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

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Ryo Kato
Bank of Japan

Takayuki Tsuruga
Graduate School of Economics, Kyoto University and
Centre for Applied Macroeconomic Analysis, ANU

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Keywords

Bank run, Financial crisis, Maturity mismatch

JEL Classification

E3, G01, G21

Address for correspondence:

(E) cama.admin@anu.edu.au

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

Ryo Kato[†] and Takayuki Tsuruga[‡]

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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.

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[†]Bank of Japan; e-mail: ryou.katou@boj.or.jp

[‡]Graduate School of Economics, Kyoto University and the Centre for Applied Macroeconomic Analysis ; e-mail: tsuruga@econ.kyoto-u.ac.jp

1 Introduction

A perception in the financial markets in the run-up to the 2007-08 financial crisis was that the banks were placed in a "safe" environment. As argued in Reinhart and Rogoff (2009, p. 214), for example, a perception held by policymakers was that "risks to the global economy had become extremely low and that, for the moment, there were no great worries." They also 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" (p. 208). In fact, reflecting such "safe" environments surrounding the banking sector, the LIBOR-OIS spread, a measure of risks of bank insolvency remained small and relatively constant, before it rose sharply in 2007.[1] A question is why the financial crisis unfolded at a time when the banking sector was considered being surrounded by such a "safe" environment.

This paper attempts to provide an explanation on how a "safe" environment could create a crisis-prone economy. To this end, we extend a model of bank runs developed by Diamond and Rajan (2012, hereafter DR). In our model, we assume that homogeneous depositors are faced with an aggregate liquidity (preference) shock that is drawn from a continuous distribution. Given the distribution of the liquidity shock, banks trade off the benefit of increasing the leverage with risks of bank runs in choosing their optimal leverage. The probability of bank runs endogenously varies as a result of the interaction between the distribution of the shock and the banks' choice of leverage. To assess the effect of "safe" environment on the bank run probability, two distributions for liquidity shocks are compared: the "risky" and "safe" distributions in the sense that the depositors' demands for liquidity are different on average.

We show that a "safer" environment can expose the banking sector to higher risks 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 fundamentals/environment in terms of the bank run probability. In particular, when the liquidity demand of depositors is expected to be low, banks feel at ease and then raise their leverage. The increased leverage can result in a higher risk of bank runs.

[1] See Thornton (2009).

While we model banks that make loans funded from demand deposits, the banks in our paper can refer to 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.) We take the "run-on repo" view that the 2007-08 financial crisis was a systemic bank run (Gorton and Metrick, 2012). In line with this view, this paper incorporates the aggregate liquidity shock into the model and assumes that "bank runs" and "financial crises" are interchangeable. Our assumption of the "safer" distribution for liquidity shock relies on the fact that the investors' supply of the short-term funds to the banking sector was rapidly growing especially in the repo market (Gorton and Metrick, 2012). The growing liquidity supply helped banks' fund-raising and promoted maturity mismatch in the banking sector. An interpretation in the context of the classic banking literature is that such a "safer" environment for banks would correspond to more willingness of the creditors (depositors) to supply funds to banks.

While the recent financial crisis revealed the significance of contagions and externalities, the adverse effect of a "safe" environment discussed by this paper relies neither on contagion nor externalities. 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 (2011) and Gersbach and Rochet (2012) discuss pecuniary externalities in models with banks.[2] In our model, we intentionally abstract financial contagion and welfare reducing/improving externalities to clarify the source of our main results. Likewise, there are a number of contributions arguing that the growing expectations of bank bailouts or the low interest rate policy by the central bank might be responsible for the crisis.[3] We do not claim that the above-mentioned factors do not play critical roles for the 2007-08 financial crisis. Rather, this paper provides an example where the crisis probability could rise in the run-up to the crisis even without these factors that may significantly affect banks' risk-taking.

[2] Kato and Tsuruga (2013) develop a model with pecuniary externalities by extending the model introduced in this paper.

[3] Examples include DR, Farhi and Tirole (2012), Jiménez, Ongena, Peydró, and Saurina (2011), and Maddaroni and Peydró (2011), to name but a few.

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. In DR, the random shock arises from the uncertainty over expectations on future income and DR 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 C_t is consumption at date t and 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) 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.

