Peer-to-Peer Lending Platforms and Stability in Banking*

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Abstract

This study examines how the advent and the expansion of peer-to-peer (P2P) lending platforms affect the soundness and stability in banking. We analyze the various bank risks by comparing two cases of competition: a benchmark case in which only banks exist in a single loan market, and the case in which the loan market is segmented and a P2P lending platform operates only in the low-credit market segment. Our findings are as follows: (i) the insolvency risk of individual banks increases when they compete with the P2P lending platform in the low-credit score consumers' markets, but (ii) the illiquidity risk of individual banks is reduced, and (iii) the total credit risk can be either increased or reduced, but likely to be reduced under mild additional assumptions, implying that the systemic risk in the banking system triggered by individual defaults will be also reduced. Our results imply that if the roles of the P2P platforms and banks are properly differentiated so that P2P lending platforms focus on the provision of credits in the low credit-score consumers' markets, and the banks concentrate more on high credit-score consumers' markets and protected deposits business, the impact of spread of P2P lending platforms on the current banking system's stability may be limited.

JEL codes: G21, G23, G28

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1 Introduction

Peer-to-peer (P2P) lending[1] platforms, some of the newest non-bank financial intermediaries, directly connect borrowers and investors via online platforms (Musatov and Perez, 2016), and they split loans into payment dependent notes, paralleling an originate-to-distribute model of lending.[2] Their innovative use of information technology is expected to reduce intermediation costs and to improve users' experiences with online financial services.

P2P lending platforms have grown dramatically in size and scale over the past decade and have drawn attentions from both investors and regulatory agencies (CGFS, 2017; Buchak et al., 2017). On one hand, potential P2P lending platforms have faced high entry barriers, unclear policy guidelines, and strict regulations that sometimes hinder innovations and hamper the players' timely adoption of new technologies (KIF, 2015).[3] On the other hand, from the perspective of financial stability, it is reasonable to maintain such barriers and regulations (e.g. Kim, 2015), considering that the financial sectors generally are still in the middle of overcoming the adverse effects of the global financial crisis. P2P lending platforms have sometimes shown problems in proper credit allocations,[4] and if they expand too rapidly without proper regulation, they may harm overall financial stability.

The observed characteristics in direct investments through P2P lending platform are as follows. First, the notes traded via FinTech platforms are often non-secured (Menon, 2015; Musatov and Perez, 2016).[5] Second, P2P lending platforms often subdivide the bonds (or notes) into small amounts and provide aftermarket trading functionality, both of which enhance liquidity.[6] For example, LendingClub investors can trade in dividend notes in the associated aftermarket before expiration and pay 1% of the bond sale price as fees. Finally,

[1]It is also referred to as FinTech credit, crowd finance, and/or marketplace lending. We use the term P2P lending to refer to all credit activities through online platforms that provide matching between investors and borrowers.

[2]CGFS (2017) describes the differences in P2P lending business models; some simply match lenders and borrowers, while others reflect the loans on their balance sheet.

[3]For example, in 2015, the Financial Supervisory Service (FSS) of Korea suspended the operation of a P2P lending platform "8 Percent" because it concluded that a financial firm that "matches" investors and borrowers should also earn the same pre-approval from the FSS as other kinds of existing financial institutions.

[4]In May 2016, one of the best-known FinTech financial platforms, LendingClub, was accused of providing USD 22M in loans to less-qualified borrowers. Consequently, then-CEO Renault Raffles and three other directors resigned or were dismissed.

[5]For this reason, we believe that it may be more reasonable to regard loan receivables handled by P2P lending platforms as notes or bills rather than bonds.

[6]In some portion of credit markets where it is difficult to raise funds through banks, small-scale divisions of bonds and funding through direct investment methods are gaining popularity. In the UK, for example, small- and medium- sized enterprises use so-called mini-bonds as a means of marketing and financing, issuing bonds to their customers and offering their products at a discount instead of interest payments (Menon, 2015).

loans via FinTech platforms are often provided to the low- and mid-level credit markets, where banks have created a credit gap by reducing the credit supply.

Despite this increased interest, the effects of P2P lending on financial stability, specifically on the banking sector, have not been well investigated yet.[7] The investments via P2P lending platforms are supposed to be duration-matched, and unable to be liquidated until the expiration date, which means that P2P lending does not create any intermediate liquidity problem. In practice, however, the P2P lending platforms often adopt complicated originate-to-distribute approaches, often accompanied with associated aftermarkets that can provide the function of early liquidation.[8]

This approach is a basis for criticisms of P2P lending (Phillips, 2014). In the conventional originate-to-hold lending model, banks tend to be more cautious about lending because they carry the majority of the burden associated with the risk of defaults. On the contrary, in the P2P lending process, FinTech platforms make commissions on initial loan brokerages and exchanges in the secondary market for intermediate liquidation, while the risks of defaults are borne mostly by investors. Thus, it is highly likely that the possibilities for bad loans, or defaults, and, in the worst case, likelihood of a financial crisis, will also be increased in P2P lending.[9] Nevertheless, the originate-to-distribute approach has the advantage of financial inclusiveness by expanding the range of credit offering for low-credit-score customers (Bord and Santos, 2012) as well as providing more investment opportunities for individual and small investors (Buchak et al., 2017). Further, notes (of split loans) invested and traded through FinTech platforms are mainly non-secured bonds (i.e., with no collateral), which implies that the contagious effects from loan defaults would be limited.

