A dynamic behavioral model of the credit boom*

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Abstract

In this paper we provide a dynamic model of banking competition where bounded rationality of some competitors explains how the credit cycle is amplified. We model the economic cycle following Rötheli (2012b) where boundedly rational banks, in their Bayesian learning, overestimate probabilities of success during booms and underestimate them during recessions. The main results obtained are three. First, the model suggests pessimism/underconfidence is not a powerful driver of credit cycles. Instead, it supports it is euphoria during large upswings what seeds the next crunch. Second, the dynamization of the model provides further insight on how boundedly rational competition amplifies the credit cycle. Finally, an additional prediction is that the effects of behavioral biases are expected to be more pervasive the lower the quality of the niche markets.

Keywords: Credit cycles, banking efficiency, behavioral finance, overconfidence, pessimism

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1. INTRODUCTION

The financial crisis that begun in 2007 highlighted the importance of credit cycles. Thus, their study is gaining attention among researchers. A recent and growing field is the analysis of credit cycles under the scope of behavioral economics. For instance, Lewis (2010) and Leiser et al. (2010) trace some effects of social psychology on financial cycles. Bezemer (2011) finds that most economists that saw the crisis coming considered assumptions that were not in mainstream theory; namely, behavioral assumptions on uncertainty, bounded rationality and non-optimizing behavior.

Following this, several behavioral models of credit cycles have been proposed. Examples are Keen (2011), who offers a monetary macroeconomic model of the Financial Instability Hypothesis (Minsky, 1982a,b, 1992) that explains the Great Moderation and the Great Recession; Rötheli (2012a), who proposes a model of oligopolistic bank competition where just a minority of boundedly rational banks are enough to aggravate the credit cycle; Peón et al. (2014), who offer a model of banking competition where a credit boom is fostered solely by behavioral biases; or Boz and Mendoza (2014), who provide a model that analyzes the effects of financial innovation and overconfidence to amplify the credit cycle.

Our contribution here is to expand this literature by offering a dynamic model of banking competition where bounded rationality of some banks explains how the credit cycle is amplified. We model the economic cycle following Rötheli (2012b) where boundedly rational banks, in their Bayesian learning, overestimate probabilities of success during booms and underestimate them during recessions. In this line, we extend the model of banking competition under overconfidence by Peón et al. (2014) to consider the effects of pessimism/underconfidence in the recessive periods of the credit cycle, in order to determine whether symmetry exists regarding the effects that excessive optimism and pessimism induce in retail credit markets. The prevalence of the overconfidence bias is a classic in the behavioral literature but the effects of a malfunctioning credit market become more evident during a credit crunch. Some authors (Rötheli, 2012a) suggest rational banks would follow pessimistic banks during recessions; others (Boz and Mendoza, 2014), assuming all agents are boundedly rational, find pessimism produces amplification effects on debt just like excessive optimism. In both cases, sharper downturns of the credit cycle would follow. Our purpose is to provide further analysis of this interpretation from a theoretical point of view.

To that purpose, we then offer a dynamization of the model to determine when over- and underestimation effects are expected to be more pervasive. Which bias would be the main driver of a credit cycle, excessive optimism during upturns or pessimism during recessions? Additionally, this setup will also be useful to determine whether some market niches are expected to be more exposed to booms and busts than others.

The main results obtained are three. First, the model suggests pessimism is not a powerful driver of credit cycles. Rather than that, our model supports it is euphoria during large upswings what seeds the next crunch. This would dispute the alternative interpretation in models like Rötheli (2012a), where the interest rate decisions of a minority of boundedly rational banks induce the more rational competitors to aggravate the credit cycle during both booms and recessions. Other authors, like Boz and Mendoza (2014), also interpret pessimism has amplification effects on debt, but our opposite results are not comparable to theirs, both because they assume all agents are boundedly rational and because they consider the effects of financial innovation on cycles.

Second, the dynamization of the model provides further insight on how boundedly rational competition would amplify the credit cycle: (i) the effects are relevant particularly during upswings, (ii) the conditions for a herding behavior to appear in both booms and recessions are determined, and (iii) it is shown that only for high levels of pessimism some amplification effects over the cycle would be observed, but in such case simply cut rates would be a powerful tool for economic authorities to soften the recession, in contradiction with recessions of the kind we recently experienced. Finally, the third result we obtain is that excessive optimism as a driver of a credit boom is shown to be a plausible explanation particularly the lower the quality of the niche markets. We have not found previous results in the literature that analyzes this possibility.

The structure of the article is as follows. In Section 2 we provide a brief state of the arts on Minky's thoughts, the money endogeneity principle, and the literature of behavioral finance –mostly focused on research on overconfidence. In Section 3 we set the three basic elements of the model, namely the economic cycle described as in Rötheli (2012b), the model of banking competition during booms and a model of the recessive periods of the credit cycle considering the effects of pessimism and underconfidence. In Section 4 we offer a dynamization of the model all over the boom-bust cycle. Section 5 concludes. The proof of the main results is relegated to an Appendix.

2. State of the arts

The financial crisis that started in 2007 renewed attention on Minsky's Financial Instability Hypothesis, *FIH* (Minsky, 1982a,b), a theory of financially driven business cycles which can lead to an eventual debt-deflationary crisis. In short, Minsky asserts *stability is destabilizing*: over periods of prolonged prosperity, the economy naturally transits from hedge finance – the only income-debt relationship that ensures equilibrium in the economy- to speculative and Ponzi finance.[1] Minsky sees bankers as merchants of debt trying to profit out of it. At the beginning of the economic expansion, banks and firms act conservatively due to risk aversion caused by a memory of a not too distant financial failure. Then, good economic performance makes bankers and managers perceive risk premiums are excessive and that *it pays to lever*. Less conservative banking practices and higher leverage leads to a 'euphoric economy' and, eventually, to speculative and Ponzi schemes that lead to debt deflation and economic turmoil (Keen, 2011).

Minsky's interpretation of business cycles driven by credit is related to the Post Keynesian endogenous money model (Moore, 1988). In the era of modern liability management, bank lending operations are neither deposit nor reserve constrained: instead, loans make deposits and deposits make reserves (Lavoie, 1984). Recent research evidences banking credit booms are related to the business cycle. Jorda et al. (2011) show higher rates of credit growth relative to GDP tend to be followed by deeper recessions and slower recoveries. Carpenter and Demiralp (2010) conclude that the money multiplier is not useful to assess the effects of monetary policy on future money growth or bank lending.

