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Peer-to-Peer Lending and Bank Risks: A Closer Look

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Abstract: This study examined how the expansion of peer-to-peer (P2P) lending affects bank risks, particularly insolvency and illiquidity risks. We compared a benchmark case wherein banks are the only players in the loan market with a segmented market case wherein the loan market is segmented by borrowers' creditworthiness, P2P lending platforms operate only in the low-credit market segment, and banks operate in both low- and high-credit segments. For the segmented market case compared with the benchmark one, we find that, while banks' insolvency risk increases, their illiquidity risk decreases such that their overall risk also decreases. Our results imply that sustainable P2P lending requires an appropriate differentiation of roles between banks and P2P lending platforms—P2P lending platforms operate in the low-credit segment and banks' involvement in P2P lending is restricted—so that the growth of P2P lending is not adverse for bank stability.

Keywords: peer-to-peer lending; bank risk; insolvency risk; illiquidity risk

JEL Classification: G21, G23

1. Introduction

Peer-to-peer (P2P) lending—also known as FinTech credit, crowd-finance, or marketplace lending—refers to credit activities through online P2P lending platforms that provide direct matching between investors and borrowers and split loans into payment-dependent notes. (Committee on the Global Financial System (CGFS) of Bank for International Settlements (BIS) provided the differences among P2P lending business models: some simply match lenders and borrowers, while others reflect the loans on their balance sheets [1].) P2P lending often targets borrowers with low- and mid-level credit ratings, a group facing a reduced supply of bank loans since the collapse of the subprime loan markets and the global financial crisis of 2008. P2P lending has also demonstrated its usefulness in financial inclusiveness and as a substitute for bank loans by expanding its range of credit offers to borrowers with low-credit ratings [2] as well as by providing more investment opportunities for small institutions and retail investors [3].

P2P lending has grown dramatically in size and scale over the past decade, drawing attention from both investors and regulatory agencies [1,3]. On the one hand, unclear regulations and policy guidelines have sometimes plagued these platforms, hindering the application of new and innovative information technologies that could reduce intermediation costs and improve user experiences. (For example, in 2015, the Financial Supervisory Service of Korea suspended operations of the P2P lending platform "8 Percent" after concluding that the matching platform should be required to have the same certification as other financial institutions providing credit.) On the other hand, in terms of banking and financial stability, these regulations are reasonable. The lingering effects of the global financial crisis have become the "new normal," and, in reality, P2P lending platforms have at times failed to properly allocate credit. (In May 2016, the LendingClub, one of the best-known P2P lending platforms, was accused of providing USD 22 million in loans to underqualified borrowers. Afterwards then-CEO Renaud Laplache and three other directors resigned or were dismissed.)

Direct investments through P2P lending platforms have the following characteristics. First, the notes traded via FinTech platforms are often unsecured [4,5]. Second, P2P lending platforms often subdivide loans into a number of mini-bonds (or notes) and provide aftermarket trading functionality, both of which enhance liquidity. (In some credit markets, wherein raising funds through banks may be difficult, other funding methods are gaining in popularity, such as small-scale divisions of bonds or direct investments. In the UK, for example, small- and medium-sized enterprises use so-called mini-bonds as a means of marketing and financing. These enterprises issue bonds to their customers, who can choose discounted products rather than receiving interest payments [4].) For example, by paying a fee equal to 1% of the sales price, LendingClub investors can trade their dividend notes in the associated aftermarket (the Note Trading Platform) before they expire. Third, P2P lending platforms typically provide loans for borrowers with low- and mid-level credit ratings. This group has faced a credit gap, or a reduced supply of loans from banks, since the global financial crisis.