Considering these characteristics, this paper examines the effects of the spread of P2P lending platforms on the stability of the banking system by means of theoretical analyses adapted from Freixas and Ma (2014). Specifically, this paper evaluates stability in the banking system in the following two cases: one is where the credit market is segmented according to consumers' creditworthiness and competition between banks and P2P lending platforms operates only in the lower-rated consumers' credit market, and the other is a

[7] CGFS (2017) provide an expository note about this issue.

[8] We provide the case of LendingClub as an example. After investors and borrowers are matched, the investment funds raised by LendingClub are first transferred to a local bank called WebBank, located in Utah, USA, and the bank originates the loan. If LendingClub initiates a loan directly without going through a bank or other receiving agencies, it may be considered an unauthorized shadow banking activity. The bank delivers the loan back to LendingClub, which divide the loan into USD25 units and issues "payment-dependent notes" to be distributed to investors, the proceeds of which fund specific loans to borrowers. The principal and interests are paid to the loan note holders.

[9] See Purnanandam (2010) for detailed information.

benchmark case where there is a competition only among banks in a single credit market.

We analyze changes in various risks in the banking sector by comparing the result of competing between banks and P2P lending platforms with the benchmark case. Our results show that (i) the insolvency risk of individual banks increases when the P2P lending platform competes with banks in a low-credit market compared to that in the benchmark case, but (ii) the illiquidity risk of individual banks decreases compared to that in the benchmark case; and, thus, (iii) the systemic risk triggered by an individual institution's fail also decreases compared to that in the benchmark case.

First, in the case of insolvency risk, because the credit market is segmented by different credit ratings of consumers, investors choose projects with higher-risk if the high interest rate is applied in the low-credit-score consumers' market, similar to Boyd and De Nicolo (2005). As a result, the likelihood of defaults on individual banks' loans to low-credit-score consumers will increase. Second, in the case of illiquidity risk, because the proportion of protected deposits received by banks increases with market segmentation, the marginal cash flow level that prevents bank-runs is lowered. This effect is more than sufficient to cancel out that of increasing risky loan proportions driven by the market segmentation. Third, the risk of contagion of the banking crisis is also lowered for the same reason discussed in the illiquidity risk case. Our results imply that if P2P lending platforms and banks play different roles in credit markets, the spread of P2P lending platforms may not cause a significant problem from the perspective of the stability of the banking system. For example, regulatory agencies choose policies so that P2P lending platforms focus more on direct finance in the mid- and low-credit-score consumers' markets by brokering mini-bonds, while banks mostly concentrate on loans in the high-credit-score consumers' market and protected deposits.

Before the mid-2000s, studies regarding inter-bank competition focused on analyzing the impact of competition on financial stability (Besanko and Thakor, 1987; Keeley, 1990; Edwards and Mishkin, 1995). It is often the case that banks tend to be more risk-seeking as competition increases.[10] On the contrary, more recent studies have suggested that this is not necessarily the case (Allen and Gale, 2004; Boyd and De Nicolo, 2005; Martinez-Miera and Repullo, 2010). The U-shaped relationship between bank competition and bank failures is confirmed both by theoretical (Boyd and De Nicolo, 2005) and empirical analyses (Martinez-Miera and Repullo, 2010). However, all these studies focus on traditional and homogeneous inter-bank competition analyses, thus omitting consideration of competition between financial institutions with different types of deposit-loan models, such as banks and

[10] Carletti (2008) provides more details on previous studies about bank competition and financial stability.

P2P lending platforms, which is the main theme of our study.

Our theoretical model is constructed using the risk definition framework borrowed from Freixas and Ma (2014) with additional consideration given to the competition between banks and direct finances.[11] We seek to establish and analyze the competition effects by considering the existing difference between a traditional bank and the P2P lending platform of a new FinTech provider. We construct a model from the perspective of competition between financial intermediaries that use the different asset brokering models. As in Diamond (1997), banks and credit markets coexist in our model, but cross-participations are limited, reflecting the current operations of aftermarkets attached to P2P lending platforms. Then, the deciding factor is the change in bank's portfolio and liquidity discount rate if banks need to liquidate their long-term investments. Unlike in Diamond (1997), increasing individual participation in the secondary market does not reduce the liquidity that banks create relative to secondary markets.

Our study provides contributions distinguished from previous studies' in deriving implications for financial stability and sheds some lights on the effects of the spread P2P lending platforms and guidelines for participation in credit markets (or segments) by different financial institutions. The rest of this paper proceeds as follows. Section 2 describes the model. Section 3 compares various types of risks, such as portfolio risk, insolvency risk, liquidity risk, and contagion risk, between the two cases (one where both a bank and a P2P platform exist and the other a benchmark case where only banks compete with one another. Section 4 summarizes the results of the research and discusses relevant policy implications. Section 5 concludes the paper.

2 Model

2.1 Players and Settings

As per the Bryant-Diamond-Dybvig (BDD) model (Bryant, 1980; Diamond and Dybvig, 1983), we consider a three-period ($t = 0, 1, 2$) economy. There are two kinds of investors, *depositors* who deposit their liquidity to banks, and *lenders* who lend, via P2P lending platform, directly to entrepreneurs (borrowers) and hold their notes of loans. In our setting, unlike the BDD model, depositors are only interested in their returns, without any unanticipated consumption need at $t = 1$. Thus, if they decide to cash out their deposits at $t = 1$, it

[11] Instead, we drop the consideration about the incentives of the shareholders of banks in their model.

is because they believe that the probability of bank risks at $t = 2$ is greater than a threshold level.

