

Confidence Cycles and Liquidity Hoarding*

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Market confidence has proved to be an important factor during past economic crises. In this paper, I incorporate a model of the interbank market into a DSGE model, with the volume of lending depending on market confidence. I conduct an exercise to mimic some central bank policies: provision of liquidity and reduction of the reserve rate. My results indicate that policy actions have a limited effect on the supply of credit if they fail to influence agents' expectations. A low reserve rate policy worsens recessions due to its negative impacts on bank revenues.

JEL Codes: E58, E65, E71, G01.

1. Introduction

The global financial crisis of 2007–09 was one of the deepest and longest in modern history. Having started in the financial sector, it then spread into the real economy, causing a recession the length of which has yet to be determined. The interbank market collapsed and banks became reluctant to lend to the real sector, propagating and amplifying the crisis. Leading central banks around the globe started to introduce unconventional monetary policy measures, including liquidity provision and interest rate reductions, to stimulate lending

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and to relax banks' liquidity constraints. Yet the massive liquidity injections were not able to restore interbank lending. Banks hoarded funds in excess reserves or invested in short-term assets.¹

One possible explanation for banks' hoarding behavior is concerns about economic activity and counterparty risk. During the financial turmoil of 2008–09, European and U.S. banks reported that they were tightening their lending standards largely due to expectations of weak economic activity.² Voices from academia and policymaking bodies (e.g., Taylor and Williams 2008) suggested that assessment of counterparty risk was an important factor in the credit crunch.

The question is whether banks were overly pessimistic or whether they rationally predicted the downturn that occurred during the crisis. Financial agents' expectations are not necessarily perfect. Such agents may have limited information or a limited ability to process it. Studies³ have shown that the expectations of professional forecasters demonstrate inertia and it takes time for them to learn when changes occur. Therefore, it is not unrealistic to posit that after the onset of the crisis, when central banks started to implement unconventional measures, banks may have had generally overly pessimistic expectations. Banks' pessimism about the economic outlook could be among the factors that affected the transmission of unconventional monetary policies and explain liquidity hoarding.

This paper contributes to the literature by addressing how expectations of poor economic activity and assessments of counterparty risk among financial agents—banks—influence the functioning of the interbank market and the supply of credit to the real economy. I build a model with a continuum of heterogeneous banks that learn about economic conditions. Uncertainty takes the form of a capital

¹For evidence on hoarding, see Gale and Yorulmazer (2013) and Heider, Hoerova, and Holthausen (2015) and references therein.

²For example, in 2009, according to the Bank Lending Survey conducted by the European Central Bank, more than 70 percent of banks reported that expectations about economic activity contributed to tightening. A similar figure was reported in the United States in the Senior Loan Officer Opinion Survey on Bank Lending Practices conducted by the Federal Reserve Board.

³Examples include Andrade and Le Bihan (2013) and Coibion and Gorodnichenko (2015).

quality shock⁴ that affects banks' risky asset return. Banks are not sure whether the shock is persistent or transitory. They use the available past data on capital quality and combine it with heterogeneous private signals. The heterogeneity of return expectations gives rise to an interbank market, where, depending on their expectations, banks are endogenously divided into lenders and borrowers and the interbank market rate clears the market. Banks are risk neutral and invest everything in the asset with the highest expected return, whether it is a risky asset, a safe asset, or an interbank market loan. As the borrowers invest interbank market loans in risky assets, the lenders' evaluation of counterparty risk depends on their risky asset return expectation. When the lenders expect a low return on a risky asset, they assign a high probability to the scenario in which their borrowers will not be able to repay the debt. When the expected risk becomes too large, banks stop lending. Without access to the interbank market, the most optimistic banks reduce their lending to the real economy and pessimistic banks keep funds in reserves.

The model forms a tractable extension of the workhorse dynamic stochastic general equilibrium (DSGE) model, as only the moments of the banks' beliefs distribution matter in equilibrium. Within the framework developed, I consider the question of the efficiency of policy measures applied during an economic downturn. My model allows me to account for banks' "hoarding" behavior observed during the crisis, which is often missing from DSGE models that analyze unconventional central bank policies. I consider several types of central bank policy actions that resemble those taken during the crisis and the subsequent recession, including liquidity provision to all banks at a fixed rate and targeted liquidity provision to support lending to the real sector. I also consider the policies of reducing the rate on reserves and relaxing collateral constraints on the interbank market.⁵

My findings suggest that investor expectations and uncertainty instigate large swings in the real economy, where manufacturers are

⁴As in Gertler and Kiyotaki (2010) and Gertler and Karadi (2011). A similar stochastic component is introduced into the return to capital in Jermann and Quadrini (2012), Chugh (2013), and Zanetti (2019).

⁵Central banks' policy of relaxing collateral constraints involves widening the set of assets accepted as collateral. In my model, this takes the form of banks being willing to lend up to a higher percentage of a borrower's net worth.

dependent on credit. In my model, when banks are concerned about economic prospects, the liquidity provision policy reduces the magnitude of the crisis, but its effect is limited. Moreover, a significant share of the funds received from the central bank is invested in safe assets instead of flowing into the real economy. This result is in line with the observed behavior of banks. It also suggests that making policy evaluations without accounting for investor sentiment and market volatility may overstate policy efficiency. Lowering the policy rate makes hoarding less attractive but reduces bank revenues, resulting in even worse outcomes than in the case of no central bank action.

This paper is related to several strands of literature. First, there is a growing literature on adaptive learning in DSGE models.⁶ Milani (2011), Slobodyan and Wouters (2012), Rychalovska (2016), and Aguilar and Vázquez (2021), among others, show that models with imperfect information explain the data better than models with rational expectations. Under adaptive learning, agents gradually learn the parameters of the model. In contrast to those studies, I employ somewhat less sophisticated learning, with the agents learning only about the unobservable component of the shock to returns. At the same time, my model features a rich banking sector, making it possible to study how banks' expectations transmit into the economy. Second, there are papers on modeling the interbank market. Cui and Kaas (2017) study how expectations about credit conditions become self-fulfilling. Allen, Carletti, and Gale (2009), Gale and Yorulmazer (2013), and Heider, Hoerova, and Holthausen (2015) consider liquidity hoarding through the interbank market structure. In these models, the reason for banks to hoard liquidity is anticipation of a liquidity shock. My interbank market structure can be extended for a liquidity shock, but I focus on the role of counterparty

⁶This paper is broadly related to the literature on the importance of imperfect information in business cycle fluctuations. Studies have shown that imperfect information and higher-order expectations in firms' price setting can explain the observed persistence in business cycle fluctuations. Examples include Woodford (2001), Makowiak, Moench, and Wiederholt (2009), and Crucini, Shintani, and Tsuruga (2015) for models with flexible prices, and Nimark (2008) and Angeletos and La'O (2009) for models with nominal rigidities. Empirical assessments of the role of information can be found in Coibion, Gorodnichenko, and Ropele (2019) and Okuda, Tsuruga, and Zanetti (2019).

risk. Bank heterogeneity in a DSGE model is introduced by Hilberg and Hollmayr (2011), who study liquidity provision and relaxation of collateral constraints. In their work, bank heterogeneity is caused by exogenous separation into investment and commercial banks; only investment banks are allowed to borrow from the central bank. I consider a different interbank market structure consisting of a number of *ex ante* identical banks which differ *ex post* depending on their subjective beliefs.

There is literature on the role of the financial sector and credit in the economy. Studies have incorporated the banking sector into general equilibrium models. Examples include Curdia and Woodford (2011), Gertler and Karadi (2011), Gertler and Kiyotaki (2010), and Negro et al. (2017). Having introduced the financial sector, these papers address central banks' crisis-mitigation policies. While the first two papers consider the effects of policies on the transfer of credit between households and financial intermediaries, the latter two analyze credit supply to entrepreneurs subject to a liquidity constraint of the Kiyotaki and Moore (2008) type. My study also addresses the efficiency of central bank policy, but accounts for the role of investor sentiment.

This paper is organized as follows. First, I present the main building blocks of my banking sector, then I proceed with the rest of the model's blocks. In Section 3, I calibrate the parameters specific to my model, as well as the size of the crisis shocks. I compare the crisis dynamics in the model with those observed in the euro zone in 2008–09. Having roughly matched the euro-area downturn, I compare my model with the baseline without a heterogeneous banking sector and show the role of bank expectations and interbank lending. Then I model the policy responses and show how their efficiency is affected by market pessimism.

2. The Model

In this section, I describe the banking sector and beliefs formation. I then input the banking sector into a linearized DSGE model as in Gertler and Karadi (2011). In their model, agents have perfect expectations about future risky asset returns. I modify this assumption, making the returns on the risky asset uncertain. Another difference is that, in Gertler and Karadi (2011), banks frictionlessly transfer

their liabilities to credit to the real sector. In my model, I allow banks to keep (hoard) liquidity if they choose to. By hoarding I mean keeping liquidity—including that provided under central bank liquidity provision policy—in reserves instead of lending it, due to higher perceived counterparty risk. Thus, it is possible to address the question of whether the liquidity provided by the central bank is transmitted to the real economy or whether it ends up in bank reserves. Last but not least, heterogeneous expectations give rise to an interbank market. In my model, the interbank market serves as a propagation mechanism, increasing or decreasing the credit supply as interbank market conditions change.

The rest of the sectors are standard as in Smets and Wouters (2007) and Gertler and Karadi (2011), so I outline them briefly. For a more rigorous discussion, I refer the reader to these papers. A simple model of the banking sector with an analytical solution is given in online Appendix D,⁷ where I show the intuition behind the impact of beliefs on interbank market allocations and possible policy effects.

