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A Model of Financial Instability and Bank Leverage

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The Safer, the Riskier: A Model of Financial Instability and Bank Leverage*

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Abstract

We examine the role of bank leverage to explain why the 2007-08 financial crisis unfolded at a time when the economy appears to be less fragile to crisis risks. To this end, we extend the model introduced by Diamond and Rajan (2012) to a variant where the probability of financial crises varies endogenously. In our model, aggregate liquidity shock plays a key role in precipitating a crisis because high liquidity demand in a highly leveraged banking system is likely to expose the economy to greater crisis risks. We consider an example of a "safe" environment where liquidity demand tends to be low on average. Using numerical analysis, we show that the "safer" environment could incentivize banks to raise their leverage, resulting in a banking system that is more vulnerable to liquidity shocks.

JEL Classification: E3, G01, G21

Keywords: Bank run; Financial crisis; Maturity mismatch

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1 Introduction

A consensus on the 2007-08 crisis is that, with hindsight, the banking sector had been exposed to high risks of insolvency before the crisis took place. Conversely, there was a widely-held perception in the run-up to the crisis that the banks were placed in a "safe" environment.[1]

Relatedly, a notable fact is that funding liquidity for banks, was quite affluent before the crisis. Gorton and Metrick (2012 a,b) point out that the market for repurchase agreements (repo), which provides short-term funding for banks and other financial institutions, rapidly grew in the periods prior to the 2007-08 crisis. In the meantime, prices of funding liquidity remained at a quite low level. For example, the TED spread, an indicator of funding liquidity, declined to historically low levels in the early 2000s and leveled off until 2006.[2] Figure 1 plots the TED spread, together with net repo funding to banks and broker-dealers from 1998:Q1 to 2008:Q4. The combination of the low prices of funding liquidity and expanding short-term funding markets implies that demand for funding liquidity by banks was low relative to the supply. In the presence of such abundant liquidity or relatively low demands for liquidity, banks can feel safe, standing a distance away from risks of financial crises. A key question is why the financial crisis unfolded at a time when the banking sector was considered surrounded by such a "safe" environment.

This paper aims to explain how a "safer" environment can increase the probability of bank runs. A key to understand this "the safer, the riskier" case is the banks' endogenous risk-taking. We show that the banks' risk-taking with higher leverage offsets, or even dominates, the exogenously improved environment in terms of the bank run probability. In particular, a "safe" environment, represented by a low demand for funding liquidity, incentivizes banks to raise their leverage. The increased leverage can result in a higher risk of bank runs.

Our model is based on the framework of bank runs developed by Diamond and Rajan (2001, 2012). In Diamond and Rajan (2001), banks' commitment to repaying demandable deposits works as a disciplinary device for banks to raise funds. While the maturity transformation promotes

[1]For example, Reinhart and Rogoff (2009, p.208) noted that the 2007-08 financial crisis came as a surprise from the viewpoint of investors because "the financial meltdown of the late 2000s was a bolt from the blue, a 'six-sigma' event."

[2]Other similar indicators of funding liquidity, such as LIBOR-OIS spread and repo rates remained at low levels as well.

financial intermediation, such funding via demandable liabilities exposes banks to some risks of bank runs. Using a simplified framework of Diamond and Rajan (2001), Diamond and Rajan (2012, hereafter DR) demonstrated how and why low interest rate policies deployed by a central bank raise banks' leverage and endangers the financial stability. In this paper, we use the DR's framework for a different purpose, that is, to answer the above-mentioned key question. To assess the effect of "safe" environment for banks, two distributions for liquidity (preference) shocks are compared: the "risky" and "safe" distributions in the sense that the depositors' demands for liquidity are high or low, on average. Our finding that "the safer, the riskier" implies that the bank run probability can increase even in the absence of any policy intervention, which is in a sharp contrast to the main focus of DR.

While we model banks funded by demand deposits following the classic literature of banking, the banks in our paper can refer to broader financial intermediaries that raise funds via short-term debts (e.g., a repo) and invest them in longer-term assets, by maturity transformation. (See Diamond and Rajan, 2001.) The lower price for funding liquidity in the pre-crisis periods can be translated into a model of classic banking where fewer depositors (i.e., suppliers of short-term funding for banks) come to banks to withdraw their deposit. In the same spirit, Gorton and Metrick (2012b) point out that the "run on repo" which happened in the 2007-08 financial crisis was a systemic bank run. In line with this view, we focus on the aggregate liquidity shock that affects depositors as the liquidity suppliers for banks. As a result, we can assume that "bank runs" and "financial crises" are interchangeable in our very stylized model.

In comparison with the early studies discussing the mechanism of financial crises, this paper relies neither on contagion nor externalities.[3] In a similar spirit of DR, there are a number of studies arguing that the growing expectations of bank bailouts or the low interest rate policy by the central banks might be responsible for the crisis.[4] We do not claim that all these factors did

[3]The role of contagion for understanding crises is emphasized by Allen and Gale (2000), Dasgupta (2004), Allen and Carletti (2006), and Acharya and Yorulmazer (2008), Allen, Babus, and Carletti (2012), and Castiglionesi, Feriozzi, and Lorenzoni (2012). Lorenzoni (2008) and Jeanne and Korinek (2010) develop models in which financially constrained borrowers take on more risks due to pecuniary externalities. Stein (2012) and Gersbach and Rochet (2012) discuss pecuniary externalities in models with banks.