Despite its growing popularity, the effects of P2P lending on major bank risks have not been investigated thoroughly. (CGFS [1] provide an expository note about this issue.) Direct investments via P2P lending platforms are supposed to be duration-matched, and they cannot be liquidated until the maturity date. This means that P2P lending is designed not to create a short-term liquidity problem. (In practice, however, some P2P lending platforms adopt more complicated originate-to-distribute approaches. LendingClub is an example: After investors and borrowers are matched, the investment funds raised by LendingClub are transferred to the WebBank (located in Utah, US), which originates from the loan and returns it to LendingClub. LendingClub then divides the loan into "payment-dependent notes" by units of USD 25, and distributes them to investors, the proceeds of which fund specific loans to borrowers. The principal and interest are paid to the loan note holders. Note that, if LendingClub initiated the loan directly, without going through a bank or depository agency, the activity would be considered as an unauthorized shadow banking activity.) Further, notes (of split loans) invested and traded through P2P lending platforms are mainly unsecured bonds (i.e., with no collateral). This implies that the contagious effects of loan defaults would be limited. Still, P2P lending platforms make commissions on initial loan brokerages and exchanges of notes in the associated aftermarkets, while investors mostly bear the risks of borrowers' defaults. (In this sense, P2P lending has some features of an originate-to-distribute model [6]. Phillips [7] uses the features as a basis for criticism of P2P lending.) Thus, P2P lending platforms would be more focused on increasing fee revenues than on proper evaluations of creditworthiness, leading to an increase in the proportion of non-performing loans. To the extent that P2P lending and bank loans act more as substitutes than as complements, competition between banks and P2P lending platforms may hamper banking prudence, given the aforementioned incentives.

Considering these characteristics and the aforementioned gap in the literature, we theoretically analyzed the effects of P2P lending on two major bank risks: (in)solvency risk and (il)liquidity risk. The idea of separating banks' illiquidity and insolvency risks was first introduced by Bagehot [8], who argued that the market itself cannot fully address the problems of an interim liquidity shock. Some researchers have criticized this view e.g., [9], but recent studies such as by Rochet and Vives [10] and Freixas and Ma [11] have supported it. The Bank for International Settlements also supports this view, having introduced the liquidity coverage ratio (LCR) and the net stable funding ratio (NSFR) requirements in Basel III. (LCR requires that a bank should hold adequate stock of unencumbered high-quality liquid assets to meet its liquidity needs for a 30 calendar day liquidity stress scenario [12]. NSFR is defined as the amount of available stable funding relative to the amount of required stable funding. This ratio should be at least 100% on an ongoing basis [13].)

Finally, while we let P2P lending refer to general lending activities rather than financing with a specific purpose, we want to note the study by Petruzzelli et al. [14], who focus on the role of crowdfunding in supporting sustainability-oriented initiatives. They find that in terms of economic importance, P2P lending becomes the most relevant crowd-finance form, (Lending-based crowdfunding collected a global volume of funds about $25 billion in 2015 [14].) implying that P2P lending should be an important issue in sustainable finance. The rest of the paper proceeds as follows. Section 2 presents the theoretical background and Section 3 describes the model. Section 4 analyzes the major bank risks—insolvency and liquidity risks—by comparing two cases: in the benchmark case, only banks exist, and in the other case, both banks and P2P platforms exist. Section 5 discusses the effects of competition on bank risks, and the importance of the isolation of P2P lending from the banking sector. Section 6 concludes the paper.

2. Theoretical Background

In this study, we compared two cases: (i) the benchmark, in which only banks exist in a single loan market, and (ii) the case wherein the loan market is segmented by borrowers' creditworthiness and P2P lending platforms operate only in the low-credit segment. Our results show that compared with the benchmark case, when P2P lending platforms and banks operate in the low-credit market the (i) insolvency risk of individual banks increases; (ii) illiquidity risk of individual banks decreases; (iii) banks' total credit risk—the sum of both risks—also decreases.

