma}{D - d} \tag{35}$$

This condition is met by many symmetric portfolios that all have repayment terms (D, d). But the size of the portfolio can only be maximal if the portfolio is chosen in a pecking order that starts with the best projects and proceeds in the order of expected success probabilities towards worse ones: to see this, imagine that the portfolio selection would not follow a cut-off structure, and that some nonzero mass m of projects with average success probability π_m was denied financing whereas a subset of projects of equal size but worse average success probability $\pi_n < \pi_m$ was financed. Then, by exchanging in the portfolio the worse projects projects for the better ones, one can increase the nominator of eqn (35) by $m \cdot (\pi_m - \pi_n)$ whereas the denominator stays the same. This "excess" in success probability can be used to enlarge the portfolio size by financing an additional mass of previously unfinanced projects that have worse quality than the portfolio average, whereby the mass is chosen such as to restore the average success probability to its original value. This shows that a portfolio which does not respect the pecking order of "best loans come first" will not be maximal in size.

Thus, there will be a unique cut-off $\hat{q}$ that will be determined by meeting the average success probability condition:

$$\begin{aligned} \frac{2\bar{p}+2\hat{q}+\lambda\varepsilon}{4} &= \frac{\rho-d+\gamma}{D-d} \\ \Rightarrow \hat{q} &= \frac{2(\rho-d+\gamma)}{D-d}-\bar{p}-\frac{\lambda\varepsilon}{2} \end{aligned} \tag{36}$$

This expression makes it obvious that the cut-off is decreasing in D, so portfolio size is increasing in D; thus when D is also chosen, we must have $D=R$. Finally, the derivative of (36) with respect to d yields $\frac{2(\rho-D+\gamma)}{(D-d)^2}$ which for $D=R$ (as it is the case here) is negative if $\gamma+\rho<R \Rightarrow \frac{\gamma}{R-r}+\frac{\rho-r}{R-r}<1$, i.e. $q+\frac{\gamma}{R-r}<1$. Note that the left side of the inequality is the average success probability from eq. (35). Thus the inequality holds, and the size of the portfolio is increasing in d, which implies $d=r$. We then have a cut-off $\hat{q}$ of

$$\begin{aligned} \hat{q} &= \frac{2(\rho-r+\gamma)}{R-r}-\bar{p}-\frac{\lambda\varepsilon}{2} \\ &= 2\left(q+\frac{\gamma}{R-r}\right)-\bar{p}-\frac{\lambda\varepsilon}{2} \end{aligned} \tag{37}$$

3. If $\mathcal{F}$ is contestable, i.e. $q\le\bar{p}-\frac{\gamma}{R-r}$, any noncontestable portfolio that maximizes size must have a size of 1 and yield gross profits of γ. For a symmetric portfolio with $D=\frac{\gamma+\rho-r(1-\bar{p})}{\bar{p}}$ and $d=r$, gross profits are exactly γ:

$$\begin{aligned} \Pi &= \bar{p}D+(1-\bar{p})r-\rho \\ &= \gamma+\rho-r(1-\bar{p})+(1-\bar{p})r-\rho \\ &= \gamma \end{aligned} \tag{38}$$

Proof of Proposition 5:

The first two statements follow directly from taking the derivative of eq. (15) with respect to q for the monopolistic and the competitive regime,

$$\frac{\partial m(q,\gamma)}{\partial q}=\begin{cases} \frac{-1}{\lambda\varepsilon} & \text{if } \bar{p}+\frac{\lambda\varepsilon}{2}-\frac{2\gamma}{R-r}<q<\bar{p}+\frac{\lambda\varepsilon}{2} \\ \frac{-2}{\lambda\varepsilon} & \text{if } \bar{p}-\frac{\gamma}{R-r}<q\le\bar{p}+\frac{\lambda\varepsilon}{2}-\frac{2\gamma}{R-r} \end{cases} \tag{39}$$