2.1 *The Financial Sector*

To capture liquidity hoarding, my model of the banking sector should be able to reproduce the following patterns. It should capture the increase in total risky asset investment when such investment is perceived to be more profitable. Further, it should match the fall in interbank lending when the evaluation of the risky asset return falls or the uncertainty about it rises. At the same time, the model should be computationally feasible. That is why I abstract from the wealth and deposit accumulation of each individual bank and instead focus on the effects of subjective beliefs about the risky asset returns of otherwise identical banks.⁸

⁷The online appendix is available with the online version of this paper at <http://www.ijcb.org>.

⁸Tracking wealth and deposit accumulation would not affect my results qualitatively but would amplify them quantitatively: it would increase the market share of riskier banks in booms and reduce it in recessions due to the financial accelerator and re-investment. The drop in credit provision would then be larger during a crisis, as there would be a larger drop in banks' net wealth on the aggregate level.

I model my banks as if they were retail branches of a representative headquarters, where the headquarters distributes funds and collects any profits from the banks. There is a continuum of retail banks normalized to one. At the beginning of each period, each existing bank receives an equal share of the total net bank wealth. Banks invest in safe or risky assets and lend to each other depending on their individual assessment of the profitability of risky assets. Households provide deposits to banks against the bank's net wealth. Because each bank has the same net wealth, it also receives the same amount of deposits.

Despite the simplifying assumption that banks receive the same amount of deposits and net wealth regardless of their portfolios, on the aggregate level funds and deposit allocation depend on the bank's portfolio riskiness and return. If a risky asset is perceived to be more profitable, the share of banks investing in it is larger. That is, a larger share of the aggregate net wealth is allocated to "riskier" banks. The same holds for household deposits: whenever the risk associated with an asset rises, fewer banks invest in it and the aggregate share of deposits in banks holding the risky asset falls.

Banks are owned by the households. Every period, a fraction $(1 - \theta)$ of retail banks exit the sector and transfer their funds to households. At that time, the same number of new branches open. They receive starting capital from the households of an amount equal to a share ω of total banking-sector assets. At the end of the period, the retail banks that do not exit transfer their net wealth back to the headquarters.

Banks allocate their funds between a safe asset paying a gross real rate, R_t^{es} , a risky asset with an uncertain gross real return, R_{t+1}^k , and interbank market lending with a gross real return of R_t^{ib} . Banks pay a gross real rate R_t on household deposits.⁹ The government provides a partial guarantee to households for deposits lost in troubled banks, whether the loss is the result of fraudulent diversion of funds or low realization of returns on the risky asset. From the

⁹Note the timing of the interest. Although it is paid in period $t+1$, the rate on the safe asset, the deposit rate, and the interbank market rate are set in period t . For the rest of the model description, I use the same convention to refer to the timing of the variables when they are decided upon.

point of view of the bank, the government guarantee does not, however, offer relief from its obligations to households. The bank must either honor its obligations or go bankrupt.¹⁰

The risky asset in the model is credit granted to intermediate goods manufacturers, who need funding to buy capital. Banks buy the claims of manufacturers, S_t , at price Q_t , with the return R_{t+1}^k being the return on capital. The uncertainty in the return comes from a “capital quality shock,” ξ_{t+1} , as in Gertler and Kiyotaki (2010) and Gertler and Karadi (2011). As opposed to physical depreciation, δ_t , it is intended to capture unexplained fluctuations in the value of capital: $Q_t \xi_t K_{t-1}$. A similar stochastic component in the return on capital is introduced in Jermann and Quadrini (2012) and Zanetti (2019) as a stochastic probability of the liquidation value of capital and in Chugh (2013) as firms’ idiosyncratic productivity.

The value of undepreciated capital is defined as the difference between the value of new capital and the value of depreciated capital:

$$(Q_{t+1} - \delta_{t+1}) \xi_{t+1} K_t. \quad (1)$$

The return on capital consists of the value of the marginal product of capital plus the value of undepreciated capital. Denoting the capital share as α , output as Y , and the price of the intermediate good as P_m :

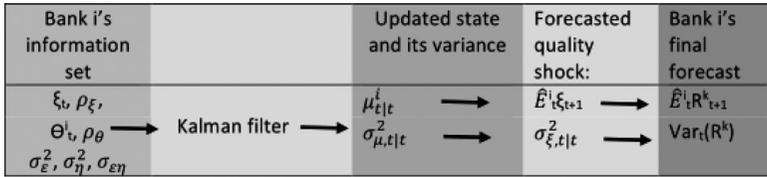
$$R_{t+1}^k = \frac{\alpha \frac{P_{m,t+1} Y_{t+1}}{K_t} + (Q_{t+1} - \delta_{t+1}) \xi_{t+1}}{Q_t}. \quad (2)$$

Equations (1) and (2) are similar to those in Gertler and Karadi (2011), but I adjust the process for the quality shock.¹¹ The latter is observable by all sectors, but the composition of the shock is unobservable. I assume that capital quality is subject to two types of shocks—persistent, μ , and transitory, ε_ξ . The combination of these

¹⁰In the event of bankruptcy, a bank is replaced by a new one.

¹¹In Gertler and Karadi (2011) the capital quality shock also affects effective capital in the production function, which would complicate the beliefs distribution enormously. That is why I focus only on capital quality affecting the resale value of capital. When comparing my results with Gertler and Karadi (2011), I adjust their model for this difference.

Figure 1. Banks' Forecast Formation



two shocks creates uncertainty in predicting future values of capital quality.

$$\xi_t = (1 - \rho_\xi)\bar{\xi} + \rho_\xi \xi_{t-1} + \mu_t + \varepsilon_{\xi,t}, \tag{3}$$

where μ_t is a persistent shock:

$$\mu_t = \rho_\mu \mu_{t-1} + v_t, \tag{4}$$

where ρ_μ and ρ_ξ are persistence parameters and v_t and $\varepsilon_{\xi,t}$ are transitory Gaussian shocks, serially uncorrelated, with zero contemporaneous correlation and variances σ_v^2 and σ_ε^2 ; $\bar{\xi}$ is the steady-state value of the capital shock. Next I explain how banks set their expectations about ξ_{t+1} .

2.1.1 Expectations Formation

Banks have access to past data on returns and they use it to form an economic forecast. There are also expert opinions, θ_t^i , which incorporate noisy signals about the value of μ_t :

$$\theta_t^i = \rho_\theta \theta_{t-1}^i + \eta_t^i, \tag{5}$$

where η_t^i is the noisy signal of bank *i*'s expert, with η_t^i denoting correlated draws from $N(\mu_t, \sigma_\eta)$.¹²

As illustrated in Figure 1, banks combine two sources of information—realizations of ξ_t and θ_t^i , using the Kalman filter, with

¹²The inclusion of expert forecast adjustments is motivated by an extensive literature that provides evidence of widespread use of expert factors in forecasting practices. For example, see Fildes et al. (2009), Franses, Kranendonk, and Lanser (2011), and Brázdkik et al. (2020).

the weights of the signals depending on their relative variance. I assume that banks act as econometricians and, having observed a long enough history of both signals, they have learned the persistence, variance, and covariance of the signals.¹³ Note that the variance of the forecasts is the same for all banks because they use the same observable and they have the same variance in their expert adjustments. A description of the Kalman filter setup is given in Appendix A.

By plugging their forecasts of the future capital quality shock, ξ_{t+1} , into (2), banks obtain their risky asset return forecast, $E_t^i \hat{R}_{t+1}^k$. Because η_t , v_t , and $\epsilon_{\xi,t}$ are normally distributed, it follows that each bank's predictions about μ_t and ξ_{t+1} from the Kalman filter and the return forecast $E^i \hat{R}_{t+1}^k$ in (2) are also normally distributed.

For the equilibrium solution of the model described below, I need the distribution of beliefs *across* banks, given that their individual signals are correlated. Denote the average and the variance of banks' return forecasts as m and σ_R^2 , respectively. In Appendix B, I describe how I model the correlated draws of expert opinions in (5) and show that, by construction, the variance of this noise *across* banks equals the variance of the noise in the individual signals. The variance of the bank return forecast in (2) is then the same for each bank and equals the variance of the forecasts *across* banks: σ_R^2 . Appendix C shows how the mean and the variance are derived as a function of banks' signals. Both the mean and the variance of the return expectations enter the rest of the model as state variables.

Two questions can be raised here: whether the noise in the idiosyncratic signals averages away, and whether banks incorporate other banks' expert opinions into their signal extraction problem. To address both of them, I assume that the noise in the expert opinions is correlated with the correlation coefficient ρ^c .¹⁴ This correlation can be interpreted in two ways. First, experts tend to react to similar news in similar ways—being overly optimistic or overly pessimistic. Second, even though I do not model information sharing among banks, I retain the possibility of convergence of their opinions. That is, when the correlation coefficient is one, the expert

¹³They can be learned, for example, by using maximum likelihood estimation.

¹⁴ ρ^c is the Pearson correlation coefficient for each pair of experts.

opinions are fully converged and are the same. Conversely, when ρ^c is zero, they are fully diverged.

PROPOSITION 1. *When the expert opinions are correlated with $0 < |\rho^c| < 1$, the mean of the banks' forecasts is different from the true mean.*

Proof. See Appendix B.

Appendix B shows that such a correlation among expert opinions shifts the average of the draws relative to the mean of the distribution, so that the errors are not averaged away. I assume that the correlation coefficient lies between zero and unity.¹⁵ The correlation in my model serves as a theoretical foundation for banks to have different beliefs. It also pins down the mean of banks' beliefs as a function of the mean of the shock distribution, that is, how far banks' average belief is from the true distributional mean (see (B.3) in Appendix B).

2.1.2 The Interbank Market and Banks' Problem

At time t , banks choose their portfolio allocation: they invest a share of their funds in the risky asset, α_t^i , with bank i 's subjective expectation about the gross return on the risky asset being $E^i \hat{R}_{t+1}^k$; they leave a share in their reserves (or hoard), h_t , and receive the gross real return on the safe asset, R_t^{res} ; and they lend on the interbank market, $(1 - \alpha_t^i - h_t^i)$, or borrow on the interbank market, Λ_t^i , with the gross real interbank market rate to be paid at $t + 1$ being R_t^{ib} .