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

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

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

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

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.[4]

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 at normal times by m:

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

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

[4] 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.

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 $A\left(r_{12}\right)$. Then, $A\left(r_{12}\right)$ can be expressed as

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

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 $A'\left(r_{12}\right)\leq 0$.[5]

Bankers become insolvent if the solvency condition $D\leq A\left(r_{12}\right)$ 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:

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

where r_{12}^* strictly decreases with D since $A'\left(\cdot\right)\leq 0$.[6] 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), the latter reflects the supply and demand in the liquidity market.

[5] See the Appendix A.1 for the proof.
[6] Note that $r_{12}^*(D)\equiv A^{-1}(D)$ and, by the inverse function thorem, $r_{12}^{*\prime}(D)=-1/A'<0$.

2.4 Market equilibrium

At 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.

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.[7] 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' maximization problem is given by

$$\begin{aligned} \max_{D} \int_{0}^{\theta^*(D)} & \left\{\theta \log\left(\theta m\right) + \left(1-\theta\right)\log\left[\left(1-\theta\right) r_{12} m\right]\right\} dF\left(\theta\right) \\ & + \int_{\theta^*(D)}^{1} \left[\theta \log\left(e_1 + X_1\right) + \left(1-\theta\right)\log\left(e_2\right)\right] dF\left(\theta\right), \end{aligned} \tag{10}$$

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

$$\begin{aligned} & \left\{\theta^* \log\left(\frac{\theta^* m^*}{e_1 + X_1}\right) + \left(1-\theta^*\right)\log\left[\frac{\left(1-\theta^*\right) r_{12}^* m^*}{e_2}\right]\right\} \pi'\left(\theta^*\right)\theta^{*\prime}\left(D\right) \\ = & \int_{0}^{\theta^*} \left[\frac{1}{m}\left(1 - \frac{e_2}{r_{12}^2}\frac{\partial r_{12}}{\partial D}\right) + \frac{1-\theta}{r_{12}}\frac{\partial r_{12}}{\partial D}\right] dF\left(\theta\right), \end{aligned} \tag{11}$$

where $m^* = e_1 + D + e_2/r_{12}^*$. By the definition of $\pi\left(\theta\right)$, $\pi'\left(\theta^*\right)$ is equal to $-f\left(\theta^*\right)$, where $f\left(\theta^*\right)$ 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

[7] 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.

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 term 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

We calibrate the model to the banking system in the advanced economy. There are five model parameters: the maximum productivity of entrepreneurs' projects ($\bar{Y}_2$), households' endowment at dates 1 and 2 (e_1, e_2), the value of liquidated project (X_1), and the bankers' collection skill (γ). For the distribution of θ, we assume that θ is generated from the beta distribution.

Two targets are matched with the data for calibrating $\bar{Y}_2$ and e_1. The first target is the average bank capital ratio of 10.32 percent. The targeted bank capital ratio in the benchmark simulation is taken from the U.S. data before the 2000s. Kishan and Opiela (2000) investigate the balance-sheet items of federally insured commercial banks over 1980:Q1-1995:Q4 and report the equity capital ratios based on different sizes of banks. From Table 1 of Kishan and Opiela (2000), we calculate that the weighted average of equity capital ratios is 6.55 percent. We also note that bank capital ratios differ, depending on definitions of bank capital and bank assets. Estrella, Park, and Peristiani (2000) report that the risk-weighted capital ratio, defined as the ratio of tier 1 capital to risk-weighted assets, was 14.1 percent for commercial banks during 1989-1993. Taking the simple average of the bank capital ratios in the two empirical studies, we obtain the target value of the bank capital ratio of 10.32 percent.

The second target is the crisis probability of 4.65 percent. We take the target crisis probability from the Basel Committee on Banking Supervision (2010, hereafter BCBS). BCBS (2010) reports two empirical crisis probabilities for 11 advanced economies over 1985-2009, based on the datasets of Reinhart and Rogoff (2008) and Laeven and Valencia (2008).[8] The empirical probabilities are 5.2 percent in Reinhart and Rogoff (2008) and 4.1 percent in Laeven and Valencia (2008). Our target probability is 4.65 percent, the average of the crisis probabilities based on the two datasets.