First, regarding insolvency risk, borrowers in the low-credit segment would choose higher-risk, higher-return projects because the interest rate applied to the low-credit market segment would be higher than that applied to the benchmark case, as in Boyd and De Nicolo [15]. As a result, the likelihood of borrowers' defaults on individual bank loans increases in the low-credit segment, leading to higher insolvency risk. Second, regarding illiquidity risk, the proportion of protected deposits in a bank's deposit portfolio would increase with loan market segmentation, as a result of banks substituting for P2P lending platforms. This would lower the level of critical cash flow that would prevent a bank run, resulting in a lower illiquidity risk. Third, in the segmented market case, a bank's combined credit risk is smaller than that in the benchmark case, implying that the decreased illiquidity risk would be great enough to cancel out the increased insolvency risk.

We further investigated the effect of competition and the implication of the separation of P2P lending and banking and find that competition is more likely to reduce the combined credit risk in the segmented market case than in the benchmark case. This result also implies that once banks begin to participate in P2P lending, either directly or indirectly, it would adversely affect the combined risk because it would lessen the competition in the segmented market case. Our results imply that sustainable P2P lending requires an appropriate separation of roles between banks and P2P lending platforms. If P2P lending platforms and banks are differentiated in their roles for separate market segments, the spread of the former may not pose a significant problem in terms of bank risks. Regulatory agencies, however, would have to limit P2P lending platforms' brokerage of mini-bonds or notes outside their associated aftermarkets. At the same time, they may have to prevent banks or their subsidiaries from joining the trades of split notes in the aftermarkets of P2P lending platforms and let the banks focus on the high-credit market segments and protected deposits business.

Before the mid-2000s, studies on inter-bank competition focused on analyzing the impact of competition on financial stability [16–18]. Often, as competition increases, banks become more risk-seeking (See Carletti [19] for more details on previous studies on bank competition and financial stability). However, recent studies have suggested that this is not necessarily the case [15,20,21]. The U-shaped relationship between bank competition and bank failure has been confirmed by both theoretical [15] and empirical analyses [21]. These studies are traditional, homogeneous inter-bank competition analyses, and they do not involve financial institutions that do not follow the deposit-loan model.

More recent studies have investigated the coexistence of P2P lending platforms and banks. Thakor and Merton [22] suggested that banks have a stronger incentive to manage a trust, but P2P lending platforms tend to experience more adverse effects from a loss of trust. De Roure et al. [23]

found that P2P lenders tend to be bottom fishers, P2P loans are riskier, and the risk-adjusted interest rates for P2P loans are lower than those for bank loans. Tang [24] found that P2P platforms are essentially substitutes for banks and mostly serve the same borrower population, despite their unique potential. Finally, Vallee and Zeng [25] and Balyuk [26] studied the informational role of P2P lending and its relationship with investors and banks, respectively.

A strand of the recent banking literature has adopted global games, which are games of incomplete information wherein each player obtains a private signal about the true state with a small amount of noise, and his/her higher-order beliefs also affect the outcome [27,28]. Goldstein and Pauzner [29] and Rochet and Vives [10] are two well-known global game-based bank run models. Goldstein and Pauzner [29] directly extend the Bryant–Diamond–Dybvig (BDD) model [30,31] by incorporating the actual interim liquidity needs of consumer-depositors. Our study is close to Rochet and Vives [10] and Freixas and Ma [11], who focus on depositors' speculative runs on unprotected bank deposits. Nevertheless, it is distinct because we extend the model to incorporate the situation wherein heterogeneous types of financial institutions co-exist in the market.

In addition to the finance literature, studies such as Cusumano [32], Einav et al. [33], and Sundararajan [34] emphasize the positive aspects of competition in platform economies, which open the chance of entry for small players and enhance efficiency. However, their focus is often the sharing of horizontally diversified, and sometimes idle, "physical" facilities. Due to this difference, there are limitations to applying the implications to the case of P2P lending in the current paper.

To the best of our knowledge, this study is one of the first works, if not the first, to implement a full theoretical analysis of the effects of the competition between P2P lending platform and banks on bank failure risks, specifically in the strand of microeconomic banking literature such as Rochet and Vives [10], Goldstein and Pauzner [29] and Freixas and Ma [11], which consider only homogeneous banks. This study also provides related policy implications that it is necessary for a regulatory authority to supervise the P2P lending platforms separately from the existing banking sector to promote the sustainable development of alternative lending.