Lending on the interbank market is risky. I assume that not repaying part of a loan and not repaying the full amount are equally costly for borrowers and that the cost is exclusion from the interbank market. That is, a lender only has to consider the probability that

¹⁵With my estimate of the correlation of expert opinions in SPF output growth forecasts larger than 0.73, this assumption is quite realistic. I used the individual forecasts from the ECB Survey of Professional Forecasters (SPF) from 1999:Q1 to 2020:Q4. I took the forecasts of output growth in the next two quarters as the closest proxy for the quarterly return predictions in my model. I calculated the correlations of the individual predictions over time using the formula $\rho^c(i) = Cov(X(i)X(j))/\sqrt{Var(X_i)Var(X_j)}$ and took the simple average.

a borrower's return is smaller than his liabilities and disregard the set of possible partial loan repayments.¹⁶ The subjective probability that the loan will be repaid at $t + 1$, denoted as p_t^i , is reflected in the interbank market rate.

Risk-neutral borrowers are willing to borrow infinitely and do not endogenize the effect of high demand for loans on the interbank market rate. As will be shown in Section 2.1.3, with infinite demand for loans, the interbank market collapses. The interbank market rate spikes, lenders' loan repayment probabilities go to zero, and the infinitely high rate causes demand to fall to zero. As a result, there are neither lenders nor borrowers on the market.¹⁷ To avoid this situation, I limit a bank's borrowing to its share of liabilities— λ_b . In the next section I calibrate λ_b to match the interbank lending series. Because I assume that net worth is averaged up at the beginning of the period, all borrowers borrow the same amount— λ_b . For a lender or a hoarding bank, $\Lambda_t^i = 0$.

The bank problem can be formalized as

$$\max_{\alpha_t^i, h_t^i, \Lambda_t^i} \alpha_t^i E_t^i \hat{R}_{t+1}^k + h_t^i R_t^{res} + (1 - \alpha_t^i - h_t^i) p_t^i R_t^{ib} + (E_t^i \hat{R}_{t+1}^k - R_t^{ib}) \Lambda_t^i, \quad (6)$$

subject to

$$\Lambda_t^i = 0 \text{ or } \lambda_b.$$

The linearity of the problem in (6) results in a corner solution for α^i and h^i . Depending on the risky asset return forecast, a bank either invests everything: $\alpha^i = 1$ and $h^i = 0$; hoards everything: $\alpha^i = 0$ and $h^i = 1$; or lends everything: $\alpha^i = 0$ and $h^i = 0$. Additionally, an investing bank which forecasts the risky asset return to be higher than the interbank market rate borrows as much as possible: $\Lambda_t^i = \lambda_b$.

¹⁶I abstract from the agency problem here for the sake of tractability, assuming that banks will honor their debts unless their returns do not allow them to do so. I also choose not to model limited liability and default decisions in the utility function. My banks are owned by households, which absorb the banks' losses.

¹⁷Note that with a decrease in demand, the interbank rate should fall, causing some lending and borrowing to resume. However, without any limit on borrowing, even when there are few borrowers on the market, they will demand an infinite amount, leading to a market collapse.

The bank’s expected risky asset return on a unit of its funds plus those borrowed on the interbank market, λ_b , is $(1 + \lambda_b) E^i \hat{R}_{t+i}^k$. For a bank to be able to honor its interbank market loan, assuming that debt to the household has priority, the return should be higher than the payments to the household (R_t times the amount of deposits per bank b_t) plus the interbank loan repayment: $\lambda_b R_t^{ib}$. Each bank’s subjective probability of borrowers being able to meet their obligations can be written as the probability of the borrowers’ return being larger than their obligations:

$$\begin{aligned}
 p_t^i &= Prob \left((1 + \lambda_b) E^i \hat{R}_{t+1}^k \geq R_t b_t^i + \lambda_b R_t^{ib} \right) \\
 &= 1 - Prob \left(E^i \hat{R}_{t+1}^k < \frac{R_t b_t^i + \lambda_b R_t^{ib}}{(1 + \lambda_b)} \right). \tag{7}
 \end{aligned}$$

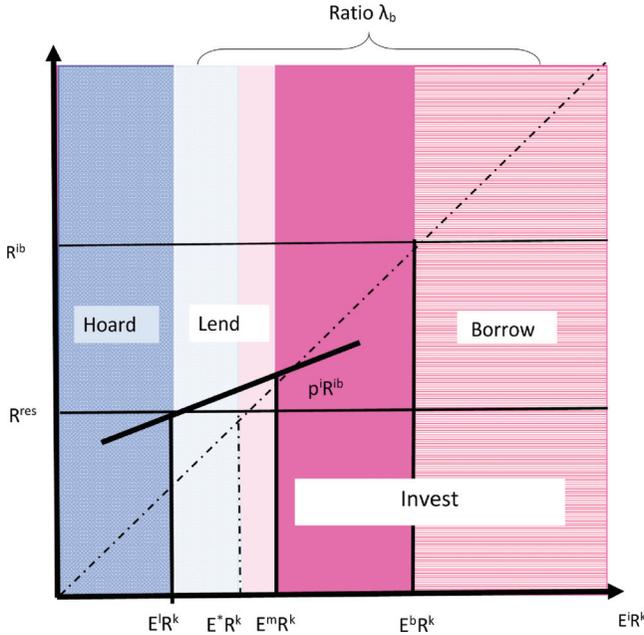
Recall that there are two distributions to distinguish. First, there is the distribution of beliefs *across* banks. Second, there is the belief of *an individual bank*, which is also a random variable distributed normally with mean $E^i \hat{R}_{t+1}^k$ and variance σ_R^2 . Then, each bank’s subjective probability, given its individual forecast, can be rewritten as the cumulative distribution function of the normal distribution, F , with mean $E^i \hat{R}_{t+1}^k$ and variance σ_R^2 :

$$p_t^i = 1 - F_{E^i \hat{R}_{t+1}^k, \sigma_R^2} \left(\frac{R_t b_t + \lambda_b R_t^{ib}}{1 + \lambda_b} \right). \tag{8}$$

Note that each borrower borrows the same amount—the share of the net worth, λ_b , which is the same across banks; all banks receive the same amount of deposits b_t and all banks pay the same interbank market, and deposit rates. It follows that the individual probabilities in (8) differ only in terms of the return expectations, $E^i \hat{R}_{t+1}^k$.

Banks’ investment decisions are illustrated in Figure 2. The horizontal axis shows the beliefs of individual banks, and the rates of return appear on the vertical axis. The time notations are dropped for convenience. The expected return from interbank lending, $p^i R^{ib}$, is plotted as a function of the individual return expectations $E^i \hat{R}^k$. The marginal lender is a banker who is indifferent between lending and hoarding, with beliefs denoted as $E^l \hat{R}^k$ such that $p^l R^{ib} = R^{res}$. Their beliefs are determined by the intersection of $p^i R^{ib}$ and the

Figure 2. Banks' Expectations and Investment Decisions



Note: Dotted blue area—hoarders; white transparent area—lenders; solid pink area—direct investors; red striped area—borrowers. The solid line, $p^i R^{ib}$, shows the expected interbank market return as a function of the individual risky asset return expectations. On the vertical axis are interest rates: the interbank market rate, R^{ib} , and the safe asset rate, R^{res} . The horizontal axis shows banks' expectations of the risky asset return, $E^i R^k$. $E^l R^k$ is the expectation of a marginal lender, $E^m R^k$ is that of a marginal investor, and $E^b R^k$ is that of a marginal borrower. $E^* R^k$ depicts the expectation of a marginal investor when the interbank market is not functioning.

safe asset return. The marginal investor is a banker who is indifferent between the risky asset and lending on the interbank market. I denote their beliefs as $E^m \hat{R}^k = p^m R^{ib}$. These beliefs are at the intersection of the 45-degree line and the $p^i R^{ib}$ curve in the figure. The marginal borrower is indifferent between borrowing on the interbank market or not, and is defined as $E^b \hat{R}^k = R^{ib}$ at the intersection of the interbank rate and the 45-degree line. The banks with return expectations lying between the marginal lender and the marginal investor make up the set of lenders (the white transparent area).

The area to the right of the marginal borrower’s beliefs (the red striped area) shows the set of borrowers. (See the online version of the paper at <http://www.ijcb.org> for figures in color.) The interbank market rate is endogenously determined by equalizing the share of lenders with the share of borrowers multiplied by λ_b .¹⁸

Knowing the distribution of beliefs across banks, it is straightforward to find the interbank market allocations by integrating the corresponding areas of Figure 2. The share of banks investing in the real economy at time t is the share of banks with beliefs equal to or higher than those of the marginal investor, which is the integral over the set of investors in Figure 2:

$$s_t^{inv} = \int_{E_t^m \hat{R}_{t+1}^k}^{\infty} f(x) dx = 1 - F_{m, \sigma_R^2} \left(E_t^m \hat{R}_{t+1}^k \right), \tag{9}$$

where $F_{m, \sigma_R^2} \left(E_t^m \hat{R}_{t+1}^k \right) = Prob(E_t^i \hat{R}_{t+1}^k < E_t^m \hat{R}_{t+1}^k)$ is the cumulative distribution function for the normal distribution.