[4]Examples include Farhi and Tirole (2012), Jiménez, Ongena, Peydró and Saurina (2014), and Maddaroni and Peydró (2011). The low interest rate policy is closely related to the risk-taking channel of monetary policy. Angeloni, Faia, and Lo Duca (2014) introduce demandable deposits as a disciplinary device in Diamond and Rajan (2001)

not play critical roles for the 2007-08 crisis. Rather, this paper provides an example where the crisis probability rises even without these factors such as policy interventions and externalities.

The rest of the paper is organized as follows. Section 2 introduces the model. In Section 3, we discuss the main numerical results with some robustness checks. Section 4 concludes.

2 The Model

2.1 Setup

We consider a variation of the economy developed by DR in which the bankers are intermediating the funds from households to entrepreneurs via maturity transformation. Most of the assumptions are maintained in line with the original DR model except for the households' preference and the flow of their income. In DR, households' utility function is given by $U(C_1, C_2) = \log(C_1) + \log(C_2)$, where C_t is consumption at date t. Also, DR assume that the random shock arises from the uncertainty over expectations on future income and consider finite discrete aggregate states. By contrast, we eliminate uncertainty with respect to households' income while incorporating a more straightforward random shock regarding liquidity preference into our model. Specifically, households' utility function is given by $U(C_1, C_2) = \theta \log(C_1) + (1 - \theta) \log(C_2)$, where θ is a continuous random variable with a support $\theta \in (0, 1)$. Here, θ can be interpreted as a "liquidity shock," which indicates how much liquidity is needed at date-1 consumption. Seemingly, the utility function takes the same form as the expected utility in Allen and Gale (1998). However, we emphasize that there is neither an early consumer nor a late consumer in this economy. Our model includes only single type of households, who are subject to perfectly correlated liquidity shocks across households. In our model, θ is the only source of the aggregate uncertainty, which precipitates a crisis in this economy. The utility function provides the advantage that we can focus on aggregate uncertainty and an endogenously changing crisis probability in a straightforward manner.

Following DR, we assume three types of agents: (i) households, (ii) entrepreneurs, and (iii)

into their dynamic stochastic general equilibrium model and study the monetary transmission in the model with endogenous probability of bank runs.

bankers. As assumed by DR, while the households are risk averse, the entrepreneurs and bankers are risk-neutral.

The economy lasts for three dates ($t = 0, 1, 2$). At date 0, households are born with a unit of a good. By assumption, no household consumes at date 0. Rather, they deposit all the date-0 endowments into banks. Bankers compete to offer the most attractive promised deposit payment D to households (per unit of endowment deposited). Then, bankers lend the households' endowment to entrepreneurs. Each entrepreneur invests a unit of the good to launch a long-term project at date 0. These transactions are settled before the realization of the liquidity shock.

At date 1, the liquidity shock θ is realized. Households determine the date-1 withdrawal w_1 to smooth out their consumption, given the realized θ (and their fixed endowment at dates 1 and 2). Turning to entrepreneur's project, each of the projects yields a random output $\tilde{Y}_2$ at its completion at date 2. Outcomes of projects follow a uniform distribution with a support $[0, \bar{Y}_2]$. In this model, there is no aggregate uncertainty in $\tilde{Y}_2$, and thus the financial stability entirely relies on the aggregate uncertainty in θ. If a project is prematurely liquidated, the project produces $X_1\,(< 1)$ at date 1. If each banker needs to liquidate all projects to meet a high liquidity demand (i.e., full withdrawal of the deposit), a crisis takes place at date 1. Otherwise, at date 2, households consume the rest of deposits together with the date-2 endowment.

In the following sections, we first describe the agent's decisions *after* the realization of θ and then the bankers' choice of D *before* the realization of θ.

2.2 Demand for liquidity

A household chooses its withdrawal w_1, given deposit face value D, the one-period gross interest rate r_{12} (from date 1 to 2), and the liquidity shock θ. The interest rate r_{12} represents the price for liquidity, which equates the demand (withdrawal) with the supply (liquidated projects) of liquidity. Throughout this paper, we focus on an economy in which storage technology is not available to households and bankers.[5]

[5] In the appendix, which is available upon request, we present the model with storage and show that our main results are essentially the same as in the model without storage.