Combining this result with $\frac{\partial\mathcal{D}_\lambda}{\partial m}=-\frac{\partial\mathcal{A}_\lambda}{\partial m}=\frac{\lambda\varepsilon}{2}$ yields

$$\frac{\partial\mathcal{D}_\lambda}{\partial q}=\frac{\partial\mathcal{D}_\lambda}{\partial m}\cdot\frac{\partial m}{\partial q}=\begin{cases} -\frac{1}{2} & \text{if } \bar{p}+\frac{\lambda\varepsilon}{2}-\frac{2\gamma}{R-r}<q<\bar{p}+\frac{\lambda\varepsilon}{2} \\ -1 & \text{if } \bar{p}-\frac{\gamma}{R-r}<q\le\bar{p}+\frac{\lambda\varepsilon}{2}-\frac{2\gamma}{R-r} \end{cases} \tag{40}$$

which proves the third statement.

Proof of Proposition 6:

To prove the statement, let's look at the gross profit function in the presence of competition: for $q > \bar{p} - \frac{\gamma}{R-r}$, it reads

$$\Pi_\lambda(q,\gamma) = \begin{cases} \max\{0,(R-r)(\bar{p}-q)\} & \text{if } 0 \leq \lambda \leq \frac{2|q-\bar{p}|}{\varepsilon} \\ (R-r)\frac{(2\bar{p}-2q+\lambda\varepsilon)^2}{8\lambda\varepsilon} & \text{if } \frac{2|q-\bar{p}|}{\varepsilon} < \lambda \leq \frac{2(q-\bar{p})}{\varepsilon} + \frac{4\gamma}{\varepsilon(R-r)} \\ \gamma\left[1 - \frac{2\left(q-\bar{p}+\frac{\gamma}{R-r}\right)}{\lambda\varepsilon}\right] & \text{if } \frac{2(q-\bar{p})}{\varepsilon} + \frac{4\gamma}{\varepsilon(R-r)} < \lambda < 1 \end{cases} \tag{41}$$

whilst for $q \leq \bar{p} - \frac{\gamma}{R-r}$ gross profits are independent of λ,

$$\Pi_\lambda(q,\gamma) = \gamma \text{ for all } \lambda \in [0,1) \tag{42}$$

Despite its piecewise structure, the function is continuous everywhere. Specifically, note that the transition between monopolistic and competitive regimes occurs at $\lambda = \frac{2(q-\bar{p})}{\varepsilon} + \frac{4\gamma}{\varepsilon(R-r)}$, which substituted into the competitive profit function yields the same profits as when approaching the threshold from the monopolistic side: $\Pi = \frac{\gamma^2}{(q-\bar{p})(R-r)+2\gamma}$

Taking derivative with respect to λ, one obtains the marginal returns to information for $q > \bar{p} - \frac{\gamma}{R-r}$ as

$$\frac{\partial \Pi_\lambda}{\partial \lambda}(q,\gamma) = \begin{cases} 0 & \text{if } 0 \leq \lambda \leq \frac{2|q-\bar{p}|}{\varepsilon} \\ (R-r)\left(\frac{\varepsilon}{8} - \frac{(\bar{p}-q)^2}{2\lambda^2\varepsilon}\right) & \text{if } \frac{2|q-\bar{p}|}{\varepsilon} < \lambda \leq \frac{2(q-\bar{p})}{\varepsilon} + \frac{4\gamma}{\varepsilon(R-r)} \\ \frac{2\gamma\left(q-\bar{p}+\frac{\gamma}{R-r}\right)}{\lambda^2\varepsilon} & \text{if } \frac{2(q-\bar{p})}{\varepsilon} + \frac{4\gamma}{\varepsilon(R-r)} < \lambda < 1 \end{cases} \tag{43}$$