The share of banks borrowing on the interbank market can be defined as the probability that their belief is higher than the interbank interest rate, which is the integral over the set of borrowers in Figure 2:

$$s_t^b = \int_{R_t^{ib}}^{\infty} f(x) dx = 1 - F_{m, \sigma_R^2} \left(R_t^{ib} \right). \tag{10}$$

The share of banks lending is then defined as the probability that their belief is higher than that of the marginal lender $E_t^l \hat{R}_{t+1}^k$ by integrating over the set of lenders:

¹⁸In online Appendix D, for a simplified setting I consider the equilibrium, in which the interbank market collapses. Bankers are then divided into investors (the pink and red striped area) and hoarders (the dotted blue area). The intersection of the 45-degree line and the safe asset rate determines the marginal investor when the interbank market is not functioning, $E^* R^k$. Bankers to the right of $E^* R^k$ invest, while those to the left hoard.

$$\begin{aligned}
 s_t^l &= \int_{E_t^l \hat{R}_{t+1}^k}^{E_t^m \hat{R}_{t+1}^k} f(x) dx \\
 &= F_{m, \sigma_R^2} \left(E_t^m \hat{R}_{t+1}^k \right) - F_{m, \sigma_R^2} \left(E_t^l \hat{R}_{t+1}^k \right). \quad (11)
 \end{aligned}$$

The share of those keeping money in reserves (hoarding) is then defined as the share of those neither investing nor lending $(1 - s_t^{inv} - s_t^l)$. Multiplying these shares by the total funds of the banking sector, I obtain the respective amounts of credit, borrowing, lending, and hoarding.

2.1.3 Interbank Market Clearing

For the interbank market to clear, demand should be equal to supply. Borrowers demand a share of borrowers' funds $\Lambda_t^i = \lambda_b$, and lenders supply all their funds available:

$$s_t^l = \lambda_b s_t^b.$$

Plugging in the expressions for the shares (10) and (11), one can rewrite the market clearing condition in terms of cumulative distribution functions of the normal distribution:

$$F_{m, \sigma_R^2} \left(E_t^m \hat{R}_{t+1}^k \right) - F_{m, \sigma_R^2} \left(E_t^l \hat{R}_{t+1}^k \right) = \lambda_b \left(1 - F_{m, \sigma_R^2} \left(R_t^{ib} \right) \right). \quad (12)$$

The mean and variance of beliefs across banks enter (12) as the moments of the cumulative density function. In addition, the variance enters the definitions of the marginal investor and the marginal lender: $E_t^m \hat{R}_{t+1}^k = p_t^m R_t^{ib}$ and $E_t^l \hat{R}_{t+1}^k$ such that $p_t^l R_t^{ib} = R_t^{res}$. Combining these two definitions and (12) produces a solution for the interbank market rate and the corresponding amount of lending. The conditions for the equilibrium to exist and its properties for a simple model are analyzed in online Appendix D.

Note that for the model to have a solution with a functional interbank market, banks' borrowing must be restricted. That is, λ_b has to be a finite number. Suppose for a moment that this is not the case and the supply of loans is finite and nonzero. As the demand

for bank loans goes to infinity, the interbank market rate also goes to infinity, causing demand to fall to zero in (12):

$$\begin{aligned} \frac{1}{\lambda_b} \left[F_{m,\sigma_R^2} \left(E_t^m \hat{R}_{t+1}^k \right) - F_{m,\sigma_R^2} \left(E_t^l \hat{R}_{t+1}^k \right) \right] &= 1 - F_{m,\sigma_R^2} \left(R_t^{ib} \right), \\ \lim_{\lambda_b \rightarrow +\infty} \frac{1}{\lambda_b} \left[F_{m,\sigma_R^2} \left(E_t^m \hat{R}_{t+1}^k \right) - F_{m,\sigma_R^2} \left(E_t^l \hat{R}_{t+1}^k \right) \right] &= 0 \\ \Rightarrow 1 - F_{m,\sigma_R^2} \left(R_t^{ib} \right) \rightarrow 0 &\Rightarrow R_t^{ib} \rightarrow \infty. \end{aligned}$$

With an infinite interbank market rate, the probability of lending as evaluated by any banker, including the marginal lender and the marginal investor, is zero in limit: $\lim_{R_t^{ib} \rightarrow \infty} p_t^i R_t^{ib} = 0 \times \infty$.¹⁹ The solution for the marginal lender does not exist, as in $p_t^l R_t^{ib} = R_t^{res}$ the left-hand side is approaching zero but the right-hand side is positive.

2.1.4 Banks' Net Worth and the Financial Accelerator

Recall that the government provides a partial guarantee for households' deposits. Households can recover a fraction $1 - \lambda$ of their deposits. Similarly to Gertler and Karadi (2011), I define a bank's net worth as N_t^i , and B_t^i are the deposits from households. However, in my model banks can invest in three types of assets: risky $Q_t S_t^i$, safe (hoarding) Res_t^i , and interbank loans $Lend_t^i$, so the bank's balance sheet in my model is given by

$$Q_t S_t^i + Res_t^i + Lend_t^i = N_t^i + B_t^i, \tag{13}$$

where, given each asset return, the evolution of a bank's net worth over time can be formulated as

$$N_{t+1}^i = R_{t+1}^k Q_t S_t^i + R_t^{ib} Lend_t^i + R_t^{res} Res_t^i - R_t B_t^i. \tag{14}$$

Note that, for a borrower, the term $R_t^{ib} Lend_t^i$ is negative and is equal to $R_t^{ib} (-\lambda_b N_t^i)$.

As the agency problem is a slight modification of that in Gertler and Karadi (2011), I put the solution in online Appendix F

¹⁹To see this, multiply p_t^i in (8) by R_t^{ib} and send both λ_b and R_t^{ib} to ∞ .

and present here the resulting aggregate constraint. Denoting the banking-sector leverage ratio as φ_t , the constraint is

$$(Q_t S_t + Res_t) = \frac{\eta_t}{\lambda - v_t (1 - s_t^h)} N_t = \varphi_t N_t, \quad (15)$$

where λ is the fraction of assets that cannot be recovered and v_t and η_t are functions of future returns described in online Appendix F.

To finalize the law of motion for banks' net worth, recall that in each period a fraction $(1 - \theta)$ of the bankers exit and take a share $(1 - \theta)$ of the banking assets. At the same time, households transfer a fraction ω of the exit value to the new bankers. That is, the law of motion for banks' aggregated net worth is given by

$$N_{t+1} = \theta \left\{ [(1 - s_t^h) (R_{t+1}^k - R_t) + s_t^h (R_t^{res} - R_t)] \varphi_t + R_t \right\} N_t + \omega (Q_t S_{t-1} + Res_{t-1}). \quad (16)$$

The first term on the right-hand side in Equation (16) (in curly brackets) shows the net wealth accumulation of banks that stay in the banking sector for the next period—there is an exogenous fraction θ of these. Their return equals the return on the risky asset, $(R_{t+1}^k - R_t)$, and there is a share $(1 - s_t^h)$ of them who do not hoard but either invest themselves or lend to other banks. Those who hoard—a share s_t^h of banks—receive returns on the safe asset. The last term in Equation (16) represents the transfers from households to the new entering banks.

2.1.5 Credit-Support Policies

I consider several credit-support policies. Under the first two, the central bank funds asset purchases through intermediaries. Untargeted liquidity provision is modeled as the funding of a share ψ_t of a bank's asset purchases:

$$Q_t S_t + Res_t = \varphi_t N_t + \psi_t (Q_t S_t + Res_t).$$

For targeted credit support, the central bank limits the set of assets to be purchased to risky claims on firms. Let ψ_t^{tar} denote the fraction of risky assets funded by the central bank. Then

$$Q_t S_t + Res_t = \varphi_t N_t + \psi_t^{tar} Q_t S_t.$$

A bank pays R_t for central bank support. There are, however, operational costs of conducting the policy, $\tau\psi_t(Q_t S_t + Res_t)$ or $\tau\psi_t^{tar} Q_t S_t$. I assume that both policies are equally costly. I model the policy and its costs consistent with Gertler and Karadi (2011), so that the central bank selects ψ_t and ψ_t^{tar} as a proportion of the rise in the risk premium. When there are disturbances in the economy, the risk premium rises above the steady-state level.

$$\psi_t = \kappa (R_{t+1}^k - R_t - (\overline{Rk} - \overline{R})), \tag{17}$$

where κ is a reaction parameter.

I further consider relaxing the collateral constraint on the inter-bank market and lowering the real gross return on the safe asset, R_t^{res} , both of which involve no operational costs. Relaxing the collateral constraint takes the form of increasing the fraction of borrowers' liabilities at which borrowing is restricted— λ_b . The increase in this fraction, denoted as ∇_t^λ , and the reduction in R_t^{res} , ∇_t^R , follow the same decision rule as the two previous policies considered:

$$\nabla_t^i = \kappa^i (R_{t+1}^k - R_t - (\overline{Rk} - \overline{R})),$$

where i stands either for λ or for R^{res} . I allow for a different feedback parameter κ^i in the rules.

2.2 The Rest of the Model

Here I sketch the rest of the model. The key model equations are presented in online Appendix G.

Households. There is a representative risk-averse household which maximizes an infinite sum of expected discounted utility. The household extracts utility from consumption and disutility from labor. The utility features external habits in consumption. Households can deposit their savings in banks; bank deposits are guaranteed by the government up to a fraction $(1 - \lambda)$.

Intermediate Goods Producers. The perfectly competitive intermediate good producers use the Cobb-Douglas production function to combine labor and capital. Investment in capital should be made one period in advance. To invest in the next period's capital, K_t , intermediate goods producers issue claims S_t at price Q_t^S . The value of the capital they can buy at price Q_t^K is then $Q_t^K K_t = Q_t^S S_t$. In the next period, intermediate goods producers sell the depreciated capital to capital producers at the market price Q_{t+1}^K . Because of the perfect competition among intermediate goods producers, the price of capital equals the price of producers' claims: $Q_t^K = Q_t^S \equiv Q_t$. The amount of depreciated capital is equal to $\delta_t (U_t) \xi_t K_{t-1}$, where δ_t is the physical depreciation rate and ξ_t reflects the capital quality shock discussed above. At $t + 1$, the firm pays a gross return $R_{k,t+1}$ to the bankers per each unit of investment. As firms are identical, investment in capital pays the same return to all banks.