The loans provided via P2P lending platforms are supposed to be split into payment-dependent *notes* and can be traded in the accompanied aftermarkets at $t = 1$, in a similar way to the (incomplete) market example in Diamond and Dybvig (1983). We assume that trades occur only between the lenders, which would unavoidably limit the effects of the trades within a P2P lending platform, and prevent the "hacking" of the market (e.g. Jacklin, 1987).

Similar to the BDD model, investors are assumed to be the only active agents in the sense that they make strategic decisions at $t = 1$ while both entrepreneurs (borrowers) and financial institutions (banks and P2P lending platforms) are passive agents. The depositors decide whether they withdraw their deposits early or not at $t = 1$. The lenders trade their notes of loans between themselves at $t = 1$ in the accompanied aftermarket. Entrepreneurs are cashless, but have long-term, productive, yet potentially risky projects. Each entrepreneur's project requires one unit of initial investment at $t = 0$ and will be completed at $t = 2$.

A bank's portfolio of deposits (per depositor) consists of protected deposits, F, and unprotected deposits, D, which is promised to be delivered at $t = 2$ if the bank is solvent.[12] Depositors require and accept the exogenous gross rate of return $R(> 1)$ on the unprotected deposits while it is zero for the protected deposits. Thus, the initial amount of unprotected deposit at $t = 0$ is D/R. We normalize the amount of total initial deposits as one, $F + D/R = 1$. Depositors can withdraw their unprotected deposit early at $t = 1$ with a penalty before the entrepreneurs' risky projects mature at $t = 2$.[13] Depositors are assumed to receive nothing if the bank fails at $t = 2$. For simplicity, the values of F and D are assumed to be exogenous.

A P2P lending platform does not have a depository function (i.e. $F = 0$), and only matches lenders and borrowers. A lender's ex post return at $t = 2$ is determined by the returns from successful loans. We assume that the amount of investment per lender at $t = 0$ is normalized as 1.

For simplicity, we reflect the effects of competitiveness in loan markets simply by the exogenous change in the value of interest rates, and concentrate on deriving implications on stability in banking. Following the convention, debts are assumed to be raised competitively, and all financial institutions in the same loan market (segment) provide a single lending rate to all the entrepreneurs.

[12] For simplicity, we assume no equity in the bank's portfolio.

[13] According to Rochet and Vives (2004), the stop of rolling over wholesale deposits such as certificate of deposit (CD) is an example of this case.

2.2 Timing of Game

At $t = 0$, loans are jointly financed by a continuum of investors. For the sake of comparison and simplicity, a lender is assumed to hold split notes of all types of borrowers' loans, the same way as (unprotected) deposits are diversified via bank.

At $t = 1$, an investor receives a private noisy signal $s = \theta + \epsilon$ about random cash flows, denoted by θ, generated from the (unit) loan portfolio. ϵ is i.i.d., and follows a probability distribution with zero mean. A depositor can recover as much as $qD(< D/R)$, or $q < 1/R$, by paying an early withdrawal penalty of $(1 - q)D$, given that the bank has not failed at $t = 1$ $(0 < q < 1)$, and, similarly, a lender decides whether to sell her diversified note in the aftermarket. Both the depositor's and the lender's decision in the first period depend on the observation of their private signals. In case a P2P lending platform operates, we use F' and D' instead of F and D to denote the protected and unprotected deposits, respectively.

Provided an early withdrawal is requested, a bank should liquidate its assets by discounting the unit portfolio of loans that generates expected cash flow of θ by $\frac{1}{1+\lambda}$. We assume $\frac{1}{1+\lambda} \leq q$, which means that a bank's early liquidation of long-term loans is more costly than an investor's early liquidation of short-term loans or deposits. If the bank's ex post cash flow at $t = 2$, which is the sum of the recovered loan and the value of its remaining assets, is less than the amount to redeem, bank failure occurs.

In case of lending via P2P lending platform, the notes are assumed to be tradable in the associated aftermarkets. We also assume here that investors are randomly matched and trade their notes; if lender i and j whose signals are $s_i > s_j$, respectively, are matched, then j sells his (portfolio of) notes at s_j.[14] Thus, the traded notes would be "discounted" with respect to the risk, or the standard deviation[15] because the price now follows the probability distribution of random noise ϵ_j ($\epsilon_i > \epsilon_j$, WLOG) is drawn from $2(1 - F(\epsilon))f(\epsilon)$, first order stochastic dominated by $f(\epsilon)$ where $f()$ (and $F()$) is probability density (and distribution) of noise ϵ. For simplicity, let the expected discount rate be $k\sigma$ where k is a constant and σ is the standard deviation of noise ϵ. We assume that $(1 - k\sigma) > q > 1/(1 + \lambda)$ so that the notes are expected to be least discounted at $t = 1$.

At $t = 2$, the bank delivers either the promised deposit D if it is solvent, or zero if it fails. For investments via P2P lending platform, only the cashflow generated from loans

[14] In fact, only a fraction of the notes, not the whole portfolio, would be traded in the aftermarkets. This assumption is adopted to avoid theoretical problems with the measurement emerging from the abuse of the law of large numbers. This setting also implies that no speculative trade in the sense of Harrison and Kreps (1978) would happen.