Moment matching of the bank capital ratio and the crisis probability results in $\bar{Y}_2 = 2.656$ and $e_1 = 0.297$. We also assume that $e_2 = e_1$, meaning that the households' income flow remains the same during the two periods.

In terms of assigning values for other parameters, we note that the model cannot appropriately predict rates of return (e.g., r_{12}) which are empirically comparable to the data. This is because the model does not specify the length of a period. Specifying the length of a period would be a completely arbitrary choice (e.g., one month, one year, or even longer) and thus parameters in our model can be calibrated completely flexibly. Therefore, rather than specifying the length of a period, we simply follow the parameterization of DR (i.e., $X_1 = 0.95$ and $\gamma = 0.90$). Nevertheless, under these parameter choices, the model generates theoretically reasonable values of $D > 1$ and $E(r_{12}) > 1$ in the benchmark calibrations.

The remaining parameters required to solve the model are those for the distribution of θ. We set 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. Unfortunately, there is no solid empirical evidence on these parameters. Therefore, we set $\mu_\theta = 0.5$ and $\sigma_\theta = 0.05$ as benchmark parameterization and then 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 0.583.

Figure 1 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,

[8] The 11 countries are Belgium, Canada, France, Germany, Italy, Japan, the Netherlands, Sweden, Switzerland, the United Kingdom, and the United States.

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.

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 4.65 percent in the initial "risky" distribution with $\mu_\theta = 0.50$ (Case 1 in Table 1). With the lower mean of 0.35 in the "safer" distribution, the probability of a crisis declines from 4.65 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 5.66 percent. Therefore, it is not always true that the "safer" the economy, the more secure the banking system.

Figure 2 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 2).

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 3 plots π and D against

μ_θ, while other paramters (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 3, 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 stochstic 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.[9] 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 4 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) $D < 2$ because D is a face value of demand deposits; (ii) the expected bank capital ratio is strictly higher than 3.5 percent, which is substantially low, relative to the capital-asset ratios reported by Kishan and Opiela (2000); (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. We focused on the

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

liquidity preference that had relatively abated as reflected in the LIBOR-OIS spread. We translated the observations as a decline in the mean of shocks to liquidity preference. Using a variant of Diamond and Rajan (2012), we explored how such a "safe" enviroment surrounding the banking system affects the probability of financial crises, via endogenously determined bank leverage. While we acknowledge that various other potential factors, such as imperfect information, irrational overoptimism, and externalities, contributed, triggered, and exacerbated the crisis, our numerical simulations performed here may provide an explaination why the 2007-08 financial crisis unfolded amid an economic environment favorable to the banking system.

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A Appendix

A.1 The sign of $A'(r_{12})$

In this appendix, we show that $A'(r_t) \leq 0$. From (6), $A(r_{12})$ is given by

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

Noting that $Y_2(r_{12}) = r_{12}X/\gamma$, we have

$$\begin{aligned} A(r_{12}) &= \frac{(X_1)^2}{\gamma \bar{Y}_2} r_{12} + \frac{1}{2\bar{Y}_2}\left[\frac{\gamma\left(\bar{Y}_2\right)^2}{r_{12}} - \frac{(X_1)^2}{\gamma} r_{12}\right] \\ &= \frac{(X_1)}{2\gamma \bar{Y}_2} r_{12} + \frac{1}{2\bar{Y}_2}\frac{\gamma\left(\bar{Y}_2\right)^2}{r_{12}}. \end{aligned}$$

Now, we want to show

$$\begin{aligned} A'(r_{12}) &= \frac{(X_1)^2}{2\gamma \bar{Y}_2} - \frac{\gamma\left(\bar{Y}_2\right)^2}{2\bar{Y}_2}\frac{1}{(r_{12})^2} \\ &= \frac{1}{2\bar{Y}_2\gamma}\left[(X_1)^2 - \left(\frac{\gamma \bar{Y}_2}{r_{12}}\right)^2\right] \\ &= \frac{1}{2\Delta\gamma}\left(X_1 - \frac{\gamma\bar{Y}_2}{r_{12}}\right)\left(X_1 + \frac{\gamma\bar{Y}_2}{r_{12}}\right). \end{aligned}$$