whereas there are zero marginal returns to information for $q \leq \bar{p} - \frac{\gamma}{R-r}$. Hence we already know that $\lambda_E^* = 0$ for this region, which proves the third statement of the proposition. The first statement of the proposition is equally obvious because profits and marginal returns to information for this case are the same as in the planner's benchmark. It thus only remains to show that marginal returns under threat of competition are lower than those attained under monopoly. Denote the difference in marginal returns to information as

$$\begin{aligned} \Delta(\lambda) &\equiv (R-r)\left(\frac{\varepsilon}{8} - \frac{(\bar{p}-q)^2}{2\lambda^2\varepsilon}\right) - \frac{2\gamma\left(q-\bar{p}+\frac{\gamma}{R-r}\right)}{\lambda^2\varepsilon} \\ &= \frac{(R-r)\varepsilon}{8} - \frac{\left((q-\bar{p})(R-r)+2\gamma\right)^2}{2(R-r)\lambda^2\varepsilon} \end{aligned} \tag{44}$$

This term is non-negative if

$$\begin{aligned} &\frac{1}{8}(R-r)\varepsilon \cdot 2(R-r)\lambda^2\varepsilon - \left((q-\bar{p})(R-r)+2\gamma\right)^2 \geq 0 \\ \Leftrightarrow &\left((R-r)\frac{\lambda\varepsilon}{2}\right)^2 - \left((q-\bar{p})(R-r)+2\gamma\right)^2 \geq 0 \end{aligned} \tag{45}$$

Substituting into this expression the threshold between monopolistic and competitive regimes, $\lambda = \frac{2(q-\bar{p})}{\varepsilon} + \frac{4\gamma}{\varepsilon(R-r)}$, we see that the left-hand side of this inequality becomes zero. For any larger value of λ it will obviously remain positive. Thus, marginal returns to information are continuous at the threshold, and for higher λ marginal returns to information under competition are strictly less than under monopoly. q.e.d.

Proof of Proposition 7:

Under the conditions stated in the proposition, a reduction of competition has two effects on credit: As one can see by taking the total derivative wrt. γ,

$$\frac{\mathrm{d}}{\mathrm{d}\gamma}\left(m^E_{\lambda^*_E(\gamma)}(q,\gamma)\right) = \frac{\partial m^E_\lambda}{\partial\gamma} + \left.\frac{\partial m^E_\lambda}{\partial\lambda}\right|_{\lambda=\lambda^*_E} \cdot \frac{\partial\lambda^*_E}{\partial\gamma} \tag{46}$$

there is a *direct* effect and an *indirect* one via λ. The two effects have opposite sign: for constant information level, less competition results in less cross-subsidization and thus less credit. However, less competition also raises information precision which again prompts more cross-subsidization and more credit. I show here that the first effect prevails:

First, note that

$$\frac{\partial m^E_\lambda}{\partial\lambda} = \frac{\partial}{\partial\lambda}\left(1 - \frac{2(q-\bar{p}+\frac{\gamma}{R-r})}{\lambda\varepsilon}\right) = \frac{1-m^E_\lambda}{\lambda} \tag{47}$$

and, as a consequence of $\Pi^E_\lambda = \gamma m^E_\lambda$,

$$\frac{\partial\Pi^E_\lambda}{\partial\lambda} = \gamma\frac{1-m^E_\lambda}{\lambda} \tag{48}$$

From here I take derivatives and obtain

$$\frac{\partial^2\Pi^E_\lambda}{\partial\lambda^2} = -\frac{2\gamma}{\lambda^2}(1-m^E_\lambda) \text{ and} \tag{49}$$

$$\frac{\partial^2\Pi^E_\lambda}{\partial\lambda\partial\gamma} = \frac{1-m^E_\lambda}{\lambda} + \frac{2\gamma}{\lambda^2\varepsilon(R-r)} \tag{50}$$