In our view, the behavioral finance literature could provide a plausible approach to interpret how Minsky's claim that stability is destabilizing may happen. Behavioral economics has identified a wide range of anomalies that challenge standard theories, from consumption to finance, from crime to voting, from charitable giving to labor supply (DellaVigna, 2009). Psychology provides alternative interpretations to standard *homo economicus* about how people do behave (as opposite to how they should behave). Two

[1] The *FIH* stresses the relationship between volumes of debt accumulated by the private sector and the debt payments (interests and principal) associated to them, compared to the income generated from the investments that debt finances. Hedge financing agents are able to meet all their financial obligations with the cash flows generated by the assets they own. Speculative finance units can pay the interest on their debt, but need to 'roll over' their liabilities as they expire. Finally, for Ponzi subjects, the cash flows from operations are not enough to meet either the principal or the interest on their debt, so they are forced to increase their indebtedness, or sell assets to meet the payments required.

classics of this positive interpretation are bounded rationality (Simon 1955, 1959) and prospect theory (Kahneman and Tversky, 1979). Simon (1955, 1959) criticizes the assumption of rationality and suggests people are boundedly rational, with utility maximization being replaced by satisficing: since information is vast but we have limited information-processing abilities, we construct simplified models of the world to make decisions. On the other hand, Kahneman and Tversky (1979) offered an alternative view to the expected utility hypothesis that better explains empirical evidence of how people make choices under uncertainty.

The presence of boundedly rational agents may make rational competitors in the same market to herd –i.e., to mimic their competitors. Empirical evidence of herding is vast, for instance, in the context of financial markets (Lakonishok et al., 1992; Hwang and Salmon, 2004; Jegadeesh and Kim, 2010). Herding could be rational for agents concerned about their reputation in the market (Scharfstein and Stein, 1990) or because they perceive it to be a safer course of action: if they are wrong, their competitors will be wrong as well (Jegadeesh and Kim, 2010). Peón and Calvo (2013) explain the rationale for herding in retail credit banking: it is not just that banks may not be aware they are understating risks, it is that they may be aware of them, but not following the trend would leave them out of the game. Following competitors reduces risk of underperformance, while those who do not herd may lose market share.

The model we provide here shows overconfidence fostered by excessive optimism during the upswing of the economic cycle could be used to interpret how the business cycle is amplified by banking credit booms. The prevalence of overconfidence is a classic in the behavioral literature. De Bondt and Thaler (1995), for instance, consider it to be the more robust finding in the psychology of judgment. Plous (1993) highlights overconfidence is not only prevalent, but more potentially catastrophic than any other problem in judgment and decision making.[2]

Much of this prevalence comes from the fact that overconfidence can manifest itself in different instances. For example, Moore and Healy (2008) identify three: overconfidence in estimating our own performance (overestimation); in estimating our own performance relative to others (overplacement or 'better-than-average' effect); and having an excessive precision to estimate future uncertainty (overprecision). Moore and Healy (2008)'s model

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[2] However, the debate is still vivid today: ecological (Brunswikian) and error (Thurstonian) models have criticized this alleged prevalence of overconfidence. See Moore and Healey (2008).

is also a classic in the literature as it succeeds to explain how both over- and underconfidence may coexist in two of their different manifestations (estimation and placement) when people apply the Bayesian principle of updating beliefs from prior beliefs based on data observed.

Many anomalies have been related to overconfidence and its different manifestations, both in financial markets and managers' decision making. On one hand, overconfidence in financial markets can make investors overstate their risk tolerance (Hirshleifer, 2001; Barberis and Thaler, 2003) and foster market anomalies such as excess volatility and return predictability (Daniel et al., 1998), excessive trading (Kyle and Wang, 1997; Odean, 1998, 1999), the forward premium puzzle (Burnside et al., 2011), sensation seeking (Grinblatt and Keloharju, 2009), and portfolio under-diversification (Goetzmann and Kumar, 2008), among others.

On the other hand, research is vast on behavioral corporate finance and overconfidence. Executives appear to be particularly prone to display overconfidence (Moore, 1977). This includes evidence of overconfidence effects on corporate takeovers (Roll, 1986), high rates of business failure (Camerer and Lovallo, 1999), high rates of corporate merger and acquisition (Malmendier and Tate, 2005a,b), lower dividend payout (Deshmukh et al., 2010), higher cash holdings (Huang et al., 2012) and corporate diversification (Malmendier and Tate, 2008; Andreou et al., 2012).

In particular, Niu (2010) provides evidence that banks managed by overconfident CEOs take more risk. This may happen either because they overestimate the precision of exogenous noisy signals (Gervais et al., 2011) or they overestimate their ability to predict the future (Hackbarth, 2008. This could also induce higher risk taking due to CEO option-based compensation (Chen et al., 2006; Mehran and Rosenberg, 2008). Overconfidence might also be reinforced in some cases by an 'illusion of control': judging a positive outcome to be a consequence of their acts when in fact they were simply lucky, even when they know that success or failure depends on chance (Hens and Bachmann, 2008).

In this paper we follow the first approach (overestimation of probabilities) to analyze how increased risk-taking would affect the volumes and rates of credit banks would grant to the economy. Nonetheless, upswings, when based on credit booms, are often induced by financial innovations (Brown, 1997). The development of financial innovations such as the collateralized debt obligations (CDO) or the credit default swaps (CDS) surely would have made the consequences of overconfidence over leverage more severe, also fostering demand-side effects (Brown, 2007). Under the money endogeneity principle, the supply of reserves is horizontal at the central bank's target and, since they pay low or even zero rates, banks continually innovate to reduce the quantity of reserves they need to hold, increasing the rate of return on equity within regulatory constraints (Wray, 2007). This was evident for Alan Greenspan himself, who complained how easy it was for CEOs to craft financial statements to deceive the public (Friedman and Friedman, 2009). The scandal involving Bernard Madoff has also put under question how well the financial system is being monitorized. This approach regarding the effects of financial innovation is, however, beyond the scope of our paper. Boz and Mendoza (2014) provide a model of financial innovation and overconfidence in the context of the U.S. credit crisis, showing that financial innovation can lead to significant underestimation of risk.

3. THE BASICS OF THE MODEL

For the purposes of this paper we model overconfidence as overestimation of probabilities of success –i.e., the probability that a loan is fully repaid– during the upswing of the business cycle, fed by excessive optimism, while underconfidence means underestimation of probabilities of success, fed by pessimism during the economic crises. In order to take our model to a dynamic setup, three theoretical analyses are previously introduced. First, how a duopoly of banks would compete in a static setup when one of them is biased in terms of excessive optimism and overconfidence. Second, how the same duopoly would compete if the boundedly rational bank is instead biased in terms of pessimism and underconfidence. Third, we borrow Rötheli's (2012a,b) theoretical and empirical description of the stylized dynamics of credit risk assessment to model how boundedly rational expectations and rational expectations on probabilities of success change all over the business cycle.

The reason why we assume not all banks are boundedly rational is that results would be weaker in that case. Instead, one of the goals will be to determine whether herding results appear and under which circumstances.