Given that a crisis is not taking place, the households' maximization problem is given by

$$\max_{w_1} \quad \theta \log C_1 + (1-\theta) \log C_2, \tag{1}$$

$$\text{s.t. } C_1 = e_1 + w_1 \tag{2}$$

$$C_2 = e_2 + r_{12}(D - w_1), \tag{3}$$

where e_t is the household's endowment at date t. Here, θ determines the need for liquidity for each date. If θ is low, households' deposits are likely to be fully repaid by bankers over the two periods, which means that the households smooth out their consumption. If θ exceeds a threshold value, however, the households' deposits are not fully repaid. Then, a crisis (i.e., a run on the entire banking system) takes place and each household receives X_1 at date 1 and nothing at date 2 from the bankers. Thus, the households fail to smooth out their consumption and end up with $C_1 = e_1 + X_1$ and $C_2 = e_2$. Note that, based on the "business cycle view" as argued by Gorton (1988) and Allen and Gale (1998, 2007), we implicitly assume an information structure in which crises are precipitated as a Nash equilibrium when bankers are revealed to be insolvent.[6]

When the households can smooth out their consumption, the intertemporal first-order condition for consumption $[\theta/(1-\theta)](C_1/C_2)^{-1} = r_{12}$ is satisfied. Due to the budget constraints (2) and (3), the withdrawal can be written as

$$w_1 = \theta\left(\frac{e_2}{r_{12}} + D\right) - (1-\theta)\, e_1. \tag{4}$$

It is convenient to define the households' lifetime income in normal times by m:

$$m = e_1 + D + \frac{e_2}{r_{12}}. \tag{5}$$

The log-utility implies that consumption in normal times is proportional to m, namely, $C_1 = \theta m$

[6]Other types of Nash equilibriums, including a coordinated bank holiday, could exist depending on the information structure. A quick fix to exclude such equilibriums is to assume a belief that, while all households are in fact homogeneous, an infinitesimally small number of households may have different preferences from others. Allen and Gale (1998, 2007) discuss this in more detail.

and $C_2 = (1-\theta)\, r_{12} m$.

2.3 Banks assets and supply of liquidity

Entrepreneurs and bankers in our model replicate those in DR. Each banker is a relationship lender that has obtained special knowledge of the entrepreneurs' business, and this knowledge ensures the banker's collection skill to acquire a fraction $\gamma \tilde{Y}_2 (< \tilde{Y}_2)$ of the output from the entrepreneurs. The collection skill is assumed to be not transferable to other lenders. Following DR, we denote the realization of $\tilde{Y}_2$ by Y_2 and assume that Y_2 becomes known at date 1. As in DR, we assume that each banker lends to enough entrepreneurs. As a result, all the symmetric bankers share an identical portfolio. Let the bankers' assets be $A(r_{12})$. Then, $A(r_{12})$ can be expressed as

$$A(r_{12}) = \frac{1}{\bar{Y}_2} \int_0^{Y_2(r_{12})} X_1 dY_2 + \frac{1}{\bar{Y}_2} \int_{Y_2(r_{12})}^{\bar{Y}_2} \frac{\gamma Y_2}{r_{12}} dY_2, \tag{6}$$

where the first term of the equation indicates the supply of liquidity (i.e., the values of liquidated projects), while the second term represents completed projects evaluated at $t = 1$. In (6), $Y_2(r_{12})$ denotes the cut-off level of return on projects satisfying $Y_2(r_{12}) = r_{12} X_1 / \gamma$. The cut-off level of return on projects can be understood from the bankers' liquidation decision: if they liquidate a project to meet households' liquidity demand, they would obtain X_1 at date 1. Conversely, if they let the project continue, the present value of the continued project is $\gamma Y_2 / r_{12}$. Taking r_{12} as given, bankers' liquidation decision is made by comparing X_1 with $\gamma Y_2 / r_{12}$. This comparison determines the cut-off level of return on projects. Furthermore, it can be easily shown that $A'(r_{12}) < 0$ for the economically meaningful range of r_{12}.[7]

Bankers become insolvent if the solvency condition $D \leq A(r_{12})$ is violated. In this case, crises are precipitated: the bankers liquidate all of the entrepreneurs' projects, repay X_1 to households, and lose all their assets. We then define the threshold interest rate r_{12}^*, which satisfies the solvency condition with equality:

$$D = A(r_{12}^*), \tag{7}$$

[7] The proof is available upon request in the separate appendix.

where r_{12}^{*} strictly decreases with D since $A'(\cdot) \leq 0$.[8] In other words, a higher level of D requires a lower level of the threshold interest rate r_{12}^{*}, which can be written as $r_{12}^{*} = A^{-1}(D) \equiv r_{12}^{*}(D)$, for the bankers to be solvent. Note that there is a clear distinction between the threshold interest rate, r_{12}^{*} and the price of liquidity, r_{12}. While the former is solely determined by D in (7) at date 0, the latter reflects the supply and demand in the liquidity market at date 1.

2.4 Market equilibrium

In normal times, the following liquidity market clearing condition holds:

$$\theta\left(\frac{e_2}{r_{12}} + D\right) - (1-\theta)\, e_1 = \frac{(X_1)^2\, r_{12}}{\gamma \bar{Y}_2}, \tag{8}$$

which has two roots for r_{12} but gives only one positive r_{12}. The left-hand side of the equation points to liquidity demand (4), while the right-hand side indicates supply from project liquidation shown in (6).