[15] If we assume that the iid noise ϵ follows $N(0, \sigma^2)$, the discount can be approximated as $\sigma/\sqrt{3}$.

other than non-performing ones is recovered for an individual investor i.

2.3 Market Segmentation

When both banks and P2P lending platforms coexist, the loan market is assumed to be segmented into high- and low-credit markets, based on borrowers' credit ratings, and the competition between banks and P2P lending platforms is assumed to occur only in the low-credit market. In addition, we assume that investors would not switch their choice of institution, bank or P2P platform, at $t = 1$.[16]

Unprotected deposit D can be fully withdrawn at $t = 1$ with penalty$(1 - q)D$. P2P loans are repaid at $t = 2$, but only from performing notes. They can be traded at $t = 1$ with expected discount of $k\sigma$.[17] Table 1 summarizes investment characteristics classified by institutional settings of banks and P2P platforms, timing, decision, and liquidity flows.

Investment (and decision)	Banks only (single market)	Banks (high-/low-credit segments)	P2P platforms (low-credit segment)
Demand deposit amount (insured, at t=0)	F	$F' > F$	0
Investment amount (uninsured, at t=0)	D/R	D'/R	1 (normalized)
Investor's choice at t=1	Withdrawal(of qD) or waiting	Withdrawal(of qD') or waiting	Trade (with discount) between i and j
Investor's return at t=2 (bank failure)	Loss	Loss	Cash flow from performing loan
Investor's return at t=2 (bank solvency)	Delivery of agreed amount D	Delivery of agreed amount D'	

Table 1: Timing, decision, and liquidity flows for different institutional settings

We assume that the expected rate of returns from deposit and direct lending are the same, and that investors choose one of them according to their preference. In this case, as Diamond (1997) notes, increased participation in direct finance causes the banking sector to shrink, primarily through reduced holdings of long-term assets. We can expect that the portion of protected deposits in a single bank's portfolio, F, would be greater than that in the benchmark case, reflecting that P2P lending platforms are non-depository institutions. Thus, we assume that $D > D'$ and $F < F'$.

[16]For example, without the assumption, investors of unprotected bank deposits can withdraw early and purchase the notes at $t = 1$.

[17]This part is not reflected in the model yet, and to be completed later.

2.4 Cashflow from Loan

We follow the cashflow model of Freixas and Ma (2014). The probability of success by entrepreneurs of type b with the higher b implying the better type, following a uniform distribution $U(0, B]$, is

$$P_b = \begin{cases} 1 & \text{if} \quad b \in [1/(x-r), B] \\ b(x-r) & \text{if} \quad b \in (0, 1/(x-r)) \end{cases}$$

where x is a gross return ($x > 1$ if successful, 0 otherwise), $r \in [1, x]$ is the gross loan rate charged by financial institutions. The benefit of this setting is that we can distinguish risk-free loans and risky loans based on the type of entrepreneur b. Assuming that b follows a uniform distribution between 0 and B, the proportion of risk-free loans out of total loans can be derived as $\alpha \equiv (B - 1/(x-r))/B$ (Freixas and Ma, 2014). Thus, the higher the value of α, the more secure the loan portfolio of the financial institution, and the value of α increases as the value of B increases. The first derivative of α with respect to the market interest rate, r, leads to the following equation

$$\partial\alpha/\partial r = -1/B(x-r)^2 < 0. \tag{1}$$

The ratio of non-performing loans to risky loans is referred to as γ. The cashflow generated from the unit portfolio of loan, θ, can then be expressed as

$$\theta \equiv \alpha r + (1-r)[0 \cdot \gamma + r \cdot (1-\gamma)] = r - (1-\alpha)r\gamma \tag{2}$$

Assuming that γ follows a uniform distribution $U[0, 1]$,[18] the expected value of the ratio of non-performing loans to risky loans in the model, $E(\gamma)$, is 1/2.[19] Thus, a lender's ex ante return from a loan via P2P lending platform is $(1+\alpha)r/2 - 1$.

Finally, we assume that D (and D'), R, and ϵ are determined in a way that makes the expected rate of return from a unit deposit portfolio be $(1+\alpha)r/2-1$, same as the expected rate of return from direct loan.

[18] Freixas and Ma (2014) show that γ follows a uniform distribution between 0 and 1 if type b follows a uniform distribution $(0, B]$ and the entrepreneur's utility function is a specific form of quadratic function.

[19] Consequently, the volatility of the cashflow is determined only by the ratio of risk-free loans, α.

3 Comparison of Risks

Following Rochet and Vives (2004) and Freixas and Ma (2014), we treat insolvency risk and illiquidity risk separately.[20] We first use the competition between only banks as a benchmark, and compare the benchmark result with the result from where both banks and P2P lending platforms coexist.

When the loan market is divided into two segments, high- and low-credit, we assume that the entrepreneurs will be also separated into the high-credit and the low-credit markets by the value of their type b. The interest rate provided in the high-credit market (market 2), r_2, is supposed to be lower than the interest rate given in the low-credit market (market 1), r_1 ($r_1 > r_2$). Whether an entrepreneur can receive a loan from the high-credit market or should go to the low-credit loan market is supposed to be determined by the threshold $\hat{B}$; only the entrepreneur with $b \geq \bar{B}$ can receive a loan from market 2. We assume $\hat{B} > 1/(x - r_2)$ so that the loan in the high-credit market becomes a risk-free loan.