3.1 Excessive optimism and overconfidence during booms

We model a duopoly of banks as in Peón et al. (2014). The banking sector meets potential borrowers, who may be of different types, high-quality and low-quality (denoted by subscripts h and l, respectively), though there are neither adverse selection problems nor agency problems between shareholders and managers. For model tractability we assume (i) banks' risk-neutrality, (ii) the existence of an unlimited source of deposits at a given competitive rate of return, r, $r \geq 0$, (iii) deposits can only be invested in loans (no interbank market) and are hold until maturity (no liquidity restrictions), (iv) the Central Bank requires no reserves, and (v) banks are confronted with two linear downward sloping demand functions for loans, one for each type of borrower, such that $L(r_h) = \alpha - \beta \cdot r_h$ and $L(r_l) = \alpha - \beta \cdot r_l$, $\alpha, \beta > 0$.[3] Finally, banks have a linear cost function $C(L) = c \cdot L$, $c > 0$.

Key to the model is the definition of two types of banks, banks of type A and of type B. Bank A is unbiased while bank B is boundedly rational in terms of excessive optimism. In particular, the two types of borrowers, high- and low-quality borrowers, are associated to the probabilities of success[4] θ_h and θ_l, respectively, $0 < \theta_l < \theta_h < 1$. Two key assumptions of the model are

Assumption 1. $\theta_h^B = \theta_h^A$, $\theta_l^B > \theta_l^A$

In what follows we will denote θ_l^A as θ_l and θ_l^B as θ_l^O, where the superscript O stands for overconfident, so $0 < \theta_l < \theta_l^O < \theta_h < 1$.

Assumption 2. The parameters of the model are such that they satisfy $\alpha > \beta \dfrac{1 + r + c - \theta_l^O}{\theta_l^O}$.

Assumption 1 sets overestimation of probabilities of success as the main driver of the model: a bank of type A observes the true probabilities of success of both types of borrowers, whereas a bank of type B estimates an unbiased probability for high-quality borrowers, but a lower probability of default by low-quality borrowers. Assumption 2 ensures that the size of the market is large enough to guarantee interest rates are well defined (meaning they are neither negative nor they exceed the maximum possible value α/β in the possible equilibria of the model).[5]

[3] For tractability, we assume an identical demand function for both types of borrowers. Nonetheless, this assumption implies the use of identical parameters for two groups, high-quality borrowers and low-quality borrowers, which are supposed to be of a different nature. In the conclusions (see Section 5) we will analyze the limitations this assumption imposes to the model.

[4] We assume that when a borrower defaults, the bank gets zero.

[5] Insofar we are exploring how banks of a different profile would compete for credit in a static setup, the approach we use to determine the banks' optimal strategies assumes for simplicity that bank lending operations are not constrained by deposits or reserves. This makes Assumption 2 acceptable under the money endogeneity

In this context, the informational efficiency of Cournot duopolistic banks is analyzed following a three-step behavioral approach (Shleifer, 2000): (i) do banks behave rationally?; (ii) may biased strategies be correlated?; (iii) are there limits of arbitrage?. Hence, we proceed in sequential order.

We first analyze the different market configurations that would appear whether banks are rational or not. The possible market configurations when banks are either both unbiased or one of them, or both, are excessively optimistic, are obtained once each bank *i*, *i*=A,B, solves

$$\begin{aligned} &\max E\left[\Pi^i\left(L_h^i, L_l^i\right)\right] = \theta_h \cdot r_h\left(L_h^i + L_h^{j*}\right)\cdot L_h^i - \left(1-\theta_h\right)\cdot L_h^i + \theta_l^{\varphi}\cdot r_l\left(L_l^i + L_l^{j*}\right)\cdot L_l^i - \left(1-\theta_l^{\varphi}\right)\cdot L_l^i - r\cdot D^i - C\left(L^i\right) \\ &s.t.: L_h^i + L_l^i = D^i \end{aligned} \quad (1)$$

where θ_l^{φ} may be equal to either θ_l or θ_l^{O} depending on whether the bank solving the program or its competitor are rational or overconfident, $L_{h(l)}^{i}$ denotes the volume of loans granted by bank *i* to high (low) quality borrowers, $L_{h(l)}^{j*}$ denotes the equilibrium volumes its competitor would grant, and D denotes deposits (which, since there is an unlimited source of them, they may be simply replaced in the target function by the constraint $L_h^i + L_l^i$).

It is easy to see that banks are symmetric Cournot competitors in the market for high-quality borrowers and that the decision problem between high- and low-quality markets is separable (L_h^* and L_l^* are independent).[6] Hence, volumes and rates in the high-quality market are identical in all scenarios. Instead, in the low-quality market the possible outcomes are a rational duopoly with both banks unbiased, either an asymmetric duopoly or a monopoly when one bank is unbiased and the other boundedly rational, and a biased duopoly when both banks are biased. Table 1 summarizes the solutions in terms of volumes and rates in each possible scenario.

principle. Nonetheless, since the eventual purpose of the model is to extend it to a dynamic setup in Section 4, it might be a more elegant construction to model the credit boom assuming the endogenous model right away.

[6] It is easy to prove that if we assumed banks had convex cost functions, L_h^* and L_l^* would be intertwined, such that behavioral biases could feed externalities even in market niches where all participants are unbiased.

High-quality market	$L_h^{A*} = L_h^{B*} = \dfrac{\alpha+\beta}{3} - \dfrac{\beta\cdot(1+r+c)}{3}\cdot\dfrac{1}{\theta_h}$	$r_h^* = \dfrac{\alpha}{3\beta} + \dfrac{2\cdot[1+r+c-\theta_h]}{3\theta_h}$
Rational duopoly	$L_{l,rD}^{A*} = L_{l,rD}^{B*} = \dfrac{\alpha+\beta}{3} - \dfrac{\beta\cdot(1+r+c)}{3}\cdot\dfrac{1}{\theta_l}$	$r_{l,rD}^* = \dfrac{\alpha}{3\beta} + \dfrac{2\cdot[1+r+c-\theta_l]}{3\theta_l}$
Asymmetric duopoly	$L_{l,aD}^{A*} = \dfrac{\alpha+\beta}{3} - \dfrac{\beta\cdot(1+r+c)}{3}\cdot\left(\dfrac{2}{\theta_l} - \dfrac{1}{\theta_l^O}\right)$ $L_{l,aD}^{B*} = \dfrac{\alpha+\beta}{3} - \dfrac{\beta\cdot(1+r+c)}{3}\cdot\left(\dfrac{2}{\theta_l^O} - \dfrac{1}{\theta_l}\right)$	$r_{l,aD}^* = \dfrac{\alpha-2\beta}{3\beta} + \dfrac{1+r+c}{3}\cdot\left[\dfrac{1}{\theta_l} + \dfrac{1}{\theta_l^O}\right]$
Monopoly	$L_{l,M}^* = \dfrac{\alpha+\beta}{2} - \dfrac{\beta\cdot(1+r+c)}{2}\cdot\dfrac{1}{\theta_l^O}$	$r_{l,M}^* = \dfrac{\alpha}{2\beta} + \dfrac{1+r+c-\theta_l^O}{2\theta_l^O}$
Biased duopoly	$L_{l,bD}^{A*} = L_{l,bD}^{B*} = \dfrac{\alpha+\beta}{3} - \dfrac{\beta\cdot(1+r+c)}{3}\cdot\dfrac{1}{\theta_l^O}$	$r_{l,bD}^* = \dfrac{\alpha}{3\beta} + \dfrac{2\cdot[1+r+c-\theta_l^O]}{3\theta_l^O}$