Capital-Producing Firms. Capital-producing firms are competitive. They buy depreciated capital from intermediate goods producers, renovate it at the unit costs, and sell it at the unit price. They also produce new capital and sell it at price Q_t . There are no adjustment costs for renovating worn-out capital, but there are flow adjustment costs when producing new capital.

Final Goods Producers. Final goods producers are monopolistic competitors who set their prices to maximize their profit. I follow the Calvo-pricing convention as in Calvo (1983) and each period allow only a fraction γ of firms to optimize their prices.

The Government and the Central Bank. There is an inflation-targeting central bank which reacts to the deviation of inflation from the target and to the output gap using a Taylor-like rule. The government collects lump-sum taxes from households, makes lump-sum transfers to households, and accepts reserves (the safe asset). It also bears some of the costs of conducting credit support policy.

3. Calibration and Simulations

To compare my results with the literature, where possible I follow the calibration choices of Gertler and Karadi (2011); I list their parameter choices in Table H.1 in online Appendix H. There are, however, some parameters specific to my model, which can be grouped

Table 1. Interbank Market Parameters and Implied Steady-State Values

Interbank Market Parameters		
$\bar{E}\xi$	1	Average steady-state belief about ξ
σ_R^2	0.01	Variance of return expectations
λ_b	0.19	Collateral constraint on interbank market
Implied Steady-State Values		Observed Values
$R^{ib} - R$	0.27 p.p.	0.2 p.p.
s^h	40.71%	40%
Note: The data for the calibrated moments come from Eurostat and the ECB Statistical Data Warehouse.		

into parameters defining interbank market allocations (in Table 1) and parameters necessary for banks' filtering problem (in Table 2). Recall that I only need the *average* prediction of the future realization of capital quality.

The first group of parameters includes the steady-state moments of banks' beliefs distribution, m and σ_R^2 , and the collateral constraint, λ_b . I assume that the average steady-state belief about the capital quality shock coincides with the steady-state value of the shock: $\bar{E}\xi = 1$. Also note that the steady-state value of $\bar{E}\xi$ is a linear combination of ρ_c and $\bar{\theta}$ (see Appendix C). Thus, by fixing the steady-state prediction of $\bar{E}\xi$, I do not need to specify the latter parameters. The average return expectation follows from (2):

$$\bar{R}^k = \frac{\alpha \frac{\bar{P}_m \bar{Y}}{K} + (\bar{Q} - \delta)}{\bar{Q}}.$$

Though it is not straightforward to find empirical counterparts for σ_R^2 and λ_b , these parameters are pinned down by the interbank market allocations, for which data are available. In particular, in Table 1, I roughly match the steady-state values of the interbank market rate and the share of loans in bank portfolios with their euro-area pre-crisis counterparts.²⁰ In my model, banks exchange loans for one period on the interbank market, with the period being one

²⁰For the pre-crisis period, I take the averages of the values in 2000–06.

**Table 2. Calibrated Exogenous Shocks
for the Kalman Filter**

σ_{η}^2	0.005	Variance of expert opinion shock
σ_{ε}^2	0.0076	Variance of econometric shock
$\sigma_{\varepsilon\eta}$	0.7	Covariance of econometric and expert opinion shock
σ_v^2	0.002	Variance of persistent shock to capital quality
ρ_{θ}	0.66	Persistence of expert opinion shock
ρ_{ξ}	0.66	Persistence of capital quality shock
ρ_{μ}	0.66	Persistence of persistent shock to capital quality

quarter. Therefore, the three-month EURIBOR is a natural choice for the empirical counterpart for the model interbank rate. I calculate the share of hoarded assets as $(1 - \text{share of loans})$. The share of loans is the ratio of total loans to the total assets of European banks. Total loans comprise loans to enterprises and MFIs (monetary and financial institutions). In my model, what is not lent either to banks or to firms is hoarded.²¹

To solve the model, I further need to define the parameters for banks' forecast formation in Figure 1. These are the variance and covariance of the econometric and expert opinion signals, the variance of the persistent shock to capital quality, and their persistence. The variances are pinned down by the above-defined steady-state variance of return expectations, σ_R^2 , as described in Appendix C, and by the share of expert adjustments in the final forecast.²² I set the ratio of $\sigma_{\eta}^2/\sigma_{\varepsilon}^2$ equal to 0.66, and the resulting steady-state share of expert adjustments is then 0.36. In Table 2, the covariance between the econometric forecast and expert adjustment is set to

²¹Note that in my model, reserves also represent safe assets, but in reality there is a range of assets that can be considered "safe." This also explains the relatively large steady-state share of hoarded assets. The steady-state safe rate, defined by the commonly used value for β , is 4 percent per annum, clearly above the EURIBOR in 2000–06. To facilitate comparison of my results with the literature, instead of changing β , I choose to target the difference between the EURIBOR and the safe rate, evaluated at 0.2 percentage point.

²²For example, Fildes et al. (2009) analyze a data set containing 70,000 business organizations and their forecasts. They find that the mean expert adjustment for monthly forecasts varies between 18 percent and 46 percent depending on the type of business.

Table 3. Calibrated Crisis Shocks and Policy Responses

$\sigma_{\varepsilon,crisis}^2$	0.05	Transitory crisis shock to capital quality
$\sigma_{\varepsilon\eta,crisis}^2$	0.05	Expert opinion pessimistic shock
κ^λ	2.5	Policy reaction for collateral constraint
κ^R	0.1	Policy reaction for reserve rate

match the correlation between the SPF forecast for GDP growth and its actual realization,²³ $\sigma_{\varepsilon\eta} = 0.7$. The persistence of the capital quality shock is $\rho_\xi = 0.66$, as in Gertler and Karadi (2011). I set the persistence of all other shocks the same, at 0.66 for both the persistent shock and the expert opinions shock.²⁴

With the parameters described above, I then proceed with an analysis of the linearized model and its performance relative to the baseline with homogeneous expectations.²⁵ The extended set of impulse responses is presented in online Appendix I.

3.1 Defining a Crisis

I consider several types of crises, with the shocks and policy responses calibrated in Table 3. First, there is a transitory negative shock to capital quality, ξ_t . To make the dynamics of my model comparable with the literature, I consider a 5 percent shock, as in Gertler and Karadi (2011). They calibrate this value to match a 10 percent decline in the effective capital stock over a two-year period.

The second type of crisis is a negative 5 percent transitory shock combined with banks' belief that it was a permanent shock.²⁶ That

²³I use the one-year-ahead forecast of real GDP growth taken from the ECB Survey of Professional Forecasters.

²⁴In previous research—Audzei (2012)—I calculated the persistence of the expert opinions shock using the SPF GDP forecast. The resulting value was very close to the current calibration—0.61.

²⁵The model is simulated using Dynare 4. The baseline model is the one by Gertler and Karadi (2011); the Dynare code for it was downloaded from P. Karadi's web page: <https://sites.google.com/site/pkaradi696/research>.

²⁶This is modeled as a shock to banks' average expert opinion about the persistent component of ξ_t : a shock to $\bar{E}_t\mu_{t+1}$ as in (C.5) in Appendix C, rather than as a shock to θ and adjusting it for the correlation parameter. Recall that in the model it is the average belief that matters for the simulations.

Table 4. Crisis Impact on the Observed and Modeled Series

Variable	Euro Area	Model No Expect. Shock	Model With Expect. Shock
Banks' equity, % change	-23	-19	-25
Cost of borrowing, % change	-22	-12	-15
Loans to corporations, % change	-14.8	-12	-15
YoY output growth, %	-4.16	-3.5	-5.2

Note: The data are from the ECB Statistical Data Warehouse, except for output growth, which is from the AWM database.

is, this crisis is a combination of poor asset returns and banks believing that poor returns will persist in the future.

A comparison of how the two types of crisis modeled match the observed downturn of 2008–09 for the selected variables is given in Table 4.²⁷ As the table shows, despite the simplicity of the banking sector, the model with sentiment shocks matches the observed downturn in banks' equity, fall in corporate loans and output growth, and decline in the cost of borrowing reasonably well. Next, I begin to analyze the role of expectations and central bank policies in mitigating the crisis.

Last, to demonstrate the impact of belief shocks alone, I show a crisis without a shock to ξ_t but with banks believing in a 5 percent drop in the persistent component of ξ_t . In other words, I consider a crisis without an expectational (pessimistic) shock, a crisis

²⁷I assume that the “crisis” shock in the euro area occurred in 2008:Q4–2009:Q1, when the drop in output was the most pronounced. Unlike the model, the euro-zone economy was not in the steady state in the quarters preceding the crisis and the shock could have been anticipated by financial markets. I consider 2007:Q1 as the pre-crisis value and compare it with 2009:Q1 for output growth and the cost of borrowing for non-financial corporations. The model counterparts are output and banks' return on risky assets, respectively. Loans to corporations are the series “loans other than revolving loans and overdrafts, convenience and extended credit card debt, up to 1 year initial rate fixation, up to and including EUR 1 million, new business coverage, denominated in euro.” As the series are very volatile but demonstrate a clear drop in 2009 relative to 2007, I use the difference in the corresponding yearly averages. The model counterpart is bank loans $Q_t S_t$. Due to data availability, the change in bank equity is calculated as the percentage difference in the bank equity to total assets ratio in 2008:Q4 relative to 2007:Q4 in the euro area.

with an expectational (pessimistic) shock, and a pure expectational (pessimistic) shock, respectively.

The policy reaction parameter for the reserve rate is set to match the decline in the policy rate in 2008–09 relative to the pre-crisis 10-year average. The resulting deviation from the steady state during the crisis is a fall of 0.23 percentage point. The collateral constraint in my model does not have an intuitive empirical counterpart. The value is set for illustrative purposes, and alternative values are discussed.