3.1 Insolvency Risk

Benchmark: Competition between Banks

We draw on Freixas and Ma (2014) for our benchmark. Two effects of competition on banking soundness are i) the risk-shifting reduction effect, which is the result of lower risk-seeking tendencies as interest rates decline due to intensified competition, and ii) buffer-reduction effect, which is the lower capacity to afford loan loss as interest margins decline due to intensified competition and deteriorated the profitability. The effect of competition on the soundness of banks depends on which effect dominates.

Insolvency happens if the ex post cashflow is smaller than the aggregate amount of bank deposits, or if the following inequality

$$\theta = r - (1 - \alpha)r\gamma \geq F + D \tag{3}$$

is not satisfied. If the cash flow generated from the unit portfolio of loans is greater than the deposit amount $F+D$, the deposit portfolio can be considered as solvent. From equation (3), the critical level of loan loss determining solvency is derived as $\hat{\gamma} \equiv (r-(F+D))/((1-\alpha)r)$.

[20] The separation of illiquidity and insolvency risk was first introduced by Bagehot (1873), who argues that market mechanism itself cannot fully address the liquidity shock. Since then, there have been some criticisms on this view; however, more recently, Rochet and Vives (2004) supported this argument with the global game approach (Morris and Shin, 2001). We use a simplified version of their model (without interbank market) here.

Since γ follows a uniform distribution between [0, 1], even if a loan loss occurs up to the critical level, there is no problem with the soundness of the financial institution. Thus, the probability of insolvency risk, ρ_{SR} is defined as $\rho_{SR} \equiv 1 - \hat{\gamma}$. By simple rearrangement in terms of interest rate, it is expressed as

$$\rho_{SR} \equiv 1 - \hat{\gamma} = (F + D - \alpha r)/(1 - \alpha)r$$

Considering that α is also a function of r, we can get the first derivative of ρ_{SR}. To simplify the procedure, we take the first derivative of $1 - \rho_{SR}$ rather than ρ_{SR}, which is $1 - \rho_{SR} \equiv \hat{\gamma} = (r - (F + D))/(1 - \alpha)r$, as

$$\begin{aligned} \frac{\partial(1 - \rho_{SR})}{\partial r} &= \frac{[(1-\alpha)r - \partial((1-\alpha)r)/\partial r(r - (F + D))]}{(1-\alpha)^2 r^2} \\ &= \frac{[\frac{\partial \alpha}{\partial r} r^2 + ((1-\alpha) - \frac{\partial \alpha}{\partial r} r(F + D))]}{(1-\alpha)^2 r^2}. \end{aligned} \quad (4)$$

which can be summarized as the first-order derivative of ρ_{SR} for insolvency risk as

$$\frac{\partial \rho_{SR}}{\partial r} = \frac{-1}{(1-\alpha)^2 r^2} \frac{\partial \alpha}{\partial r}(r^2 - x(F + D)). \quad (5)$$

The risk-free loan ratio α is a monotone decreasing function in r. Thus, the insolvency risk ρ_{SR} declines only under the condition of $r^2 - x(F + D) > 0$, which is a necessary and sufficient condition. In other words, if the interest rate is somehow exogenous, the competition contributes to the reduction of the insolvency risk, but the competition in the other situation leads to the decrease of the buffering capital due to the decrease of the profits, thus increasing insolvency risk if $r^2 - x(F + D) < 0$.

Competition between Bank and P2P Lending Platform

Now, we investigate the low-credit loan market in the segmented market case. A P2P lending platform itself has no problem of insolvency like a bank. The problem, however, is more about the lenders' expected loss since they now directly take the risk from their lending. If a bank and a P2P lending platform compete, only the bank receives deposits protected by deposit insurance. As we assume, the amount of protected deposit in this case, denoted by F', will be larger than that in the benchmark case ($F' > F$). The condition for the cash flow of the bank's soundness is now represented as

$$\hat{\theta} = \frac{\hat{B}}{B}[r_1 - (1-\alpha_1)r_1\gamma] + \frac{B-\hat{B}}{B}r_2 \geq F' + D' \tag{6}$$

where α_1 is the ratio of a bank's risk-free loan in the low-credit market and r_1 and r_2 are the interest rates in low- and high-credit markets, respectively. Note that $r_1 > r > r_2$, and $\alpha_1 = (\hat{B} - 1/(x-r))/\hat{B} < \alpha$.

From equation (6), in the segmented market case, the marginal ratio of loan loss, denoted by $\hat{\gamma}_{SR}$, is derived as

$$\hat{\gamma}_{SR} = \frac{r_1 + (B-\hat{B})r_2/\hat{B} - B(F'+D')/\hat{B}}{(1-\alpha_1)r_1}. \tag{7}$$

For the sake of comparison with the benchmark result, we assume that $F + D = F' + D'$, and that $\frac{\hat{B}}{B}r_1 + \frac{(B-\hat{B})}{B}r_2 = r$. Then, $\hat{\gamma}_{SR} = \frac{r-(F+D)}{B/\hat{B}(1-\alpha_1)r_1} = \hat{\gamma}r/r_1$. Since $r_1 > r$, the value of $\hat{\gamma}_{SR}$ is lower than that in the benchmark case. The insolvency risk of a bank in the segmented market case, $\hat{\rho}_{SR} = 1 - \hat{\gamma}_{SR}$, thus, is greater, which leads to the following proposition.