I then apply the implicit function theorem on the first-order condition that fixes λ^*_E in order to put bounds on the sensitivity of λ^*_E with respect to γ:

$$\frac{\mathrm{d}}{\mathrm{d}\gamma}\lambda^*_E(q,\gamma) = -\frac{\frac{\partial^2\Pi^E_\lambda}{\partial\lambda\partial\gamma}}{\frac{\partial^2\Pi^E_\lambda}{\partial\lambda^2} - c''(\lambda)} \leq \frac{\frac{\partial^2\Pi^E_\lambda}{\partial\lambda\partial\gamma}}{-\frac{\partial^2\Pi^E_\lambda}{\partial\lambda^2}} = \frac{\frac{1-m^E_\lambda}{\lambda} + \frac{2\gamma}{\lambda^2\varepsilon(R-r)}}{\frac{2\gamma}{\lambda^2}(1-m^E_\lambda)} \tag{51}$$

The inequality results from the fact that I assumed a convex cost function, so $c'' \geq 0$. Simplifying further, I obtain

$$\frac{\mathrm{d}}{\mathrm{d}\gamma}\lambda^*_E(q,\gamma) \leq \frac{\lambda}{2\gamma} + \frac{1}{\varepsilon(R-r)(1-m^E_\lambda)} \tag{52}$$

and

$$\frac{\partial m^E_\lambda}{\partial\lambda}\frac{\mathrm{d}\lambda}{\mathrm{d}\gamma} \leq \frac{1-m^E_\lambda}{2\gamma} + \frac{1}{\varepsilon\lambda(R-r)} \tag{53}$$

The sum of direct and indirect effect then yields

$$\frac{\mathrm{d}}{\mathrm{d}\gamma}\left(m^E_{\lambda^*_E(\gamma)}(q,\gamma)\right) \leq \frac{1-m^E_\lambda}{2\gamma} - \frac{1}{\varepsilon\lambda(R-r)} \tag{54}$$

Substituting the definition of m^E_λ, I have

$$\frac{\mathrm{d}}{\mathrm{d}\gamma}\left(m^E_{\lambda^*_E(\gamma)}(q,\gamma)\right) \leq \frac{q-\bar{p}}{\gamma\lambda\varepsilon} + \frac{1}{\lambda\varepsilon(R-r)} - \frac{1}{\varepsilon\lambda(R-r)} = \frac{q-\bar{p}}{\gamma\lambda\varepsilon} \tag{55}$$

Since I assumed that the average project is credit-worthy, $q < \bar{p}$ holds and the equation is negative. □

A.3 Closed-Form Solutions

For the specific cost function $c(\lambda) = c_0 \frac{\lambda}{1-\lambda}$ the model has closed-form solutions for $\lambda^*(q)$: In the monopolistic case, the first-order condition has the form

$$\frac{c_0}{(\lambda-1)^2} = b - \frac{a}{\lambda^2}$$

with $a \equiv \frac{(R-r)(\bar{p}-q)^2}{2\varepsilon}$ and $b \equiv \frac{(R-r)\varepsilon}{8}$. Solving for λ leads to a quartic equation for which the solution is known in standard tables. Two roots can be discarded because they describe local minima, so only two solutions λ_1^* and λ_2^* remain. The correct solution is identified as the only one that lies within the $[0,1]$ interval (depending on q, either the one or the other branch applies). Define

$$\begin{aligned}
\gamma &\equiv a - b - c_0 \\
\phi &\equiv 108a^2b - 108ab^2 - 108ab\gamma - 2\gamma^3 \\
\beta &\equiv \frac{\sqrt[3]{2}\gamma^2}{3a\left(\phi + \sqrt{\phi^2 - 4\gamma^6}\right)^{1/3}} + \frac{\left(\phi + \sqrt{\phi^2 - 4\gamma^6}\right)^{1/3}}{3\sqrt[3]{2}a}
\end{aligned}$$