Whereas the threshold interest rate r_{12}^{*} is solely determined by D in (7), the threshold value of θ that precipitates crises is determined by r_{12}^{*} together with (8). Let θ^{*} be the threshold value of θ that precipitates crises if and only if $\theta > \theta^{*}$. Evaluating r_{12} in (8) at $r_{12}^{*} = r_{12}^{*}(D)$, we have

$$\theta^{*} = \frac{(X_1)^2\, r_{12}^{*}/\left(\gamma \bar{Y}_2\right) + e_1}{e_1 + D + e_2/r_{12}^{*}}. \tag{9}$$

which indicates that, since $r_{12}^{*} = r_{12}^{*}(D)$ is strictly decreasing in D, θ^{*} is also strictly decreasing in D. When we emphasize this relationship between θ^{*} and D, we express θ^{*} as $\theta^{*}(D)$ and express its first derivative as $\theta^{*\prime}(D)$. We also note that, because a larger liquidity shock increases households' withdrawal, a smaller θ^{*}, by definition, points to a higher crisis probability. Denoting π as the probability of the financial crises, π can be expressed as $\pi(\theta^{*}) = 1 - F(\theta^{*})$, where $F(\theta)$ is the cumulative distribution function of θ.

[8] Note that $r_{12}^{*}(D) \equiv A^{-1}(D)$ and, by the inverse function theorem, $r_{12}^{*\prime}(D) = 1/A' < 0$.

2.5 Bankers' Choice of Leverage

Diamond and Rajan (2001) argued that demand deposits D serve as a commitment device for bankers. Demand deposits, like other short-term funding vehicles, can compensate for the lack of transferability of the bankers' collection skill to others (e.g., households) and thus promote liquidity creation. In line with this argument, the bankers in our model need to determine the face value of deposits before observing θ. As a result of competition, the bankers make a competitive offer of deposits for households. The competitive offer maximizes the household welfare taking the distribution of θ as given.[9] Here, given θ, the choice of D has a one-to-one relationship with the bank leverage. The bank leverage in our model can be defined as $D/\left[A\left(r_{12}\right)-D\right]$ and is determined once D is chosen. Therefore, in our model, the optimal choice of D and the optimal choice of bank leverage can be treated interchangeably.

Formally, the bankers choose D to maximize

$$\begin{aligned} &\int_0^{\theta^*(D)} \left\{\theta \log\left(\theta m\right) + (1-\theta)\log\left[(1-\theta)\, r_{12} m\right]\right\} dF\left(\theta\right) \\ &\quad + \int_{\theta^*(D)}^{1} \left[\theta \log\left(e_1 + X_1\right) + (1-\theta)\log\left(e_2\right)\right] dF\left(\theta\right), \end{aligned} \tag{10}$$

subject to (5), (8), (9), and $r_{12}^* = r_{12}^*(D)$ from (7). Here the first term of (10) corresponds to the utility from consumption under no crisis, while the second term points to the utility from consumption under a crisis. The integral is taken over $\theta \in (0, \theta^*]$ for the first term, because any θ that is lower than or equal to the threshold value does not precipitate crises. In contrast, the second term indicates that bankers recognize that consumption smoothing is impossible for $\theta > \theta^*$.

The first-order condition for D is given by

$$\begin{aligned} &\left\{\theta^* \log\left(\frac{\theta^* m^*}{e_1 + X_1}\right) + (1-\theta^*)\log\left[\frac{(1-\theta^*)\, r_{12}^* m^*}{e_2}\right]\right\} \pi'\left(\theta^*\right)\theta^{*\prime}\left(D\right) \\ = &\int_0^{\theta^*} \left[\frac{1}{m}\left(1 - \frac{e_2}{r_{12}^2}\frac{\partial r_{12}}{\partial D}\right) + \frac{1-\theta}{r_{12}}\frac{\partial r_{12}}{\partial D}\right] dF\left(\theta\right), \end{aligned} \tag{11}$$

[9] In the model, the bankers in fact are maximizing their own profits by household welfare maximization. See Allen and Gale (1998) and DR for more details on the bankers' optimization problem.

where $m^* = e_1 + D + e_2/r_{12}^*$. By the definition of $\pi(\theta)$, $\pi'(\theta^*)$ is equal to $-f(\theta^*)$, where $f(\theta^*)$ denotes the probability density function evaluated at $\theta = \theta^*$. The partial derivative $\partial r_{12}/\partial D$ can be implicitly defined by the liquidity market clearing condition (8).

In choosing the optimal D, bankers strike the right balance between the marginal benefit and cost of increasing D on behalf of the households. The right-hand side of (11) can be interpreted as the marginal benefit of increasing D through changes in households' lifetime income and interest rate. Intuitively, a higher D allows households to receive higher income from their deposits and to enjoy more consumption at both dates. Hence, as far as $\theta \leq \theta^*$, households obtain higher returns from increasing D.

The left-hand side of (11) represents the marginal cost of increasing D. The terms in the curly brackets indicate the loss of the utility due to a crisis. The term outside the curly brackets assesses the marginal changes in the crisis probability in response to an increase in D. Hence, putting them all together, we can interpret the left-hand side as the marginal cost of increasing D.

3 Simulating the Model

3.1 Calibration

To evaluate impacts of changes in environment surrounding the banking sector, we numerically solve the model. For simulating the model, we need to determine five parameters: the maximum productivity of entrepreneurs' projects ($\bar{Y}_2$), the value of liquidated project (X_1), the bankers' collection skill (γ), and households' endowment at dates 1 and 2 (e_1, e_2). For the distribution of θ, we assume that θ is generated from the beta distribution.