Proposition 1 *When the loan market is segmented by credit-worthiness and a bank should compete with a P2P lending platform in the low-credit loan market segment, its insolvency risk is* greater *than in the benchmark case.*

The increase in the ratio of risky loans in the low-credit loan market segment (market 1) leads to an increase in the borrower's risk-seeking tendencies.

The competition in the low-credit segment between bank and P2P lending platform affects the soundness of bank in a similar way to what we previously observed in the case of inter-bank competition in a single market. That is, the decrease in interest rates from the competition reduces the insolvency risk until the interest rate reaches the threshold level, but the risk then increases if the interest rate decreases below the threshold level.

3.2 Illiquidity Risk

Benchmark: Competition between Banks

We now examine the case of bank failure due to insufficient liquidity caused by the early withdrawal of investors. This situation can occur for a bank if it must liquidate its assets urgently due to the early withdrawal of many depositors at $t = 1$, even though there is no soundness problem for a bank that can repay the debt sufficiently at $t = 2$ if there are no such early withdrawals.

The condition that illiquidity risk does not occur can be expressed as $\theta/(1+\lambda) > qD$ where q is the proportion of deposit that one can recover from early withdrawal. To meet the early withdrawal request, a bank fire-sells the portfolio of loans, which generates cash flow of θ per unit, by discounting $1/(1+\lambda)$ Following the approach of Freixas and Ma (2014) again, if only risk-free loans can generate cash flow ($\theta = \alpha r$) in the worst case, the illiquidity of the bank still does not occur if $\alpha r > (1+\lambda)qD$. Let L be the ratio of investors who took early withdrawals, or ran, in the first period. In this case, the level, L, at which the bank can survive at the first stage but experiences problems at the second stage is determined by the following inequality

$$(1-L)D > \theta - F - L(1+\lambda)qD. \tag{8}$$

When the deposit to be returned at $t = 2$ is larger than remaining liquidity from the cash flow generated by the holding unit portfolio θ, deducted by the protected deposit, F, and by the liquidity that has flowed out due to the early withdrawal at $t = 1$, $L(1+\lambda)qD$, the illiquidity risk arises.

Unlike the BDD model, depositors do not have any real liquidity needs at $t = 1$ here. Their early withdrawal decision is purely on how likely they redeem their promised return at $t = 2$. Whether a depositor i chooses to withdraw early at $t = 1$ or not is influenced by her private signal, $s_i = \theta + \epsilon_i$, and her forecasts about other depositors' behavior, which are reflected by the magnitude of L. She should choose early withdrawals, or run, if her choice is below a certain threshold level, s^*, and continue to wait until maturity at $t = 2$ otherwise, which is referred to as a switching strategy. Morris and Shin (2001) and Goldstein and Pauzner (2005) point that an investor's strategy is influenced by other investors' *beliefs* about the possibility of running. Then, ultimately, investor i needs to think about the belief on other investors' beliefs, which violates the common knowledge assumption. This situation corresponds to the setting of a "global game" where, unlike the BDD model, the probabilities of outcomes, bank run or not, can be now calculated.

Applying the Laplician property to our setting as in Freixas and Ma (2014),[21] if investor i's belief about L, the likelihood of other investors deciding to run, is set to M[22], then M is a random variable which follows the uniform distribution $U[0,1]$, and this setting applies

[21]"One should apply a uniform prior to unknown events "from the principle of insufficient reason" " (Morris and Shin, 2001, p.2).

[22]If we derive a Perfect Bayesian Equilibrium under the common prior hypothesis, we need to consider only this step by specifying a *value* (of probability of a specific type), not the *probability distribution* of M.

equally to all other investors.[23] The probability of each investor's belief that a bank will not fail at $t = 2$ due to illiquidity is the probability that L satisfies equation (8), which is

$$L < \frac{\theta - F - D}{[(1+\lambda)q - 1]D}. \tag{9}$$

Depositors are supposed to use the switching strategy, which is shown to be optimal in this case (Morris and Shin, 2001). The threshold level of the cashflow for the early withdrawal decision, θ^*, is determined at the point where the expected value of the early withdrawal at $t = 1$ equals that of the maturity withdrawal at $t = 2$, as

$$qD = \Pr(\text{survive at } t = 2 | s = s^*)D,$$

with assuming $\Pr(\text{survive at } t = 1 | s = s^*) = 1$. From Equation (9), we can infer that $\Pr(\text{survive at } t = 2 | s = s^*) = (\theta - F - D)/([(1+\lambda)q - 1]D)$, and determine the threshold level of cash flow for run, θ^*, as

$$\theta^* = F + D + q[(1+\lambda)q - 1]D. \tag{10}$$

There will possibly be a bank run if a bank's cashflow is lower than the threshold level. Let $\mu = 1 + q[(1+\lambda)q - 1]$ where $(1+\lambda)q > 1$. If the bank is illiquid despite its solvency (i.e., without a run), the range of cash flow that would be determined as

$$F + D < \theta \leq F + \mu D.$$

Similar to ρ_{SR}, we can define the probability of illiquidity risk, ρ_{LR}, as

$$\rho_{LR} = \frac{(\mu - 1)D}{(1-\alpha)r}. \tag{11}$$

The first derivative with respect to the interest rate r is

$$\frac{\partial \rho_{LR}}{\partial r} = (\mu - 1)\frac{-D}{(1-\alpha)^2}\frac{\partial(1-\alpha)}{\partial r} > 0 \tag{12}$$

Considering that $\alpha \equiv (B - 1/(x - r))/B$, the first derivative is always positive because $\partial(1-\alpha)/\partial r < 0$. As with the insolvency risk, the illiquidity risk also monotone decreases in

[23] If the Laplacian property is applied, we do not need to consider any belief higher than the second order, and it is easy to deal with the problem because it is possible to set the model in a similar way to the common prior.

r. In other words, as the competition intensifies, the decrease in r leads to the decrease in illiquidity risk.