3.2 *The Role of Expectations and the Interbank Market*

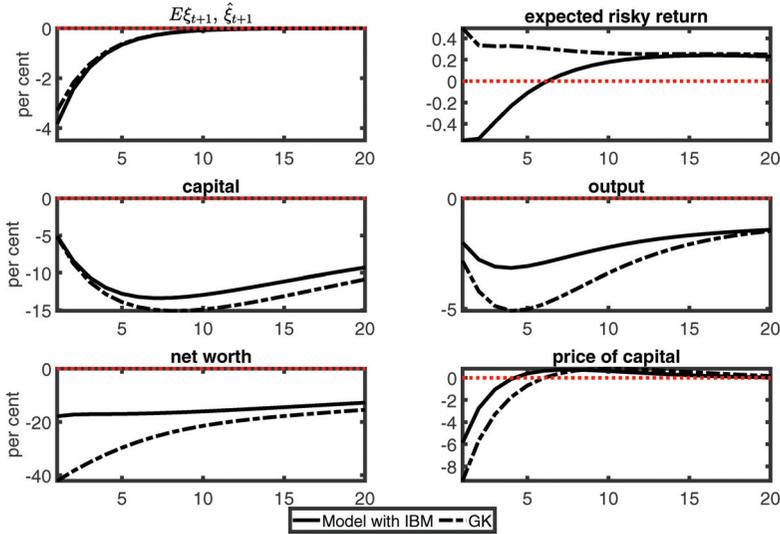
In my economy, expectations determine credit to the real sector. They also affect the functioning of the interbank market: the numbers of borrowers and lenders and the equilibrium interbank market rate. In what follows, I consider model responses linearized around the steady state with a functioning interbank market. A decrease in market expectations results in less lending between banks.²⁸

If banks have rational expectations as in Gertler and Karadi (2011), there is no interbank market and our models would have identical responses. For this reason, I treat Gertler and Karadi (2011) as a baseline to study the role of expectations and the interbank market. I begin with a comparison of the model behavior and the baseline when there is no policy response and the crisis shock is only a transitory shock to ξ_t . In this scenario, the policy rate, R_t^{res} , is set equal to the deposit rate, so that banks earn nothing on a safe asset. Figure 3 shows the responses of my model (the solid line “Model with IBM”) and the Gertler and Karadi (2011) model (the dashed and dotted lines “GK”).

In period 1 there is a temporary negative 5 percent shock to capital quality, ξ_t . Because ξ_t is itself a persistent process, it remains below the steady-state value for about 10 periods. The first subplot shows the expectations about ξ_{t+1} : $E\xi_{t+1}$ is rational expectations as in Gertler and Karadi (2011), and $\hat{\xi}_{t+1}$ is mean expectations in my model with uncertainty. In a model with perfect expectations, this will be $E_t\xi_{t+1} = \rho_\xi * \xi_t$, resulting in a decline of 3.3 percent in the

²⁸Proposition D.2 and Corollary D.1 in online Appendix D show the impact of expectations analytically in a simplified setting.

Figure 3. Crisis Simulations: Comparison with the Baseline



Note: The responses are plotted for a 5 percent transitory shock to capital quality ξ_t without a policy response from the central bank. The solid lines “Model with IBM” show the responses of my model, and the dashed and dotted lines “GK” show the responses of the baseline model of Gertler and Karadi (2011).

first period. However, in my model, whether this was a transitory or a persistent shock is not observable. Recall that agents combine two observables to form their forecasts: the historical values of ξ and the expert opinions on the value of the persistent shock to ξ_t . Even when the experts assume the persistent shock to be zero, the analysis of historical observations leaves a possibility for it to exist. Consequently, even in a model in which expert opinions are not distorted, the future values of ξ_t are underestimated. This further translates into a lower average expected return in my model than in the baseline response, in which the expected return is growing due to an increasing marginal product of capital.

When ξ_t is hit by a shock, there is an immediate decline in the contemporaneous return on banks’ investments. This lowers their returns and has a negative effect on their net worth. With lower net worth, current net investments fall and the price of capital decreases.

The price of capital also reflects the capital's resale value. Consequently, the fall in the price of capital contributes to a further decline in banks' worth. The fall in net worth leads to declines in both safe and risky asset holdings. With lower net worth, banks are able to attract fewer deposits from households, as their deposits are limited to a fraction of their net worth through the agency problem. Hence, capital falls even more, as banks simply have less funds to invest.

Now compare the responses of this model with Gertler and Karadi (2011). In my model, banks do not invest all their funds in the risky asset but leave some in the safe one. Consequently, only a proportion of banks' net worth is affected by the fall in risky asset returns. As a result, my model demonstrates about half the fall in aggregated net worth as that in Gertler and Karadi (2011). As shown in Table 4, when it comes to the net worth of financial intermediaries, the fall in my model is closer to the actual data. This is not surprising, as banks in reality have more diversified portfolios than banks in the benchmark model, which only hold the risky asset. The smaller drop in net worth explains the smaller fall in capital and output. Thus, in my model, when a shock of the same magnitude hits the economy, banks are less liquidity constrained than in Gertler and Karadi (2011).

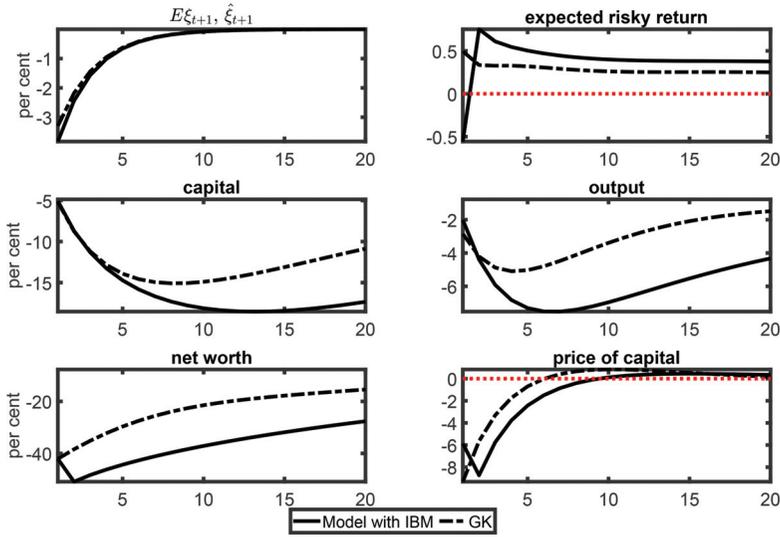
Because the baseline model features only a capital asset and demonstrates a larger fall in net worth, to isolate the role of the interbank market I simulate my model controlling for the difference in net worth.²⁹

This comparison is shown in Figure 4, with the expanded set of impulse responses presented in online Appendix I. With net worth reduced as much as in the baseline (the dashed and dotted lines "GK"), the recession is larger in my model (the solid line "Model with IBM"). The resulting decline in output is more than 1.5 times greater than in the baseline, being the result of both imperfect expectations and the interbank market adjustment to the shock: a fall in the loan repayment probability evaluated by the marginal lender and a decline in the volume of lending.

Now consider the effect of different crisis shocks in my model: a "fundamental" shock to capital quality, ξ , only, a pure expectational

²⁹For this purpose I calculate impulse responses while substituting the initial fall in net worth from the baseline.

Figure 4. Crisis Simulations: Comparable Net Worth



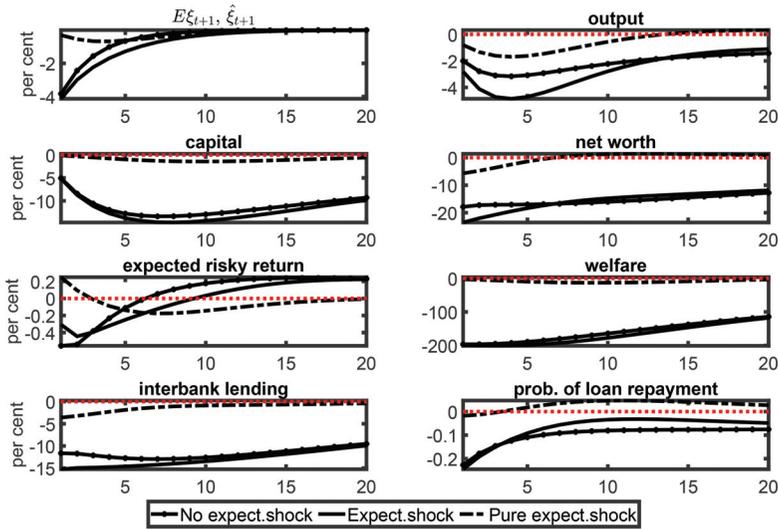
Note: The responses are plotted for a 5 percent transitory shock to capital quality ξ_t without a policy response from the central bank. The solid lines “Model with IBM” show the responses of my model, and the dashed and dotted lines “GK” show the responses of the baseline model of Gertler and Karadi (2011).

shock, and a combination of the two. A comparison of all the shocks is shown in Figure 5.

The responses to a fundamental shock alone (the solid lines with dots “No expect. shock”) resemble those in Figure 4, with inter-bank lending and the loan repayment probability evaluated by the marginal lender falling, thus contributing to a further decline in investment.