In terms of assigning values for parameters, we borrow parameter values from DR whenever feasible. We take $\bar{Y}_2 = 3.5$, $X_1 = 0.95$ and $\gamma = 0.90$ from DR. In parameterizing households' endowment, we do not borrow parameter values from DR since our model differs from DR in terms of the assumption on the aggregate uncertainty. For this reason, we calibrate e_1 and e_2 to ensure that two targets are matched with the U.S. data. The first target is the bank capital ratio of 10.3

percent. The targeted bank capital ratio is taken from the U.S. data in 2007.[10] The second target is the crisis probability of 4.76 percent. We take the target crisis probability from Laeven and Valencia (2013) who report that there were two banking crises in the U.S. between 1970 and 2011. Given their finding, the frequency of banking crises in the U.S. is 4.76 percent per year (i.e., 2/42 = 0.0476). We employ this value as a proxy for the crisis probability in the U.S. banking sector.[11] Moment matching of the bank capital ratio and the crisis probability results in $e_1 = 0.305$ and $e_2 = 0.405$. The calibrated values of e_t give rise to a plausible pattern in the economy before the crisis. Namely, households' income is expected to grow in the run-up to the crisis, which was also observed in the U.S. economy.

The remaining parameters required to solve the model are those for the distribution of θ. We set benchmark parameters for the beta distribution to ensure that $\mu_\theta = 0.5$ and $\sigma_\theta = 0.05$, where μ_θ and σ_θ denote the mean and the standard deviation of θ, respectively.[12] The liquidity preference shocks are, by nature, unobservable and there is no solid empirical counterpart on these parameters. Hence, we perform extensive robustness analysis for these parameters.

We numerically compute the equilibrium by solving the system of nonlinear equations. The equations in the system are (8) and (11) together with the definitions of r_{12}^*, θ^*, m, and m^*. The first column of Table 1 shows the computation results under the benchmark calibration. Bankers set the level of the deposit face value D at 1.052 and the resulting θ^* is 0.584.

Figure 2 plots the households' expected utility over a variety of deposit face values D. The figure also articulates the sub-components of the utility. The smooth bell shape of the utility can be understood as the weighted average of the two sub-components, (i) the expected utility in the absence of a run $E(U|\text{no run})$ and (ii) the expected utility under a run $E(U|\text{run})$. In the figure, the probability of a crisis is represented by the ratio of the distance along the vertical axis between the solid and the upper dashed lines to that between the upper and lower dashed lines.

[10] The data source is from the World Development Indicators published by the World Bank.

[11] We also used the frequency of banking crises in North America reported by Reinhart and Rogoff (2013) for robustness analysis. While our calibrated values of e_t differ slightly from the benchmark calibration, the results are qualitatively unaltered.

[12] In parameterizing μ_θ, we follow DR who assumed the equal weight on the date-1 utility and the date-2 utility.

3.2 Results

The experiment that we perform here investigates changes in the distribution of the underlying shock θ. Table 1 compares the crisis probabilities for a few cases where we change μ_θ while keeping σ_θ unchanged. Recall that the probability of a crisis was targeted at 4.76 percent in the initial "risky" distribution with $\mu_\theta = 0.50$ (Case 1 in Table 1). Now, suppose that μ_θ declines to 0.35, which corresponds to a "safer" environment in our model.[13]

With the lower mean of 0.35 in the "safer" distribution, the probability of a crisis declines from 4.76 to 0.0004 percent (Case 2 in Table 1), *if bankers keep their leverage unchanged at the level under Case 1.* Thus, a decrease in μ_θ implies that bankers find that crises are precipitated by extremely small upper tail risks (i.e., a risk of a large θ). Put differently, they recognize that the fundamentals are safe.

This is not the end of the story, however. Table 1 also reports that, when μ_θ declines, the bank leverage increases (i.e., $D = 1.21$ in Case 3). In our model, bankers have a strong incentive to raise D when they face a smaller upper tail risk. Though a higher leverage gives rise to higher returns to households, it also increases the risk of bankers' insolvency. As a result, the high leverage elevates the crisis probability to 5.77 percent. Therefore, it is not always true that the "safer" the economy, the more secure the banking system.

Figure 3 shows how bank leverage affects the crisis probability through θ^*. If bankers do not react to the change in the distribution of θ, θ^* remains unchanged at $\theta^* = \theta_R^* (= 0.58)$. In the safer distribution in Cases 2 and 3, this θ_R^* implies a crisis probability of nearly zero. However, if bankers react to the changes in fundamentals correctly, θ^* decreases from θ_R^* to $\theta_S^* (= 0.43)$, giving rise to a higher crisis probability (region A in Figure 3).

What policy-relevant lesson can we learn from our analysis? To assess crisis risks in the banking sector, it is essential to take into account the bankers' own behaviors and responses to the environments, together with the environments surrounding them. Otherwise, risk assessment, particularly when assuming the bankers' behavior held unchanged, can give rise to an over-optimistic conclu-

[13] The value of the lower $\mu_\theta = 0.35$ can be inferred by the actual decline in the TED spread observed in the early 2000s. (See Figure 1.) We confirmed that the size of the decline in the TED spread is comparable to that in the corresponding price of funding liquidity in our model, $E\,(r_{12}|\text{no run})$.

sion (a too low crisis probability estimate, for example). To accurately estimate crisis probabilities, risks must be assessed based on the detailed knowledge about the banks' risk-taking, including their endogenous reactions to changes in environments surrounding them.