The total risk of a bank, $\rho_{TR} = Pr(\theta < \theta^*)$, is the sum of the insolvency risk, ρ_{SR}, and the illiquidity risk, ρ_{LR}, which is derived as

$$\rho_{TR} = \frac{(F + \mu D) - \alpha r}{(1-\alpha)r}. \tag{13}$$

As the interest rate, r, decreases, ρ_{TR} decreases if and only if $r^2 > x(F + \mu D)$. This inequality implies that due to competition between financial institutions, the threshold level of the interest rate which satisfies $r^2 - x(F + D) > 0$ for the case of insolvency risk is lower than the threshold level for illiquidity risk.

Competition between Bank and P2P Lending Platform

Now we investigate the case in which some banks are replaced by P2P platforms. For comparison, let us assume that (direct) investors will earn $\theta/(1 + \lambda)$ at $t = 1$, regardless of the illiquidity risk of a bank, when they trade in their notes in the aftermarket. If the worst-case scenario generates cash flow only from a risk-free loans, the cash flow of the bank in the segmented market, $\hat{\theta}$ is derived as

$$\hat{\theta} = \frac{B - \hat{B}}{B} r_2 + \frac{\hat{B}}{B} \alpha_1 r_1. \tag{14}$$

This threshold level of cash flow may be lower or higher than that in the benchmark case (αr). On the contrary, the cash flow to decide the early withdrawal is determined as

$$\hat{\theta}^* = F' + (1 + q[(1 + \lambda)q - 1])D' = F' + \mu D'. \tag{15}$$

If we apply the assumption of $F + D = F' + D'$ used to analyze insolvency risk again, this cash flow level is lower than that derived from the benchmark case, θ^*. The illiquidity risk in the segmented market case is derived as

$$\hat{\rho}_{LR} = \frac{(\mu - 1)D'}{(1 - \alpha_1)r_1} \tag{16}$$

Knowing that $D' < D$, $\alpha_1 < \alpha$, and $r < r_1$, we have the following proposition.

Proposition 2 *The probability of a bank's illiquidity risk is* lower *when the market is segmented by credit-worthiness and a bank compete with a P2P platform, given that the ratio of* *risk-free loans in the low-credit market is sufficiently low.*

Like the benchmark case, the total credit risk of a bank, $\hat{\rho}_{TR} = \Pr(\hat{\theta} < \hat{\theta}^*)$, is the sum of the insolvency risk, $\hat{\rho}_{SR}$, and the illiquidity risk, $\hat{\rho}_{LR}$, which is derived as

$$\hat{\rho}_{TR} = \hat{\rho}_{SR} + \hat{\rho}_{LR} = 1 - \frac{\hat{B}(r - (F' + D'))}{B(1-\alpha_1)r_1} + \frac{(\mu - 1)D'}{(1-\alpha_1)r_1}.$$

which can be rewritten, knowing that $B(1-\alpha_1)/\hat{B} = (1-\alpha)$, as

$$\begin{aligned} \hat{\rho}_{TR} &= \frac{(1-\alpha)r_1}{(1-\alpha)r_1} - \frac{(r - (F' + D'))}{(1-\alpha)r_1} + \frac{(\mu - 1)D'(B/\hat{B})}{(1-\alpha)r_1} \\ &= \frac{F' + ((B/\hat{B})(\mu - 1) + 1)D' - r + (1-\alpha)r_1}{(1-\alpha)r_1}. \end{aligned} \tag{17}$$

Mathematically, $\hat{\rho}_{TR} < \rho_{TR}$ if $F' + ((B/\hat{B})(\mu - 1) + 1)D' - r < ((F + \mu D) - r)r_1/r$.

Proposition 3 gives a sufficient condition under which total credit risk of bank $\hat{\rho}_{TR}$ would lower than the benchmark result ρ_{TR}, or $\hat{\rho}_{TR} < \rho_{TR}$.

Proposition 3 *Given the assumptions, if $F' \geq (B/\hat{B})F$ and $D' \leq (B/\hat{B})D$, the total credit risk of a bank when the loan market is segmented by borrowers' creditworthiness and a P2P lending platform operates is lower than the total credit risk in the benchmark case.*

From equation (16), we can conclude that competition in the low-credit market reduces the probability of illiquidity risk due to a reduction in interest rates. Note however, its effect on a bank's total credit risk is similar to what we observe in the previous case (a decrease in the interest rate due to some degree of competition reduces the probability of total risk), but it increases again when the interest rate falls below a threshold level. The threshold level of interest rate in the low-credit market is greater than that in the benchmark, but, given that the interest rate in the low-credit market should be high, the two interest rates cannot be directly compared.

3.3 Summary and Discussion

For the insolvency risk case, if the loan market is segmented by credit ratings and banks charge the higher interest rate for borrowers in the low-credit segment, investors choose high-risk projects, as in Boyd and De Nicolo (2005), which leads increased default probability of low-credit borrowers. For the illiquidity risk case, because the protected deposit ratio for a bank increases in the segmented market case, the effect from the lowered threshold cash flow level that triggers a run is greater than the effect from the increased risky loan ratio due to the increased competition between a P2P platform and a bank in the segmented market.