3. Model

We follow the basic settings and notations of Freixas and Ma [11], (Freixas and Ma [11] can also be regarded as an extension of the BDD model, which is the de facto standard model and the starting point in the microeconomics of banking.) with modifications, extensions, and clarifications where necessary.

3.1. Players and Settings

As per the standard Bryant–Diamond–Dybvig (BDD) model, we consider a one-good, three-period ($t = 0, 1, 2$) economy wherein all agents are assumed to be risk-neutral. There are two types of investors: *depositors* who deposit their liquidity in banks, and *P2P lenders* who lend directly to entrepreneurs (borrowers) via P2P lending platforms and hold these entrepreneurs' loan notes. Similar to the BDD model, depositors are assumed to be homogeneous. At $t = 1$, the depositors decide whether to withdraw their deposits early, and the lenders trade notes amongst themselves in the accompanying aftermarket. When depositors withdraw their deposits early at $t = 1$, they incur a penalty. (In Rochet and Vives [10], unprotected deposits are mostly wholesale deposits such as certificates of deposit, and early withdrawals stop the rolling over of these deposits.) However, unlike the BDD model, we do not consider any unanticipated consumption needs at $t = 1$, which are likely to be covered by protected demand deposits such as checking accounts. We assume that depositors are interested only in the rates of return from their investments, as modeled in Rochet and Vives [10] for example, and that their decisions on the early withdrawal of their deposits solely depend on their speculation on the likelihood of realization of the promised return at $t = 2$.

P2P lending platforms do not take deposits; they only match lenders and borrowers and earn fee revenue per match. Loans via P2P lending platforms are split into payment-dependent *notes* and can be traded in the accompanying aftermarkets at $t = 1$, similar to that in the (incomplete) market example of Diamond and Dybvig [31]. We assume that trades of notes occur only between P2P lenders, limiting the effects of trades within P2P lending platforms and preventing the "hacking" of the market e.g., [35]. Moreover, we assume that banks cannot identify a borrower's type, default risk, or creditworthiness. However, we assume that P2P platforms, with their new technology, can correctly identify whether a borrower's type is higher or lower than a threshold.

Borrowers are entrepreneurs who are cashless but have long-term and productive, yet potentially risky, projects classified by their type $b \in (0, B]$, with a higher b indicating the safer entrepreneur. Each entrepreneur's project requires a unit of the loan at $t = 0$ which is to be paid back with the gross rate of return from the loan $r(> 1)$, when the project is completed at $t = 2$. There is a threshold type $\hat{B}$ such that $\hat{B} > 1/(x - r)$. Here, x denotes the gross rate of return from an entrepreneur's successful project. Borrowers of $b < \hat{B}$ and $b \geq \hat{B}$ are classified as Group 1 and Group 2, respectively. We assume that there exists a difference in the maximum value of r for Group 1 and for Group 2, respectively, which the borrowers in each group are willing to accept. Banks are supposed to be unable to identify which group a potential borrower belongs to. In contrast, P2P lending platforms, often considered to have more advanced technology, are supposed to correctly identify whether a borrower is in Group 1 or Group 2, although not the exact value of b, which creates the possibility of market segmentation.

A bank's portfolio of deposits at $t = 0$, $1 + F$, consists of the following: F is the portion of demand deposit, given the amount of loan is normalized as one, in the benchmark case with banks only, and F' in the case of P2P lending platforms also operate. (For the remainder of the paper, we use the same approach using the apostrophe.) At $t = 2$, the sum of the liquidity reserve and recouped loan with return D (and D'), $F + D$ (and $F' + D'$), must be delivered to depositors if the bank is solvent where $D > 1$ (and $D' > 1$). $F + D$ is the promised, but not all of it is necessarily protected. Note that, although not exactly the same, F is related to the liquidity reserve; a higher value of F implies that the proportion of savings deposits is lower. We assume that there is no equity in the bank's portfolio. For simplicity, we assume that if a bank fails at $t = 2$, it returns nothing but F (and F') to the depositors. As Diamond [36] noted, increased participation in direct financing causes the banking sector to shrink, primarily through the reduced holdings of long-term assets, implying the possibility of $F' > F$. Finally, we assume that the size of deposits is less than the demand for loans, causing excess demand for loans.