3.3 Robustness

Because our simulation exercise has provided only one example of the "the safer, the riskier" case, one may naturally ask whether this result is robust to changes in parameters. We thus examine the parameter ranges where "the safer, the riskier" is the case. Figure 4 plots π and D against μ_θ, while other parameters (except for σ_θ) are kept constant. The upper panel shows that the crisis probabilities are downward-sloping for a wide range of μ_θ under various σ_θ. This downward-sloping portion of the curve indicates that a "safe" environment represented by a low μ_θ raises the crisis probability if μ_θ is less than about 0.50.

In the lower panel of Figure 4, we observe that the curve for D shifts upward as σ_θ decreases, implying that a decrease in the volatility of liquidity preference shock fuels bankers' risk-taking. Using their dynamic stochastic general equilibrium model, Gertler, Kiyotaki, and Queralto (2012) also find that banks issue more short-term debt in the economy calibrated with a smaller volatility of a shock.[14] Therefore, regarding banks' risk-taking, the upward shifts in the curve are consistent with their result. On the other hand, our model further enables us to evaluate whether a decrease in volatility of shock elevates the crisis probability. Our simulation results in the upper panel suggest that, unlike the case of μ_θ, a decrease in volatility lowers the crisis probability because it dominates the effect of banks' risk-taking in terms of crisis probability.

Figure 5 also investigates whether the crisis probability remains decreasing in μ_θ even if we change other calibrated parameters e_1, $\bar{Y}_2$, γ, and X_1. Overall, the panels in the figure suggest that the curves for the crisis probabilities are downward-sloping if μ_θ is sufficiently low. In this robustness analyses, we choose the parameter ranges to ensure that our robustness analyses satisfy the following three criterions: (i) $D < 2.5$ so that the face value of demand deposit should not be unreasonably high; (ii) the expected bank capital ratio is strictly higher than 3 percent, which is

[14]In Gertler, Kiyotaki, and Queralto (2012), a shock to the aggregate capital in the economy is assumed rather than a shock to liquidity preference.

substantially low, relative to the bank capital ratio targeted for the benchmark simulation; (iii) $0.025 < \pi < 0.135$, with which we limit equilibrium crisis probabilities to a reasonable range, compared to the empirical studies.

4 Concluding remarks

We argued that the banking system can be incentivized to take on more risks by "safer" environments and thus can expose the economy to a higher crisis probability. In our experiment, we focused on the liquidity preference that had relatively abated as reflected in the data and translated it into a decline in the mean of liquidity preference shocks. Our model shows that the banks' risk-taking reacting to the improved environment often dominates the outright effect of the improved environment itself, in terms of the crisis probability. Our numerical simulations may provide an explanation why the 2007-08 financial crisis unfolded amid an economic environment favorable to the banking system. Beyond understanding the recent crisis, our main result in this paper suggests that risk assessment by policymakers should be made based not solely on environment surrounding banks, but on the banks' risk-taking together.

In terms of the normative implication, we note that Allen and Gale's (2003) argument can be applied to the present model. In other words, the laissez-faire banking sector in our model achieves the constrained-efficient allocation of risks as well as resources. As long as the planner uses the same contracting technology as the banking sector, policy interventions aiming at crisis prevention are likely to undermine welfare.[15] To examine how to reduce the crisis probability in a welfare-improving manner, the introduction of a welfare-relevant pecuniary externality into a richer model is useful in considering policy implications. For the purpose, Kato and Tsuruga (2013) develop a model with pecuniary externalities by extending the model introduced in this paper. Furthermore, other potentially important factors, such as contagion, imperfect information, and irrational over-optimism may amplify crises and enhance the importance of policy interventions for crisis prevention.

[15] On the policy perspectives, DR consider a variety of policy measures, assuming that the social planner has technologies superior to the banking sector (e.g., state-contingent bank bailouts).

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Table 1: Numerical simulation of crisis probabilities (π) for μ_θ

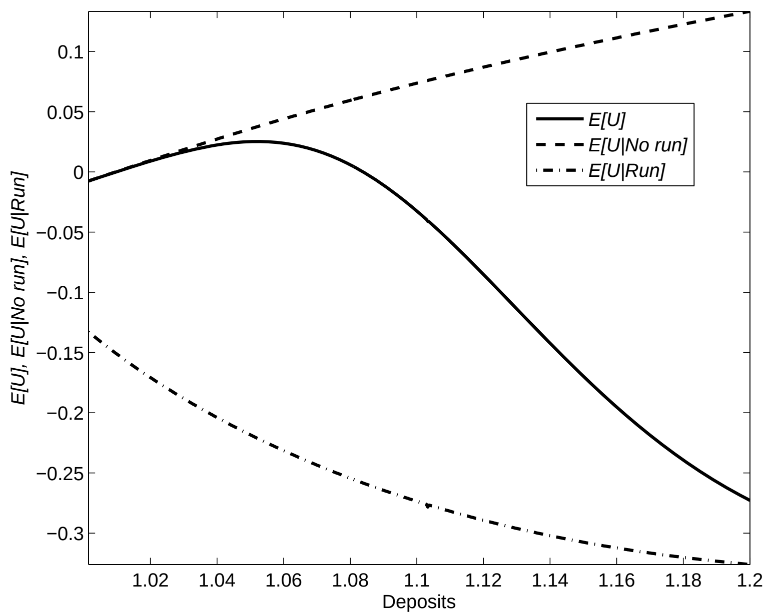
	Case 1	Case 2	Case 3
μ_θ	0.500	0.350	0.350
Crisis probability	4.760	0.0004	5.767
D	1.052	1.052	1.214
θ^*	0.584	0.584	0.431