Hence, $A'(r_t)$ depends on the sign of $X_1 - \gamma\bar{Y}_2/r_{12}$. To confirm the sign of $X_1 - \gamma\bar{Y}_2/r_{12}$, recall that $\tilde{Y}_2$ takes a value between $\left[0, \bar{Y}_2\right]$. Consider an extreme case: $\tilde{Y}_2 = \bar{Y}_2$. Then, we can define $r^{\max}$ such that

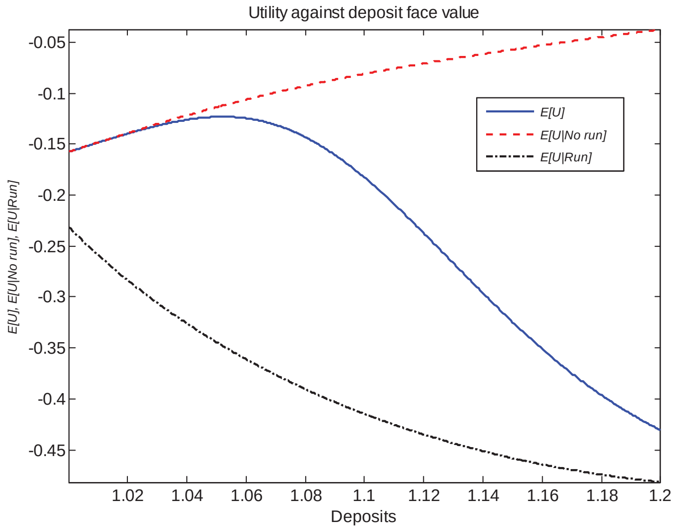
$$\bar{Y}_2 = \frac{X_1}{\gamma} r^{\max} \Leftrightarrow r^{\max} = \frac{\gamma}{X_1}\bar{Y}_2.$$

This $r^{\max}$ implies that

$$X_1 - \left.\frac{\gamma\bar{Y}_2}{r_{12}}\right|_{r_{12}=r^{\max}} = X - \frac{\gamma\bar{Y}_2}{\left(\gamma\bar{Y}_2/X_1\right)} = 0$$

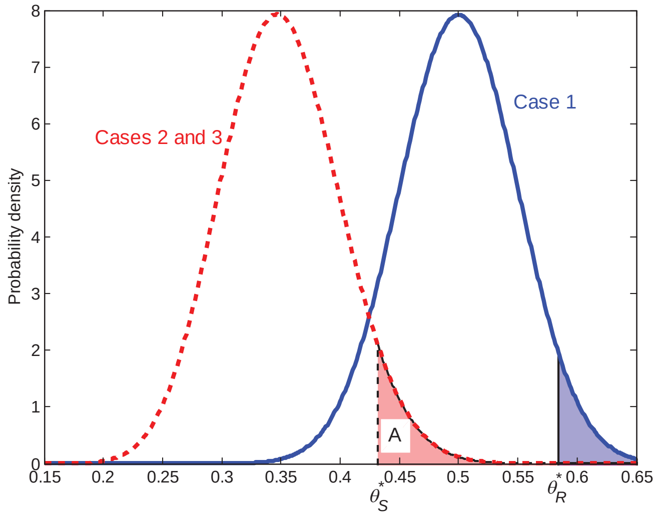
In contrast, consider the other extreme, $\tilde{Y}_2 = 0$. Then, $r_{12} = 0$, because X_1 and γ are strictly positive. Hence, $X_1 - \gamma\bar{Y}_2/r_{12} < 0$. Because $X_1 - \gamma\bar{Y}_2/r_{12}$ is continuous and monotonically increasing in r_{12}, we prove that $A'(r_{12}) \leq 0$.