A P2P lending platform does not have a depository function (i.e., $F = 0$) and it only matches P2P lenders and borrowers. We assume that all P2P lenders are homogeneous: every P2P lender has an equal share of the loans given to all borrowers such that each P2P lender has the same homogeneous loan portfolio. We also assume that the (average) investment at $t = 0$ is normalized as 1. Thus, a P2P lender's ex-post gross rate of return at $t = 2$ is the cash flow generated from successful loans. When banks and credit markets co-exist, we assume that no cross-participation—depositors' purchase of notes or lenders' purchase of loan claims—is allowed at $t = 1$. Thus, any transaction that occurs in the secondary markets attached to P2P platforms does not affect the money market. Finally, we assume that all rates are exogenous unless specified.

3.2. Timing of Game

At $t = 0$, loans are jointly financed by a continuum of investors. For simplicity, a P2P lender is homogeneous and assumed to hold split notes of all types of borrowers' loans, in the same way as (unprotected) deposits are diversified via bank.

At $t = 1$, an investor, indexed by i, receives a private noisy signal $s_i = \theta + \epsilon_i$ about a random cashflow generated from the (unit) loan portfolio, denoted by θ. Here, ϵ_i is i.i.d. and follows a probability distribution with zero mean and a small but non-zero standard deviation of σ. Each depositor who chooses to withdraw his/her deposit early will recover $qD(< D/R$ or $q < 1/R)$ by paying an early withdrawal penalty of $(1 - q)D$ where $q \in (0, 1)$ is the proportion of a deposit that one can recover from early withdrawal, given that the bank has not failed at $t = 1$. Similarly, at $t = 1$, lenders decide whether to sell or buy the diversified notes in the aftermarket. Both depositors' and P2P lenders' decisions at $t = 1$ depend on their observations of private signals.

Provided an early withdrawal of savings deposit (or loan) is requested, the bank should liquidate its long-term financial claims with discount, which generates an expected cash flow of θ multiplied by the discount factor $\frac{1}{1+\lambda}$ where λ is the discount rate. (This can be regarded as the haircut rate of the financial products in the money market. During the repo run in the last global financial crisis of 2007–2008, the average haircut on bilateral repo transactions, except for U.S. Treasuries, rose from zero in early 2007 to almost 50% at the peak of the crisis in late 2008 [37].) We assume $\frac{1}{1+\lambda} \leq q$, which means that a bank's early liquidation of long-term assets is costlier than a depositor's early liquidation of short-term assets or deposits. If the bank's ex-post cash flow at $t = 2$ (i.e., which is the sum of the recovered loan and the value of its remaining assets) is less than the amount to be redeemed, bank failure occurs.

In case of lending via P2P lending platforms, the notes are assumed to be traded within the associated aftermarkets where lenders are randomly matched and trade their notes; if lender i and j, whose signals satisfy $s_i > s_j$ without loss of generality, are matched, then j sells her/his (portfolio of) notes to i at s_j. (In fact, only a fraction of the notes and not the whole portfolio would be traded in the aftermarkets. This assumption helps to avoid theoretical problems with the measurement from abusing the law of large numbers. This setting also implies that no speculative trade in the sense of Harrison and Kreps [38] would occur.) Thus, the traded notes would be "discounted" proportional to the risk or standard deviation. (For example, if we assume that noise ϵ_j follows $N(0, \sigma^2)$, the amount of the discount can be approximated as $\sigma/\sqrt{3}$.) Note that based on our assumptions, which limit the effects of trades within associated P2P lending platforms, transactions in aftermarkets do not have any spillover effect in the banking sector.