Note: The crisis probability is expressed in terms of percent. The crisis probabilities and θ^* in Cases 1 and 3 are computed from the optimal leverage. The crisis probability and θ^* in Case 2 are computed under the assumption that the leverage in Case 1 is kept unchanged even when μ_θ is reduced to 0.35.

Figure 1: TED spread and net repo funding to banks and broker dealers

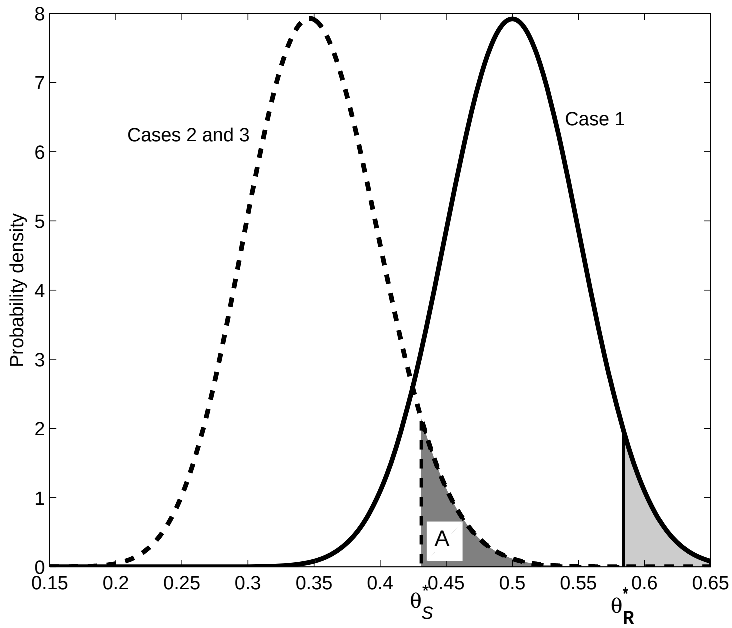
Note: The solid line represents the TED spread (the spread between 3-month LIBOR based on US dollars and 3-month Treasury Bill rate) from Federal Reserve Economic Data. The unit is percent. The dashed line shows net repo funding to banks and broker dealers taken from the Financial Accounts of the United States deflated by the Consumer Price Index for All Urban Consumers (All Items). The unit of net repo funding is billions of 2005 U.S. dollars.

Figure 2: Bankers' leverage and households' utility



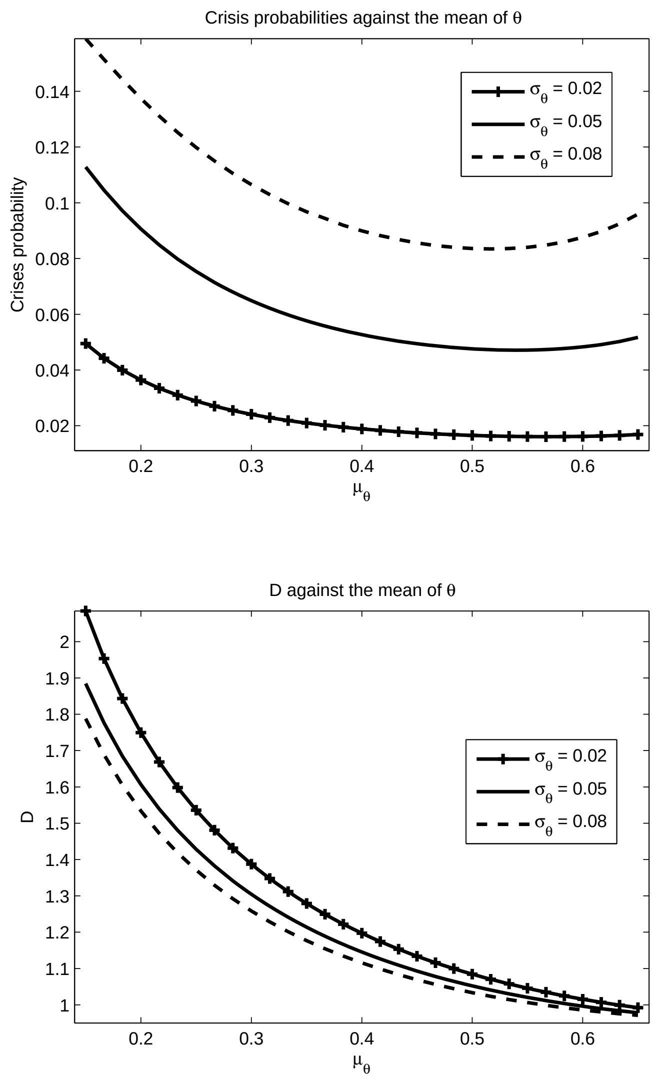
Note: The solid line represents the utility level against the face value of deposits that is computed from (10). The upward-sloping dashed line is the expected utility conditional on no bank run that is computed from the first line of (10) divided by 1-π. The downward-sloping dashed line is the expected utility conditional on a bank run that is computed from the second line of (10) divided by π . The calibration is based on the assumption that a liquidity shock follows a beta distribution with a mean of 0.50 and a standard deviation of 0.05.