When a *pure expectational* shock hits the economy (the dashed and dotted lines “Pure expect. shock”) and there is no actual drop in ξ_t , banks underestimate ξ_t for some period of time. This generates a decline in net investment, a decrease in the price of capital, and a fall in the current return on capital, followed by a decline in net worth. Capital falls initially by less than 1 percent. The decline in net worth accelerates the fall in capital in the following periods. That is, a persistent pessimistic shock can generate a small recession, as investment falls, leading to declines in output and consumption. The

Figure 5. Crisis Simulations with and without Expectational Shocks



Note: The responses are plotted for a 5 percent transitory shock to capital quality ξ without a policy response from the central bank. The expectational shock is a 5 percent fall in the average expert opinion, $\bar{E}_t\mu_{t+1}$. The solid line with dots shows the model responses to the fundamental shock only and the solid line shows those to the fundamental shock combined with the expectational shock; the dashed and dotted line illustrates the responses to the pure expectational shock.

loan repayment probability reflects lenders’ pessimism. As the pessimism shock vanishes, the loan repayment probability rises, reflecting the higher return on capital. The drop and subsequent increase then translate into the interbank lending.

If the crisis is interpreted as a combination of a shock to ξ and a shock to agent expectations (the solid lines), the resulting responses look like the sum of the pure expectational shock and no expectational shock scenarios. If one accepts the idea of the sluggishness of investor forecasts as in Andrade and Le Bihan (2013) and Coibion and Gorodnichenko (2015) leading to overly pessimistic expectations after crisis episodes, then my model with an expectational shock can serve as an illustration of the crisis, generating a similar decline in capital as in Gertler and Karadi (2011), but with the deviations in

banks' net worth matching the data due to a more realistic asset structure. That is, in my model a crisis of the same magnitude is the result of both liquidity constraints due to the financial accelerator and concerns about poor economic prospects translating into a higher counterparty risk.

To summarize, an expectational shock alone can generate some need for a policy response by the central bank. Combined with the occurrence of an actual crisis, this leads to a more severe recession. Thus, investor sentiment can be an important factor in policy design and evaluation.

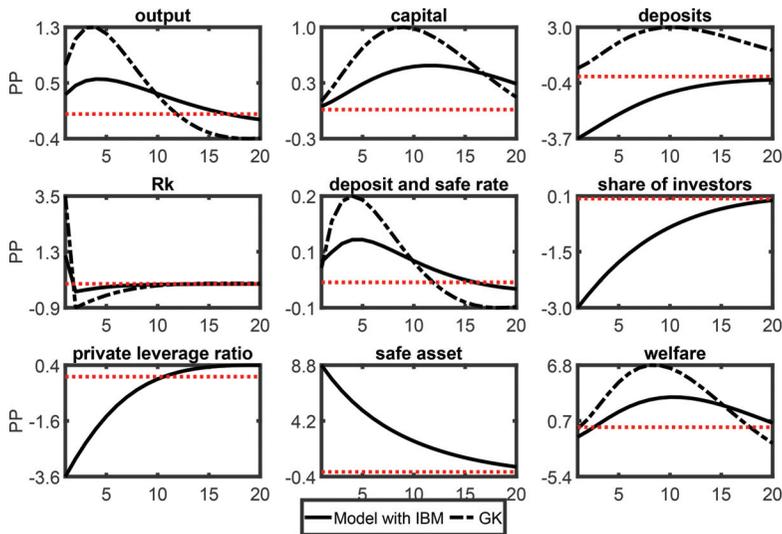
3.3 Policy Results

I begin my analysis with a comparison of the baseline model of Gertler and Karadi (2011) and my model with an interbank market and an expectational shock. In this scenario, the economy is hit by a shock to ξ_t and a wave of pessimism. The resulting simulation gives a very similar drop in output and capital as in the baseline (see the dashed line in Figure 3 and the solid line in Figure 5).³⁰ However, the policy rule in (17) is endogenous, so I simulate my model using a vector of policy responses similar to the baseline. I present the comparison in Figure 6, where I plot the percentage differences in variables with and without policy ($x = x_{policy} - x_{nopolicy}$).

As the figure shows, the policy effects in my model with an interbank market are lower and delayed. Moreover, the policy actually has a negative effect on deposits. It increases the share of hoarders by reducing the expected return on capital and increasing the safe rate. As more lenders leave the market to become hoarders, the interbank rate rises, depressing borrowing. As there are fewer investors (and a lower return on banks' aggregate capital), the private leverage ratio, as measured by borrowings from households, falls together

³⁰The comparison is complicated by the difference in capital structure. If I control for the difference in net worth as in Figure 4, then the crisis is much deeper in my model. Liquidity provision on the same scale leaves my economy in a worse recession than in the baseline model, but the effect relative to the simulation without policy is larger due to the larger initial drop. That is, I compare the policy effects under two alternative crisis views: whether banks became liquidity constrained as in the baseline; or they became liquidity constrained, but less than in the baseline, and they became concerned about economic prospects.

**Figure 6. Policy Effects vs. Baseline:
Untargeted Liquidity Provision**



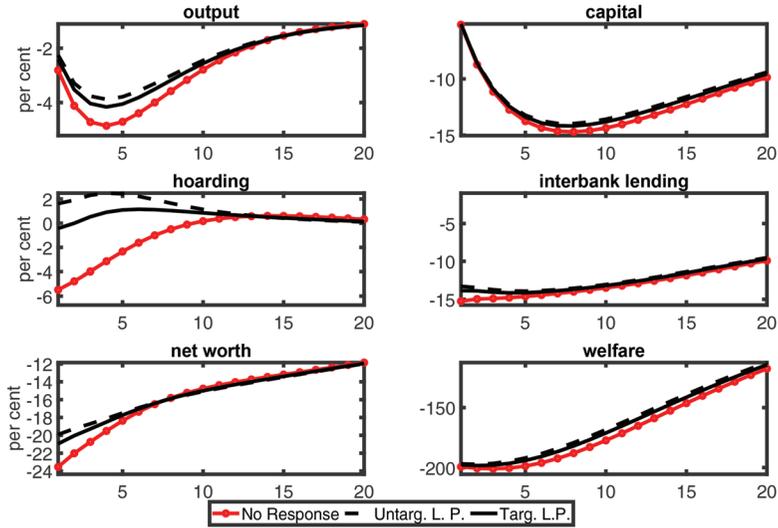
Note: The responses are plotted for a 5 percent transitory shock to capital quality ξ_t under the policy of untargeted liquidity provision. The solid lines “Model with IBM” show the responses of my model, and the dashed and dotted lines “GK” show the responses of the baseline model of Gertler and Karadi (2011).

with deposits. In a sense, the policy “crowds out” borrowing from households. Also note that the increase in safe asset holdings is more pronounced than the increase in capital assets. The share of hoarding banks—those neither investing nor lending—rises. This hoarding effect undermines the impact of liquidity provision in my model.

For an analysis of different policies, I consider the same “crisis” with a wave of investor pessimism. A comparison of targeted and untargeted liquidity provision is presented in Figure 7, while the demonstration of other policies is left for Figure I.4 in online Appendix I.³¹ First, consider the two types of liquidity provision: targeted, represented by the solid line, and untargeted, represented

³¹The policy exercises without the expectational shock would have the same qualitative results, but the recession would be smaller, as are the differences between the policies.

Figure 7. Policy Effects



Note: The responses are plotted for a 5 percent transitory shock to ξ and a 5 percent fall in the average expert opinion, $\bar{E}_t\mu_{t+1}$. The solid line with dots “No Response” shows the model response without the policy response from the central bank; “Untarg. L.P.” illustrates the case with untargeted liquidity provision, and the solid line “Targ. L.P.” shows that with targeted liquidity provision.

by the dashed line. The two policies have very similar effects on output, consumption, and capital and mitigate the crisis relative to the simulation with no policy response. The effects on households welfare, interbank market lending, or banks’ net worth are undistinguishable. The policy response is the same total amount of funds supplied to banks— $\psi(QK + Res)$ and $\psi^{tar}(QK)$ —for the untargeted and targeted policies, respectively. The main difference between the two policies is in the share of hoarded assets, *hoarding*, which is almost twice as large in the case of the untargeted policy. These predictions are in line with the results of the simple model in online Appendix D: liquidity provision helps restore credit to the real economy but also increases reserve holdings.

As for the other policies, demonstrated in Figure I.4 in online Appendix I, interest rate policy is the least efficient in my simulations. It is modeled as a decline in the reserve rate below the deposit rate, meaning that banks are making negative returns on

their reserves. In line with the simple model results, such a policy lowers the share of hoarded assets in banks' portfolios. However, it reduces banks' net worth, leading to a large drop in investment. This drop in net worth leads to even worse outcomes than in the case of no policy action in terms of output and welfare.

Relaxing the collateral constraint on the interbank market by raising λ_b allows borrowers to borrow a larger fraction of their net worth. The larger demand for interbank credit drives up the interbank market rate, reducing the number of banks willing to borrow. Thus, there are fewer borrowers on the market, but they borrow more. As a result, despite the larger volume on the interbank market, credit supply to the real economy is almost unchanged, as are safe asset positions.³²

To conclude, liquidity provision policies help mitigate the simulated crisis. However, relative to the baseline model of Gertler and Karadi (2011), my model with imperfect information and a storage asset demonstrates low efficiency of liquidity provision when banks' expectations are distorted, with delayed responses and liquidity hoarding. The policies of targeted and untargeted liquidity provision have very similar effects, with the latter resulting in more hoarding. A policy of low reserve rates makes hoarding less attractive but has a negative impact on banks' net worth, leading to worse outcomes than in the case of no policy.

4. Conclusion

In this paper I address the role of imperfect market expectations in interbank lending and how they can amplify economic fluctuations. I show that the assessment of counterparty risk can be one of the factors contributing to a credit crunch.

To study market expectations, I incorporate a heterogeneous banking sector with a continuum of risky asset return expectations. The heterogeneity of expectations gives rise to an interbank market where lenders take into account the possibility of a borrower failing to repay the loan. Imperfect information among bankers results

³²In alternative simulations, I considered different response parameters for relaxing the collateral constraint, ranging from 0.4 to 2.5. The difference in the output and capital responses is negligible.

in higher assessments of counterparty risk after crisis episodes, as bankers are not sure how persistent the negative shock will be. The interbank market serves as the shock-propagating mechanism as lending shrinks.