Table 1 Possible market outcomes

Subscripts rD, aD and bD in Table 1 denote, respectively, rational, asymmetric and biased duopoly, and subscript M denotes monopoly. In a mixed market it may happen that a rational bank reduces the credit granted to low-quality borrowers so much that it ends up driven out of the market. Setting $L_{l,aD}^{A*} = 0$ and solving for θ_l we find that whether the asymmetric market is a duopoly or a monopoly depends on a no-monopoly condition as

$$\theta_l > \theta_l^{\mathrm{M}} = \frac{2\beta\cdot(1+r+c)\cdot\theta_l^O}{(\alpha+\beta)\cdot\theta_l^O + \beta\cdot(1+r+c)}. \tag{2}$$

such that the demand for loans (α, β) and cost structure (r, c) at this market determines whether an asymmetric competition between biased and rational banks will end up as a monopoly of bank B (when $\theta_l \leq \theta_l^M$) or a duopoly (otherwise). Peón et al. (2014) show that the biased and the asymmetric markets generate a credit boom in the low-quality market above what it would be informationally efficient, with the largest credit boom coming in a biased duopoly.

Under what conditions a herd behavior is likely to appear in our model? Consider now that in this market is particularly a duopoly of banks of a different nature, one unbiased (bank A) and another biased (bank B). Banks are able to observe their competitor's estimated probabilities, such that each bank considers an *ex-ante* analysis of strategies to determine whether it is more profitable to them playing rational or biased (regardless of their true nature), given the possible alternatives the opposite bank may follow, and assuming both banks move simultaneously. By comparing the expected profits each bank would obtain under different strategies (rational or biased), it can be shown[7] that playing biased is a dominant strategy for the biased bank, while a condition for the rational bank to herd depends on a threshold bias $\theta_l^O - \theta_l^T$, where

$$\theta_l^T = \frac{6\beta \cdot (1+r+c) \cdot \theta_l \, \theta_l^O}{(\alpha+\beta) \cdot \theta_l \, \theta_l^O + \beta \cdot (1+r+c) \cdot (3\theta_l + 2\theta_l^O)} \tag{3}$$

such that when bank B is not too biased, bank A herds to grant credit as if it had biased expectations.[8] In all the three possible equilibria in the market of low-quality borrowers (a biased duopoly where bank A herds, an asymmetric duopoly where both banks use their own priors, and a monopoly by the biased bank B) a credit boom of loans of low quality at a lower-than-rational rate is generated. All credit booms are welfare increasing for low-quality borrowers, with the largest credit boom following when the rational bank herds.

Finally, limits of arbitrage in retail credit markets are implicit in the specific nature of this industry, as well as in the logic of the herd behavior analysis above. On one hand, arbitrage between close substitutes makes no sense from a micro perspective; on the other, the main drawback for arbitrage for the aggregate market to be performed by private agents refers to the impossibility for this strategy to be profitable.

Consequently, the model predicts behavioral biases by participants in the industry may explain how a credit bubble would be fed by the banking sector: optimistic banks would lead the industry while it would be rational for unbiased banks to herd under specific conditions. Limits of arbitrage imply there are no incentives for rational banks to correct the misallocations of their biased competitors. The results are in concordance with the findings in previous models, like Keen (2011) and Rötheli (2012a) above mentioned.

3.2 Pessimism and underconfidence in recessive periods

We now examine the effects of pessimism during recessions. For simplicity and clarity of exposition, we will only highlight the main differences observed when the boundedly

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[7] For a formal proof please see Peón et al. (2014).
[8] This herding condition does not apply when the no-monopoly condition is not satisfied (i.e., whenever the possible asymmetric market is a monopoly by bank B, bank A chooses not to herd and the monopoly becomes the equilibrium).

rational competitor is biased in terms of pessimism/underconfidence rather than excessive optimism and overconfidence.

Now, rather than having unbiased (type A) and overconfident (type B) banks, we have an unbiased and an underconfident bank. The simplest way to tackle this is to note that we defined unbiased and overconfident banks in terms of bad borrowers' probabilities of success, $\theta_l^O > \theta_l$, that now change to $\theta_l^U < \theta_l$ (superscript *U* stands for underconfidence). Hence, assumptions 1 and 2 now become, respectively,

Assumption 1a. $\theta_h^B = \theta_h^A$, $\theta_l^B > \theta_l^A$

and, if θ_l^A is labelled as θ_l^U and θ_l^B as θ_l , it follows that $0 < \theta_l^U < \theta_l < \theta_h < 1$.

Assumption 2a. The parameters of the model are now such that $\alpha > \beta \cdot \frac{1+r+c-\theta_l}{\theta_l}$.

Assumption 1a sets underestimation of probabilities of success as the key factor, while Assumption 2a may be proved to be the condition that ensures the size of the market is large enough to guarantee interest rates are well defined in the possible equilibria. Hence, we may go back and simply replace θ_l^O by θ_l and θ_l by θ_l^U in all formulae, such that notation A becomes now representative of the underconfident bank, and notation B of the unbiased bank. This way, no additional calculations are required.

The most important finding is that it is now the unbiased player who leads the market. On one hand, playing rational is a dominant strategy for the unbiased bank B, as it comes from a symmetrical interpretation of the results above. On the other, a condition for the pessimistic bank to herd depends on a threshold bias $\theta_l - \theta_l^{UT}$, where

$$\theta_l^{UT} = \frac{6\beta \cdot (1+r+c) \cdot \theta_l \, \theta_l^U}{(\alpha+\beta) \cdot \theta_l \, \theta_l^U + \beta \cdot (1+r+c) \cdot (3\theta_l^U + 2\theta_l)} \tag{4}$$

such that when bank A is not too pessimistic (θ_l^U above θ_l^{UT} for a given θ_l) it herds to grant credit as if it had rational expectations. This herding condition would not apply when the no-monopoly condition $\theta_l^U > \theta_l^{UM}$ is not satisfied, where the cut-off value θ_l^{UM} is now defined as

$$\theta_l^U > \theta_l^{UM} = \frac{2\beta \cdot (1+r+c)\cdot \theta_l}{(\alpha+\beta)\cdot \theta_l + \beta \cdot (1+r+c)} \tag{5}$$

This way, whenever the possible asymmetric market is a monopoly by the rational bank B, bank A chooses not to herd and the monopoly becomes the equilibrium. Consequently, there are also three possible equilibria in a recessive market: a rational duopoly, an asymmetric duopoly where both banks follow their own priors, and a monopoly by the unbiased bank B (when the no-monopoly condition does not hold). This result may be recorded as follows.