Figure 3: Comparisons for distributions for θ



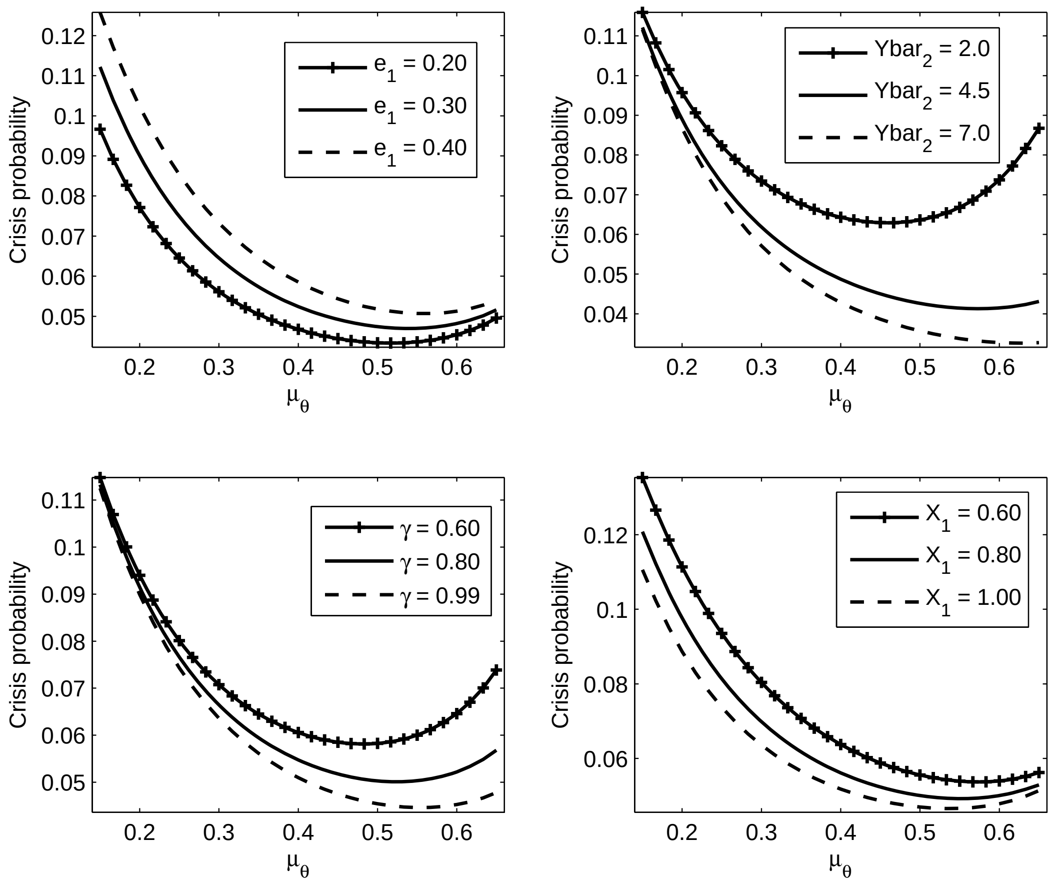
Note: The solid line represents the probability density function based on a beta distribution with a mean of 0.50 and a standard deviation of 0.05 (Case 1). The dashed line is the probability density function of a beta distribution with a smaller mean of 0.35 but with the same standard deviation (Cases 2 and 3). Here θ_R^* is the threshold value of a liquidity shock that precipitates a crisis under Cases 1 and 2, while θ_S^* is the threshold value corresponding to Case 3. The region A in the figure corresponds to the crisis probability in Case 3.

Figure 4: Crisis probabilities (π) and the optimal level of the deposit face value (D) against μ_θ



Note: The curve represents the crisis probabilities (the upper panel) and the optimal level of D (the lower panel) against the mean of θ. Each curve in both panels is plotted for σ_θ of 0.02, 0.05, and 0.08.

Figure 5: Robustness analysis



Note: The curve in each panel represents the crisis probabilities against the mean of θ. Each curve is plotted for various parameters in the model. The upper-left panel plots the crisis probability when e_1 = 0.20, 0.30, and 0.40. The upper-right panel plots the crisis probability when $\bar{Y}_2$= 2.0, 4.5, and 7.0. The lower-left panel plots the crisis probability when γ =0.60, 0.80, and 0.99. The lower-right panel plots the crisis probability when X_1= 0.60, 0.80, and 1.00.