The two solutions are then given by

$$\lambda_1^* = \frac{1}{2}\sqrt{2 + \beta - \frac{4\gamma}{3a} - \frac{2(a-2b-\gamma)}{a\sqrt{1-\beta-\frac{2\gamma}{3a}}}} - \frac{1}{2}\sqrt{1-\beta-\frac{2\gamma}{3a}} + \frac{1}{2} \tag{56}$$

$$\lambda_2^* = \frac{1}{2}\sqrt{2 + \beta - \frac{4\gamma}{3a} + \frac{2(a-2b-\gamma)}{a\sqrt{1-\beta-\frac{2\gamma}{3a}}}} + \frac{1}{2}\sqrt{1-\beta-\frac{2\gamma}{3a}} + \frac{1}{2} \tag{57}$$

In the competitive case, the first-order condition is quadratic in λ and can be solved to yield as the unique non-negative solution

$$\lambda_E^*(q,\gamma) = \frac{1}{1+\sqrt{\frac{c_0}{\delta}}} \text{ where } \delta = 2\gamma\varepsilon^{-1}(q - \bar{p} + \tfrac{\gamma}{R-r}) \tag{58}$$

A.4 Information Choice in the Dynamic Credit Cycle Model

I plot here the numerical results for banks' optimal ex-ante choice of tomorrow's screening λ^*_{t+1} as a function of today's prevailing economic state q_t. They are obtained from the dynamic credit cycle model with $\delta = 1$. Again, the solid line displays the equilibrium information choice $\lambda^*_{E,t+1}$ under competition whereas the second-best benchmark is shown with dashed lines. As long as macroeconomic shocks are relatively persistent (ϕ sufficiently large; here: $\phi = 0.8$), the results remain qualitatively similar to those of the static model (see figure 3). Note however that in anticipation of an aggregate shock (with probability $1 - \phi = 0.2$) some information is also collected for precautionary motives in states q_t in which information previously had no value.

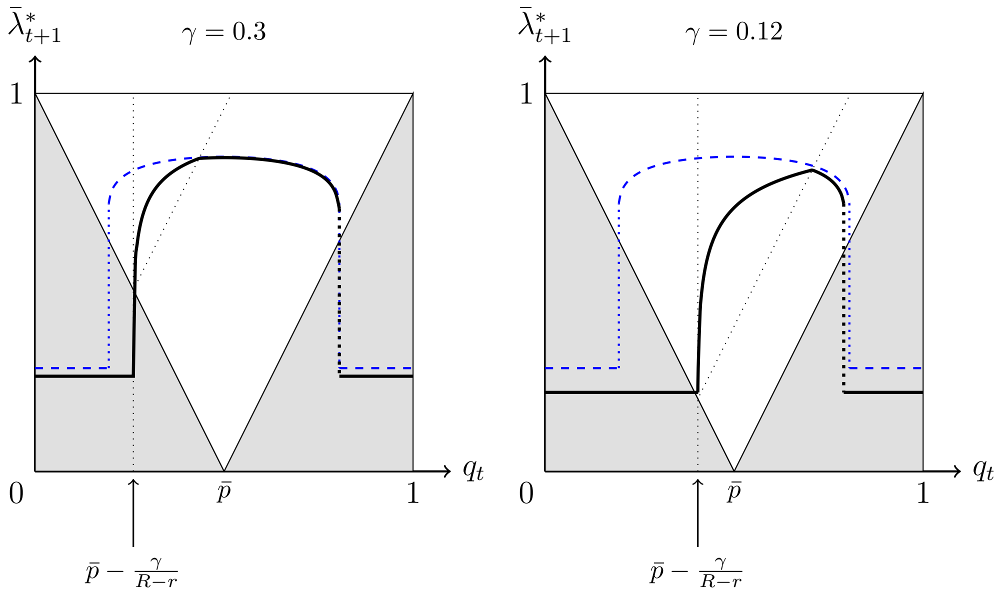

Figure 5: Information choice λ^*_{t+1} as a function of q_t under weaker (left) and stronger (right) level of competition in the presence of aggregate uncertainty ($\phi = 0.8$). All other parameters are identical to those used in figure 3.