Proposition 1. *Pessimism is not as pervasive as excessive optimism.*

When rational and overoptimistic banks compete, the biased bank drives the industry and a credit boom of loans at a lower-than-rational rate is generated.[9] On the contrary, when boundedly rational banks are bounded in terms of pessimism (underestimation of probabilities of success), rational banks lead the market. Pessimism might only partially explain the *credit crunch*, since the unbiased bank would never herd.

We find this result appealing for two reasons. First, we offer an alternative interpretation to Rötheli (2012a) for recessive markets. He suggests the cycle is amplified by boundedly rational behavior on both booms and recessions –increasing welfare during good times and reducing welfare during bad times. We on the contrary predict pessimism is not a powerful driver. Second, our model predicts it is the euphoric economy developed during large upswings what seeds the fragility of the industry during the forthcoming recession. Put it other words, it would make sense to say financial crises are seeded during upturns, with excessive optimism driving markets, while credit rationing during recessions would be a consequence of past excesses (increased non-performing loans, undercapitalization, bank defaults, etc.) rather than a situation where banks are in good shape but cut down credit because of an excessive prudence.[10]

3.3 Dynamics of credit risk assessment

We are now in need of examining how optimism/overconfidence and pessimism/under-confidence evolve along the business cycle. Here we borrow from Rötheli's (2012a,b) setup,

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[9] See Peón et al. (2014).

[10] This intuition was in Rötheli (2012b) when he agrees *"excesses in lending during good times eventually, when projects fail and creditors default, bring about a financial crisis and a downturn in economic activity"* (p. 731).

who shows how risk attitudes often change along the economic cycle. Rötheli (2012b) investigates the dynamics of banks' expectations as a mechanism that can give rise to inefficient lending cycles. Bayesian learning and the experience structure of banks could influence the loan-loss expectations and, therefore, the economic cycle. Following Rötheli (2012a), *a model of boundedly rational credit risk assessment can be built based on the assumption that bankers have a limited experience span and thus, in their Bayesian learning, overestimate the risk of default in recessions and underestimate this risk as the upswing continues for several years* (p. 2).[11]

Rötheli (2012b) empirically calibrates the transition probabilities of the Markov chain process that governs the business cycle probabilities using data from the U.S. economy. He looks at a stationary economy that can be either on 'good times' with a low level of loan losses or 'bad times' with a high level of loan losses. The transition between these two states follows a Markov chain with probabilities p (good times follow good times), q (bad times follow bad times), $1-p$ (good times are followed by bad times) and $1-q$ (bad times are followed by good times). Bankers form their default rate expectations on the correct assumption that the state of the economy follows a Markov process, but they do not know the objective transition probabilities of this stochastic process. Instead, Rötheli (2012b) assumes that they look back in time and estimate these probabilities through a Bayesian estimate of probabilities p and q by using a limited historical data sample.

It is this limitation of the memory (or experience) span that makes bankers' behavior boundedly rational. It is worth to note here that Rötheli (2012a,b) works his model out of an interpretation similar to Minsky's *FIH* that the high risk aversion in the beginning of the upswing is consequence of the memory of a recent financial failure, while risk aversion starts to decline as things gradually improve in the short term (Keen, 2011).

According to his empirical estimations, credit defaults in recessions in the U.S. are about three times higher than during upswings, the average duration of a cycle is 24 quarters (70 months), with the average recession lasting 4 quarters (11 months) and the average expansion 20 quarters (59 months). Rötheli (2012a) summarizes the stylized dynamics of credit risk assessment as follows. On one hand, rationally assessed credit default risk (probability of success) rises (falls) during recession and falls (rises) during the upswing.

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[11] Nonetheless, the assumption that recessions drive banking practices is questionable, since it might be very well the other way round (e.g. a single, but decisive event á la Lehman leads banks to contract credit leading to fall in the prices of collaterals etc.).

On the other, during the recession and the early stages of the upswing boundedly rational risk assessment is overly pessimistic, while during the later stages of the upswing boundedly rational banks form an overly optimistic assessment of credit risk.

Based on these observations, Rötheli (2012a) replicates the paths derived from the simulations with Bayesian learning as described by

$$d_t^{BRE} = d_t^{RE} + 0.677 \cdot \left(d_t^{RE} - \bar{d}\right) \tag{6}$$

and

$$d_t^{RE} = d_{t-1}^{RE} + 0.81 \cdot \left(d_{t-1}^{RE} - d_{t-2}^{RE}\right) - 0.06 \cdot \left(d_{t-1}^{RE} - \bar{d}\right) - 9 \times 10^8 \left(d_{t-1}^{RE} - \bar{d}\right)^4 \ , \tag{7}$$

where d_t^{BRE}, d_t^{RE} and $\bar{d}$ stand for boundedly rational default expectations, rational default expectations, and average default over the cycle, respectively.

4. DYNAMIC SETUP

Here we extend our model to a dynamic setup. We proceed in two stages. First, we project different paths for the unbiased and boundedly rational (both overly optimistic and pessimistic) expected probabilities of success along the economic cycle. Then, introducing those projections in our model, we solve for volumes in equilibrium. For simplicity and a better understanding of the results, we work with particular demand and cost functions that will be given below. With the aim of highlighting different market configurations that might result from this analysis, we will provide two different examples. They are detailed in subsections 4.1 and 4.2.

We project the dynamics of θ_l, θ_l^O and θ_l^U following Rötheli (2012a,b) in spirit. Having a look now at equations (6) and (7) in Section 3, two relevant remarks are in order. First, the empirically estimated bias suggests excessive optimism and pessimism amplifies the cycle by two thirds (0.677) above and below the average default rate. This gives us a good benchmark for the examples provided below. Second, equation (7) fits the stylized features of the empirical findings in Rötheli (2012b) where the quarterly default rate in good times would be 0.1831 and in bad times 0.6527. However, when trying to replicate different default rates, different estimations should be used.[12] We solve this below by providing alternative stylized estimations of the dynamics of θ_l, θ_l^O and θ_l^U that satisfy the average duration of a cycle, the about three times higher default rates in recession, and the dynamics of credit risk assessment as predicted by Rötheli.