Our results are derived from the facts that (i) a P2P lending platforms operates only in a market segment for borrowers of low-credit ratings while a bank operates in both low- and high-credit loan markets; (ii) lending is direct and loans are treated as split notes (non-secured mini-bonds); (iii) only initial lenders can trade the split notes in the associated aftermarket; and (iv) the expected returns from deposit and from lending are the same.

Lastly, we briefly discuss the case of contagion risk. Following Freixas and Ma (2014) again, suppose first that there are two banks in a single loan market. If both banks face credit risk and needs to fire-sell their assets, the discount rate applied to the fire-sales will increase from λ to λ', possibly leading to the contagion of failure (i.e., crisis). The increase in the discount rate will lead to a new kind of critical level of cashflow θ^{**} with which the probability of contagion risk can be represented as

$$\rho_{CTG} = \Pr(\theta^{*} < \theta < \theta^{**}). \tag{18}$$

Systemic risk is then defined as the probability that both institutions fail at the same time, which is defined as

$$\rho_{SYS} = \Pr(\theta < \theta^{**})^2 = \left(\frac{\theta^{**} - \alpha r}{(1-\alpha)r}\right)^2. \tag{19}$$

Differentiating with respect to the interest rate r, we have

$$\begin{aligned} \frac{\partial \rho_{SYS}}{\partial r} &= 2\Pr(\theta < \theta^{**})\frac{\partial}{\partial r}(1 - \frac{r-\theta}{(1-\alpha)r}) \\ &= 2\Pr(\theta < \theta^{**})\frac{-1}{(1-\alpha)^2 r^2}\frac{\partial \alpha}{\partial r}(r^2 - x(F + \mu' D). \end{aligned} \tag{20}$$

where $\mu' = 1 - q[1 - (1+\lambda')q] > \mu$.

If the loan market is segmented and P2P lending platforms operate only in the low-credit segment, the contagion risk (and systemic risk) of the banking sector would be lower due to our assumptions of the insulation of the banking sector from the direct finance sector, including trades of split notes, and vice versa. As the simplest (and an extreme) example, suppose that there is one bank and one P2P lending platform in the low-credit segment of our model. Then, there will be no firesales of assets by multiple banks, and, therefore, no case of further discount of assets.

In reality, the effect of bank failure can be propagated to the direct finance market, or an increase of defaults in the direct finance market can lead to a run in the banking sector, either of which cases can be regarded as a systemic crisis. The separation and isolation of banking sector and direct loan sector, as assumed in our model, would be critical to achieve the stability in banking sector.

4 Concluding Remarks

While conventional loans from banks have become increasingly difficult for potential borrowers with mid- and low-level credit ratings since the global financial crisis, direct finance via P2P lending platforms has emerged as a new finance means to fill the credit gaps, and this area is expected to grow rapidly. In this scenario, the role of banks may gradually shift to the infrastructure providers for the mid-level credit market. As we note in the introduction, especially among households and small- and mid-sized enterprises, the trend of direct financing will be strengthened.

This paper theoretically investigates the effect of the spread of FinTech platforms on the banking system, specifically various risks in the banking sector based on the approach of Freixas and Ma (2014). The observed characteristics in direct investments through P2P lending platforms are as follows. First, loans are split into payment-dependent notes, often non-secured, for enhanced liquidity, and traded via FinTech platforms (Menon, 2015; Musatov and Perez, 2016). Second, P2P platforms often provide aftermarket trading functionality, which also raises liquidity of the notes. Finally, loans supplied via FinTech platforms are often provided to the borrowers with low- and mid-level credit ratings where banks have reduced the credit supply and, thereby, created a credit gap.

Considering these characteristics, this paper compares stability in the banking sector between two cases; a benchmark case in which there is a competition only among banks in a single credit market, and a case in which the credit market is segmented according to consumers' creditworthiness and there exists a competition between banks and FinTech lending platforms in the market of low credit ratings.

Our results show that (i) the insolvency risk of individual banks increases when the FinTech platform competes with a bank in low credit rating markets compared to the insolvency risk in the benchmark case; but that (ii) compared to that in the benchmark case, the illiquidity risk of individual banks decreases when P2P platforms compete with banks; and that thus (iii) the systemic risk of the banking sector triggered by an individual bank's defaults decreases compared to the systemic risk in the benchmark case.

Our results imply that if the roles of the P2P lending platforms and banks are properly differentiated so that P2P platforms focus on the provision of credit for the borrowers of lower credit ratings while the banks focus more on high credit ratings markets and protected deposits, the systemic risk of the banking from the expansion of P2P lending may be limited. However, this implication is valid only if P2P platforms stay within the boundaries of primitive, direct finance such as issuing and circulating of payment-dependent notes, without introducing derivatives or secured loans. In the near future, if these platforms plan to extend their range of businesses, such as developing more complex or high leverage products, the implications of our results should be reconsidered and reevaluated from a different perspective.

Due to the price-taker assumption in the study, strategic behaviors and profit structures of FinTech platforms has not been examined, which is worth pursuing as a new study in the future. We also leave a couple of important tasks to future studies, which will give important policy implications: (i) empirical evidence that identifies the main reasons behind different evolution of FinTech platforms in different countries, as well as supporting our results; and (ii) how FinTech platforms will be able to have roles differentiated from banks' in advanced economies.

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