To study how imperfect expectations and/or waves of pessimism amplify crisis shocks, I consider several types of crises: with and without pessimism shocks and a crisis driven purely by pessimism. The model dynamics of the crisis with a pessimistic shock match the data reasonably well, so I use it for policy simulations. I further show that even a pure pessimism shock on its own can generate a small recession.

I consider several types of central bank policy responses, including unlimited liquidity provision, targeted credit support, and varying the interest rate on reserves. Market pessimism dampens the positive effects of policies, incentivizing banks to hoard central bank funds in reserves instead of transferring them through the bank lending channel. Compared with the model without an interbank market and rational expectations of Gertler and Karadi (2011), the policy effects are smaller and delayed.

A low policy rate (reserve rate) in my model devastates bank balance sheets and results in a worse recession than in the case of no policy response. Even though it stimulates the interbank market and increases the number of investors, the wealth effect dominates.

Appendix A. The Bank's Filtering Problem

Banks update their forecasts using the Kalman filter. The state-space representation of the filtering problem is given by the following equations.

The state equation is

$$(\mu_t) = (\rho_\mu) \times (\mu_{t-1}) + (v_t), \quad (\text{A.1})$$

where q is the variance of the i.i.d. Gaussian shock v_t .

The measurement vector consists of two types of signals: data on ξ_t and the expert opinion, θ_t^i . The measurement equation is

$$\begin{pmatrix} \xi_t \\ \theta_t^i \end{pmatrix} = \begin{pmatrix} (1 - \rho_\xi)\bar{\xi} \\ 0 \end{pmatrix} + \begin{pmatrix} 1 \\ 1 \end{pmatrix} \times \mu_t + \begin{pmatrix} \rho_\xi \\ \rho_\theta \end{pmatrix} \begin{pmatrix} \xi_{t-1} \\ \theta_{t-1}^i \end{pmatrix} + \begin{pmatrix} \varepsilon_t \\ \tilde{\eta}_t^i \end{pmatrix},$$

where ε_t and $\tilde{\eta}_t^i$ are Gaussian.³³ The measurement equation can be rewritten as

$$\tilde{\xi}_t^i = A + C\mu_t + D\tilde{\xi}_{t-1}^i + \varpi_t^i, \text{ where}$$

$$A = \begin{pmatrix} (1 - \rho_\xi)\bar{\xi} \\ 0 \end{pmatrix}, C = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, D = \begin{pmatrix} \rho_\xi \\ \rho_\theta \end{pmatrix}, \tilde{\xi}_t^i = \begin{pmatrix} \xi_t^i \\ \theta_t^i \end{pmatrix}$$

and $\varpi_t^i = (v_t, \tilde{\eta}_t^i)'$ is a vector of measurement errors with the variance-covariance matrix:

$$R = \begin{pmatrix} \sigma_\varepsilon^2 & \sigma_{\varepsilon\tilde{\eta}} \\ \sigma_{\varepsilon\tilde{\eta}} & \sigma_{\tilde{\eta}}^2 \end{pmatrix},$$

where $\sigma_{\varepsilon\tilde{\eta}}^2$ is the covariance of the errors in econometric and expert forecasts.

Appendix B. Correlation of Experts' Opinions and the Mean Market Belief and Its Variance

Proof of Proposition 1

Expert opinions, when linearized, are defined as

$$\theta_t = \rho_\theta \theta_{t-1} + \eta_t^i,$$

where η_t^i is the noise in the opinion of bank i 's expert, with $\eta_t^h \sim N(\mu_t, \sigma_\eta)$. I assume that the noise in expert opinions is correlated. That is, when one expert over/underestimates the value of a persistent shock, others tend to do the same. Technically, I model correlated draws in the following way. First, there are N ³⁴ independent draws from $N(\mu_t, \sigma_\eta)$. Then, each of the independent draws is rescaled:

$$\tilde{\eta}_t^i = \rho^c \eta_t^1 + \sqrt{1 - (\rho^c)^2} \eta_t^i, \quad h \neq 1, \tag{B.1}$$

³³ η_t^i from (5) can be rewritten as $\eta_t^i = \mu_t + \tilde{\eta}_t^i$.

³⁴In the text I assume the existence of a continuum of H banks, normalized to 1. Here, for computational purposes, I use N as the number of banks and set it equal to a "large number": $N = 100$.

where η_t^i is one of the independent draws and ρ^c is the correlation coefficient:

$$\rho^c = \frac{Cov(\bar{\eta}_t^i, \bar{\eta}_t^j)}{\sqrt{Var(\eta_t^i) Var(\eta_t^j)}}, i \neq j,$$

where $Var(\eta_t^i) = Var(\eta_t^j) = Var(\bar{\eta}_t) = \sigma_\eta^2$. The last equality comes with the observation that $Var(\bar{\eta}_t^h) = (\rho^c)^2 Var(\eta_t^1) + (1 - (\rho^c)^2) Var(\eta_t^h)$. With η_t^h and η_t^1 being drawn from the same distribution, $Var(\bar{\eta}_t^h) = ((\rho^c)^2 + 1 - (\rho^c)^2) Var(\eta_t^h) = Var(\eta_t^h)$.

Using (B.1), I thus obtain a sequence of random variables, correlated with each other with correlation coefficient ρ^c . Because in equilibrium only the average shock to market beliefs matters, I now proceed to derive its properties. The expected average belief shock can be defined as

$$\frac{1}{N} E \left(\eta_t^1 + \sum_{h=2}^N \bar{\eta}_t^h \right) = \frac{1}{N} E \left(\eta_t^1 + (N - 1) \eta_t^1 \rho^c + \sqrt{1 - (\rho^c)^2} \sum_{h=2}^N \eta_t^h \right). \tag{B.2}$$

Note that η_t^1 and $\eta_t^{h, h \neq 1}$ are independent and drawn from the same distribution. This means that the expectation of their sum equals the sum of their expectations, which are unconditional expectations μ_t . The expected average belief shock is then

$$\mu_t \frac{1}{N} \left(1 + (N - 1) \left(\rho^c + \sqrt{1 - (\rho^c)^2} \right) \right). \tag{B.3}$$

Note that with $\rho^c = 1$ in the case of perfect correlation and with $\rho^c = 0$ in the case of no correlation, the expected average of the correlated draws corresponds to the unconditional mean. Also, unless μ_t is zero, the average belief shock is not equal to the distributional mean.

The variance of the average belief shock is then

$$\sigma_\eta^2 \left(1 + (N - 1)^2 \left((\rho^c)^2 + 1 - (\rho^c)^2 \right) \right) = \sigma_\eta^2 \frac{(2 + N^2 - 2N)}{N^2}. \tag{B.4}$$

□

Appendix C. Distribution of Individual and Mean Bank Forecasts

Recall that the individual bank expectation of the risky asset return is

$$E_t^i R_{t+1}^k = E_t^i \left(\frac{\alpha P_{m,t+1} Y_{t+1}}{K_t Q_t} + \frac{(Q_{t+1} - \delta_{t+1}) \xi_{t+1}}{Q_t} \right). \quad (\text{C.1})$$

And the individual predictions of $\xi_{t+1} \sim N[E_t^i \xi_{t+1}, \sigma_\xi^2]$, where the values of $E_t^i \xi_{t+1}$, σ_ξ^2 are the results of the Kalman filter, are

$$E_t^i \xi_{t+1} = (1 - \rho_\xi) \bar{\xi} + \rho_\xi \xi_t + E_t^i \mu_{t+1}, \quad (\text{C.2})$$

$$\begin{aligned} E_t^i \mu_{t+1} &= \rho_\mu E_{t-1}^i \mu_t + k_{11} (\xi - E_{t-1}^i \mu_t - \rho_\xi \xi_{t-1} - (1 - \rho_\xi) \bar{\xi}) \\ &\quad + k_{22} (\theta_t^i - E_{t-1}^i \mu_t), \end{aligned} \quad (\text{C.3})$$

where the last equality is the Kalman-filter equation for forecasting μ with the setup described in Appendix A, and k_{11} and k_{22} are elements of the Kalman gain matrix. These elements are functions of the signal variance and persistence, so they are the same for all agents. Now, take the mean of the individual forecasts:

$$\bar{E}_t \xi_{t+1} = \rho_\xi \xi_t + \bar{E}_t \mu_{t+1}, \quad (\text{C.4})$$

$$\bar{E}_t \mu_{t+1} = \rho_\mu \bar{E}_{t-1} \mu_t + k_{11} (\xi_t - \bar{E}_{t-1} \mu_t - \rho_\xi \xi_{t-1}) + k_{22} (\bar{\theta}_t - \bar{E}_{t-1} \mu_t). \quad (\text{C.5})$$

It follows that the mean, $\bar{E}_t \mu_{t+1}$, is a linear combination of the mean expert opinion $\bar{\theta}$, which, as was shown in Appendix B, is the mean of the expert opinion shocks adjusted for the correlation.

The variance of the forecasts across banks, σ_ξ^2 , is $\sigma_\epsilon^2 + \sigma_{\mu,t|t}^2$, where $\sigma_{\mu,t|t}^2$ is the variance of the Kalman-filter forecasts, identical for all banks. We can rewrite the mean and variance of the capital quality forecast as

$$\bar{E}_t R_{t+1} = \frac{\alpha P_{m,t+1} Y_{t+1}}{K_t Q_t} + \frac{(Q_{t+1} - \delta_{t+1}) \bar{E}_t \xi_{t+1}}{Q_t}, \quad (\text{C.6})$$

$$\sigma_R^2 = \left(\frac{Q_{t+1} - \delta_{t+1}}{Q_t} \right)^2 \sigma_\xi^2. \quad (\text{C.7})$$

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