4.1 Standard scenario: credit boom by a biased duopoly

Figure 1 describes the paths probabilities θ_h, θ_l and θ_l^* (denoted here for the biased probabilities θ_l^O or θ_l^U depending on the cycle phase) would follow in this first example. We consider an average default rate of 1% for high-quality borrowers (θ_h = 0.99), an average default rate of 10% for low-quality borrowers (θ_l = 0.90), and boundedly rational default expectations described as in Equation (6).[13]

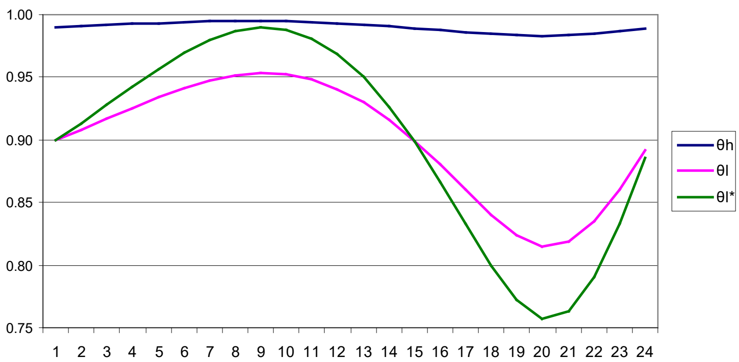

Figure 1. Probabilities of success θ_h, θ_l and θ_l^*, from quarters 1 to 24, in the first example.

We may see in Figure 1 how unbiased probabilities θ_h and θ_l fall during recessions and rise during upswings, as to replicate a credit cycle of 24 quarters where credit default rates in recessions would be about three times higher than during upswings, as empirically observed. Besides, the biased probability θ_l^* increasingly deviates from the rational estimation θ_l, such that during good times boundedly rational risk assessment is overly

[12] Note Rötheli (2012b) estimates the empirically observed default rates for the whole credit market in the US. However, in our model we separate different niche markets according to borrower qualities. Given this, we may be interested in estimating the paths for virtually any probabilities θ_h, θ_l, θ_l^O and θ_l^U in the range [0,1].

[13] Rational default expectations have been stylized here as following the processes $d_t^{RE} = d_{t-1}^{RE} + 1.1 \cdot \left(d_{t-1}^{RE} - d_{t-2}^{RE}\right) - 0.05 \cdot \left(d_{t-1}^{RE} - \bar{d}\right) - 1000 \cdot \left(d_{t-1}^{RE} - \bar{d}\right)^3 - 100000 \cdot \left(d_{t-1}^{RE} - \bar{d}\right)^4$, where $\theta_h = 1 - d_t^{RE}$, and $d_t^{RE} = d_{t-1}^{RE} + 1.13 \cdot \left(d_{t-1}^{RE} - d_{t-2}^{RE}\right) - 0.056 \cdot \left(d_{t-1}^{RE} - \bar{d}\right) - 5.6 \cdot \left(d_{t-1}^{RE} - \bar{d}\right)^3 - 100 \cdot \left(d_{t-1}^{RE} - \bar{d}\right)^4$, for $\theta_l = 1 - d_t^{RE}$.

optimistic, while during the recession and the early stages of the upswing a biased bank would make a pessimistic assessment of credit risk.

Consider the following numerical example. The demand for loans are $L(r_h) = 1 - r_h$, and $L(r_l) = 1 - r_l$, for high- and low-quality borrowers, respectively, the cost function of both banks is $C(L) = 0.05 \cdot L$, and the interest rate of deposits amounts to $r = 0.1$.[14] Introducing the projected probabilities θ_h, θ_l and θ_l^* in our model, and solving for the optimal volumes in equilibrium along the economic cycle, the paths depicted in Figure 2 are obtained.

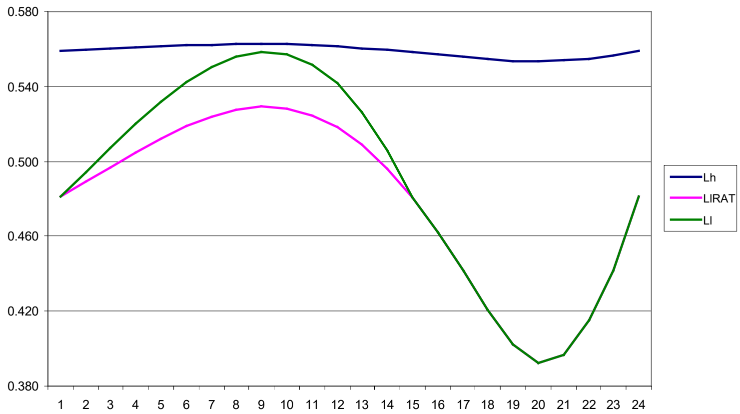

Figure 2. Loan volumes in a credit boom generated by a biased duopoly

In view of Figure 2 we may see how, during good times, loan volumes granted increasingly deviate from the volumes a duopoly of unbiased banks would grant. This occurs because the threshold bias $\theta_l^O - \theta_l^T$ determined in Eq. (3) is never exceeded, so the rational bank follows the biased during the optimistic phase –the equilibrium market here is a biased duopoly. During bad times, the bias $\theta_l - \theta_l^U$ determined in Eq. (4) is always narrow enough for the pessimistic bank to herd, so the equilibrium market is a rational duopoly. Finally, the market of high-quality borrowers follows the regular trend as in this model the decision problem between high- and low-quality markets is separable, with both banks having unbiased expectations for this type of costumers.

[14] The value for the interest rate on deposits of 0.1 we have set is clearly high under normal circumstances (that is, unless we're talking nominal values during a period of high inflation). This deserves an explanation. First, we are opportunely using a high rate in order to emphasize the effects that can be observed when the monetary authorities reduce the cost of money to a large extent (see section 4.2). Second, no matter the choice it does not affect the generality of the results: the interest rate of deposits always appears in all credit volumes and interest rates of all possible market outcomes (see Table 1) in terms of the kind (1+r+c). This way, in the example we could set instead r = 0.05 and c = 0.1, for instance, and no results would change.

This example features how a standard credit market would most often behave. To see why, we must first be aware of the following lemma.

Lemma 1*. The bias required for a bank not to follow the leader is the larger*

- **(i)** *the larger the size of the market, α;*
- **(ii)** *the lower the marginal cost of the bank;*
- **(iii)** *the lower (higher) the true probability of success θ_l during optimistic (pessimistic) times.*

Proof. See Appendix.

Lemma 1 gives a clue on why, given the assumed values of the numerical example for costs (c = 0.05, *r* = 0.1), market size and a bias coefficient of 0.677, the value θ_l^O = 0.9 is too large to yield a monopoly. We may change the parameters to get alternative market configurations, but we will face two problems. First, we know from Assumptions 2 and 2a that the higher the costs *c* and *r*, the minimum market size required for interest rates to be well-defined also increases. Second, we have seen that the empirical research by Rötheli (2012b) evidences average default rates about 1% and optimism and pessimism amplifying the cycle by a coefficient of 0.677 as we assumed.