Figure 1: Bankers' leverage and households' utility



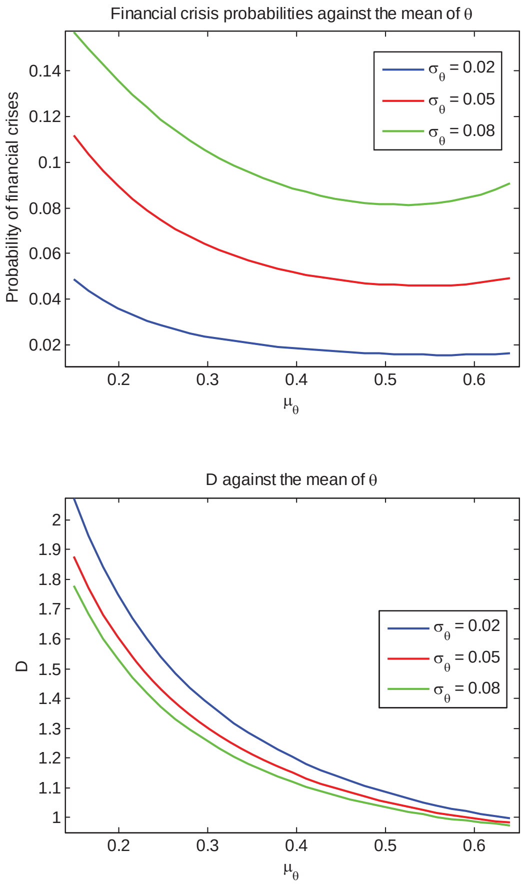
Note: The solid line represents the utility level against the face value of deposits. The upward-sloping dashed line is the expected utility conditional on no bank run, and the downward-sloping dashed line is the expected utility conditional on a bank run. The calibration is based on the assumption that a liquidity shock follows a beta distribution with a mean of 0.50 and a standard deviation of 0.05.

Figure 2: Comparisons for distributions for θ



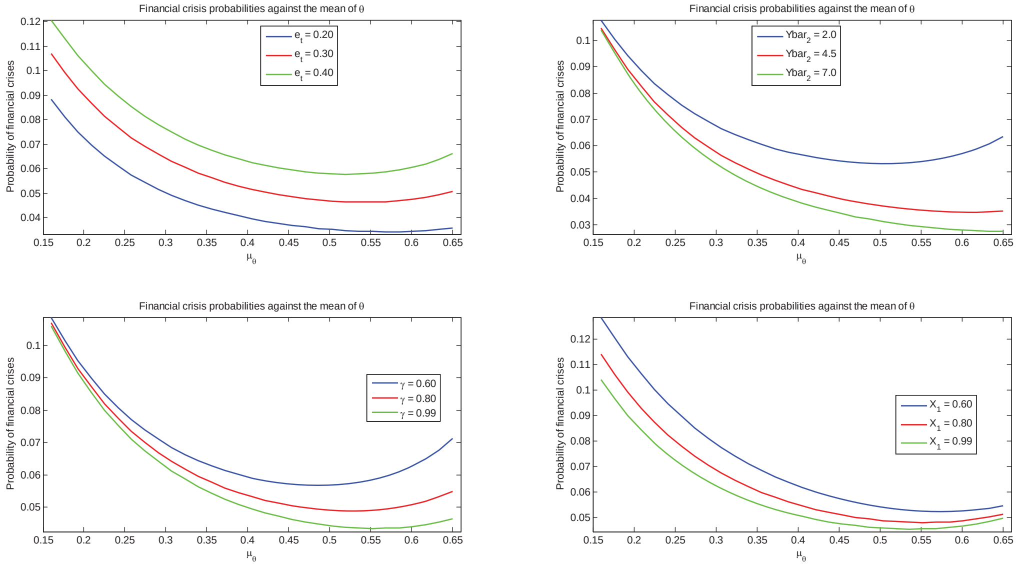
Note: The solid line represents the probability density function based on a beta distribution with a mean of 0.50 and a standard deviation of 0.05 (Case 1). The dashed line is the probability density function of a beta distribution with a smaller mean of 0.35 but with the same standard deviation (Cases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

Figure 3: Crisis probabilities (π) and D against μ_θ



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

Figure 4: Robustness analysis: crisis probabilities against μ_θ



Note: The curve in each panel represents the crisis probabilities (the upper panel) against the mean of θ. Each curve is plotted for various parameters in the model.

Table 1: Numerical simulation of crisis probability (π) for the mean of θ

	Case 1	Case 2	Case 3
μ_θ	0.500	0.350	0.350
Crisis probability	4.650	0.0004	5.657
D	1.052	1.052	1.213
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.