Therefore, scenarios with larger market sizes, higher probabilities of success and bounded rationality coefficients about those empirically observed by Rötheli (2012a,b) will yield the larger credit booms during good times and rational duopolies during recessions (i.e., no effects of underconfidence). For alternative market configurations to arise, market sizes must be narrower (and we are bounded here), the qualities of the niche markets lower, and bounded rationality coefficients must be much larger than empirically observed. This is illustrated in the next example.

4.2 A stressed scenario

Consider now a second numerical example by assuming an average default rate of 1 percent for high quality borrowers (θ_h = 0.99), of 25 percent for low-quality borrowers (θ_l = 0.75) and a boundedly rational default expectations described as:

$$d_t^{BRE} = d_t^{RE} + 1.5 \cdot \left(d_t^{RE} - \bar{d} \right). \tag{8}$$

That is, in this second example we have more than doubled the effects of excessive pessimism and optimism. Figure 3 describes the paths probabilities would follow in this case.[15]

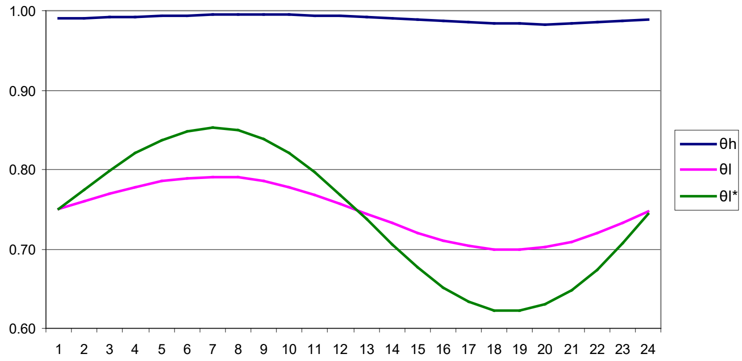

Figure 3. Probabilities of success θ_h, θ_l and θ_l^*, from quarters 1 to 24, in the second example

The interpretation of Figure 3 would be similar to that of Figure 1, but where now default rates in the low-quality market are much higher and where the deviation of boundedly rational probabilities with respect to the unbiased estimation is also much larger.

Finally, consider this stressed scenario to be characterized also by the cost function C (L)= $0.15 \cdot L$ for both banks and the interest rate of deposits $r = 0.1$. In this case, the minimum market size for interest rates to be well defined would be $\alpha = 0.67$; hence we cannot reduce the market size really much. To illustrate, we set demand for loans $L(r_h) = 0.85 - r_h$ and $L(r_l) = 0.85 - r_l$. Introducing the projected θ_h, θ_l and θ_l^* in the model, and solving for the optimal volumes of loans in equilibrium along the cycle, the amount granted to low-quality borrowers depicted in Figure 4 holds.

[15] Rational default expectations for low-quality borrowers have been stylized here as following the process $d_t^{RE} = d_{t-1}^{RE} + 1.04 \cdot \left(d_{t-1}^{RE} - d_{t-2}^{RE}\right) - 0.075 \cdot \left(d_{t-1}^{RE} - \bar{d}\right)$, for $\theta_l = 1 - d_t^{RE}$.

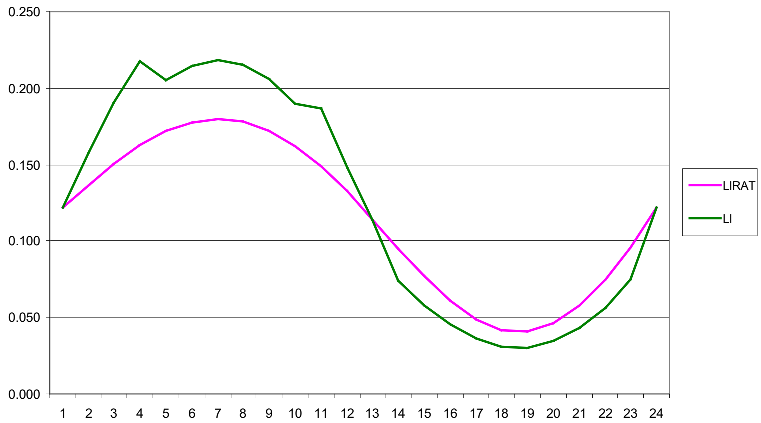

Figure 4. Loan volumes in a stressed scenario

We may see how, under this stressed scenario, market dynamics would be quite erratic. Volumes granted during the upswing rapidly deviate from the volumes a duopoly of rational banks would grant because of the larger effects of bounded rationality assumed in this example. Then, when the threshold bias $\theta_l^O - \theta_l^T$ is exceeded –which here occurs in quarter 5- the rational bank chooses not to keep on herding. Volumes fall as the market becomes an asymmetric duopoly, until in later in the downturn the bias falls again below the threshold level and the rational bank chooses to herd once again (quarter 11).

In the second phase, the biased bank rapidly changes its mood from optimistic to pessimistic as the recession hits. The rational bank now guides the market, which is now a rational duopoly only in quarter 13, an asymmetric duopoly in quarter 14, and a monopoly by the rational bank afterwards.[16] Volumes granted are close to zero, as these stressed conditions are close to qualities and market sizes that would make this type of borrowers not profitable for a rational lender. Hence, the credit crunch observed is of small size.

The dynamization of the model shows further evidence of the finding stated in Proposition 1. On one hand, excessive optimism may be a good explanation for the credit boom. The model predicts an erratic behavior for markets only under extreme conditions (low quality niches, small markets, and bounded rationality larger than empirically observed). On the other, excessive pessimism performs worse as an explanation for the credit crunch; only for high levels of pessimism some amplification effects over the cycle would be observed: the biased bank would not herd and the equilibrium would be a monopoly of the rational bank. An additional evidence of this second fact is illustrated in Figure 5.

[16] The no-monopoly condition is not satisfied during most part of the downturn, from quarters 15 to 22.

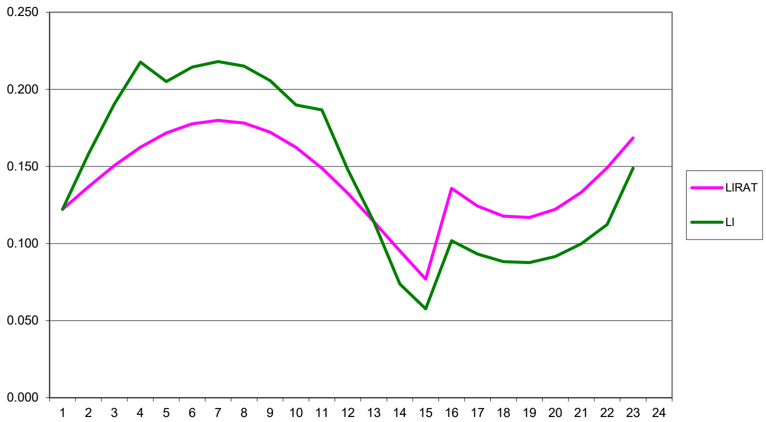

Figure 5. Monetary policy smoothing the recession

Figure 5 illustrates that not only the conditions for pessimism to have amplification effects over the cycle and a herding behavior not to appear would be quite extreme, but in such case economic authorities would have a powerful tool to soften the recession: relaxing monetary conditions. Assume that, in quarter 16, authorities try to help solving the crisis by reducing the cost of money. Now banks may finance at r = 0.02 rather than 0.1. Though the equilibrium in this stressed scenario would still be a monopoly by the rational bank, the market recovery is appreciable. However, this contradicts the empirical evidence these days where central banks all over the world –and particularly in the Euro zone- are facing strong difficulties to solve the credit crunch (see Eichengreen et al., 2011, for a discussion on the drawbacks of central banking).

Proposition 2. *Low-quality niche markets are more exposed to potential pervasive effects of bounded rationality on credit markets.*

Our behavioral explanation of the credit cycle supports the idea that it is excessive optimism what drives the boom and generates the conditions for the crunch. However, on one hand Lemma 1(iii) shows that, for optimistic markets, the lower θ_l the higher the required bias for an unbiased bank not to herd. On the other hand, probabilities are bounded to [0, 1]. Hence, there is a cap for the pervasive effects on credit markets during optimistic times: the closer probability θ_l is to 1, the lower the potential damage of bounded rationality.

5. CONCLUDING REMARKS

In this paper, we provided a dynamic model of banking competition where bounded rationality of some competitors explains how the credit cycle is amplified. First, we consider the effects of optimism/overconfidence during upswings and pessimism/underconfidence in the recessive periods of the credit cycle, in order to determine whether asymmetries exist in the herding behavior of banks. Then, we offer a dynamization of the model to determine when and where (particularly, in which market niches) over- and underestimation effects are expected to be more pervasive.

We find pessimism is not a powerful driver of credit cycles. When rational and boundedly rational banks compete, excessive optimism is expected to drive the industry during booms; during recessions, instead, rational banks lead the market. Pessimism might only partially explain the *credit crunch*, as unbiased banks are not predicted to herd in any case. Consequently, the model predicts it would make sense to say financial crises are seeded during upturns, with excessive optimism driving markets, while the credit rationing observed during recessions would be a consequence of past excesses (increasing volume of non-performing loans, banks being under-capitalizated, defaults, etc.) rather than a situation where banks cut down credit because of an excessive prudence. Our results offer an alternative interpretation to Rötheli (2012a), where boundedly rational behavior would amplify the credit cycle during both booms and recessions.

Finally, an additional finding is that bounded rationality is expected to be more pervasive on low-quality niche markets, since it is excessive optimism what drives the boom and, for optimistic markets, the lower θ_l the higher the required bias for an unbiased bank not to herd. As a consequence of having assumed linear cost functions in this model, markets are separable and no externalities are expected in niche markets where all banks are rational. This also validates our assumption, for tractability purposes, that different niche markets have identical demand functions. However, these results no longer hold when we assume convex costs. On one hand, externalities of bounded rationality on markets where all participants are rational would appear. On the other, a further analysis of these externalities would require, nonetheless, to consider different demand functions for borrowers of a different nature.

The model is a simple one to describe how banks would compete and the effects behavioral biases among the industry could induce. Further extensions should try to overcome this simplicity by considering the effects of informational asymmetries and adverse selection, alternative models of banking competition, the effects of bankruptcy costs, etc. Finally, another limitation of the model relies on the fact that it does not offer an endogenous explanation of the economic cycle. Rather than that, we take an exogenous (empirically observed) economic cycle to determine what the effects of over- and underconfidence would be. Further extensions of the model might introduce complementary explanatory variables for the optimism of the banking sector (e.g. collaterals, total amount of debt, past bankruptcies) besides the overall economic development and their rival agents' behavior to endogenize the cyclical behavior of the economy with this setup.

APPENDIX

Proof of Lemma 1. Since there will be no herding when the no-monopoly condition is not satisfied (see Peón et al., 2014), we shall only focus on a market where the possible asymmetric configuration is a duopoly. Consider first the case of a rational and an overconfident bank. Peón et al. (2014) show that the threshold level that makes an unbiased bank indifferent to herd is $\theta_l^T = \frac{6\beta \cdot (1+r+c) \cdot \theta_l \, \theta_l^O}{(\alpha+\beta) \cdot \theta_l \, \theta_l^O + \beta \cdot (1+r+c) \cdot (3\theta_l + 2\theta_l^O)}$. We may calculate the required bias for an unbiased bank not to herd (for tractability it is better to express it as a ratio θ_l^O / θ_l^T) such that it yields $\frac{\theta_l^O}{\theta_l^T} = \frac{(\alpha+\beta) \cdot \theta_l \, \theta_l^O + \beta \cdot (1+r+c) \cdot (3\theta_l + 2\theta_l^O)}{6\beta \cdot (1+r+c) \cdot \theta_l}$ which may be rearranged to

$$\frac{\theta_l^O}{\theta_l^T} = \frac{1}{2} + \frac{\alpha \cdot \theta_l^O}{6\beta \cdot (1+r+c)} + \frac{\theta_l^O}{6 \cdot (1+r+c)} + \frac{\theta_l^O}{\cdot 3\theta_l} \tag{A1}$$

Clearly, the required bias for an unbiased bank not to herd is increasing in α (and obviously in θ_l^O), and decreasing in θ_l, β, *r* and *c*.

For a duopoly of a rational and an underconfident bank we would start from equation (1) and proceed similarly. The threshold level that makes an underconfident bank indifferent to herd is $\theta_l^{UT} = \frac{6\beta \cdot (1+r+c) \cdot \theta_l \, \theta_l^U}{(\alpha+\beta) \cdot \theta_l \, \theta_l^U + \beta \cdot (1+r+c) \cdot (3\theta_l^U + 2\theta_l)}$. We may calculate the required bias for the biased bank not to herd as $\frac{\theta_l}{\theta_l^{UT}} = \frac{(\alpha+\beta) \cdot \theta_l + \beta \cdot (1+r+c) \cdot (3\theta_l^U + 2\theta_l)}{6\beta \cdot (1+r+c) \cdot \theta_l^U}$ which may be rearranged to

$$\frac{\theta_l}{\theta_l^{UT}} = \frac{1}{2} + \frac{\alpha \cdot \theta_l}{6\beta \cdot (1+r+c)} + \frac{\theta_l}{6 \cdot (1+r+c)} + \frac{\theta_l}{\cdot 3\theta_l^U} \tag{A2}$$

Clearly, the required bias for the biased bank not to herd is increasing in α and θ_l, and decreasing in β, *r*, *c* and, obviously, θ_l^U. ■

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