At $t = 2$, if the bank is solvent, it delivers the promised amount $F + D$ (and $F' + D'$), and F (and F') otherwise. For investments via P2P lending platforms, the cash flow generated from loans (excluding non-performing loans) is recovered for an individual lender i.

3.3. Borrowers' Type and Market Segmentation

Although P2P lending platforms seek to maximize the number of matches between lenders and borrowers, we argue that P2P lending platform eventually match loans only for borrowers in Group 1, and segment the loan market, based on the empirical findings by De Roure et al. [23], Tang [24]. (In this study, we combined the finding from De Roure et al. [23]—P2P lenders tend to be bottom fishers and P2P loans are riskier, with that from Tang [24]—P2P lending platforms are essential substitutes for banks, as a stylized fact for our setting. We also want to note that [39] observe a similar kind of vertical separation of the hospitality market after the entry of Airbnb. In a separate study, we investigated a condition for this type of endogenous market segmentation to occur. The key idea is that when the loan supply from banks fails to clear the loan demand due to external conditions (e.g., prudence regulation and credit rationing), the P2P lending platform can choose to either (i) compete in both market segments with a single rate, or (ii) let banks cover *everyone* in the high-credit market and capture the bigger excess loan demand as well as compete only in the low-credit market. In some cases, choosing the latter is better for P2P lending platforms.) Henceforth, we use Market 1 to denote the market segment for low-credit borrowers (Group 1) and Market 2 to denote high-credit borrowers (Group 2). When the loan market is segmented, the gross rate of return from a loan in Market 2, denoted by r_2, is supposed to be lower than that in Market 1, denoted by r_1, namely $r_1 > r_2$.

Similar to the early withdrawal of unprotected deposits, the P2P lending notes can be traded at $t = 1$ with a discount proportional to the standard deviation of private signal σ. Because we assume that investors would not switch between banks and P2P platforms at $t = 1$, (For example, without this assumption, depositors of unprotected bank deposits could withdraw early and purchase the notes at $t = 1$.) trades in the aftermarkets do not have any influence on the banking sector. Table 1 summarizes the investment characteristics classified by institutional settings, timing, decision, and cash flows.

Table 1. Timing, decision, and cash flows for different institutional settings.

Investment (and Decision)	Banks Only (Single Market)	Banks (Segmented Market)	P2P Platforms (Low-Credit Segment)
Demand deposit (protected, at t = 0)	F	F'	0
Loan (unprotected, at t = 0)	1	1	1
Investor's choice at t = 1	Withdrawal(of qD) or waiting	Withdrawal(of qD') or waiting	Trades (with discount) between lenders
Investor's return at t = 2 (bank failure)	F	F'	Cash flow from performing loans
Investor's return at t = 2 (bank solvency)	$D+F$	$D'+F'$	

3.4. Cash Flow from Loans

We adopt the result of the cash flow model by Freixas and Ma [11] which derives the probability of success according to the type of borrower b as follows

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

Note that there exists a unique threshold type of entrepreneur that determines whether a loan is risk-free or risky. Assume that b follows a uniform distribution $U(0,B]$ and that B is sufficiently high so that loans would be riskless for a large proportion of borrowers. In the same loan market, (or market segment), banks and P2P lending platforms are assumed to treat borrowers equally. That is, differentiating the rate on loans for each type of borrowers is impossible. The ratio of risk-free to total loans is derived as

$$\alpha \equiv (B - 1/(x-r))/B \;=\; 1 - 1/(B(x-r)). \tag{1}$$

The greater the value of α, the more secure is the loan portfolio.

Equation (2) is the first derivative of α with respect to r, represented as

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

implying that as the exogenous gross rate of return on loan r increases, the proportion of risk-free loans α decreases.

Let γ be the ratio of *non-performing* loans to risky loans. From a unit loan provided to borrowers, the total cash flow generated referred to as θ, can be expressed as

$$\theta \equiv \alpha r + (1-r)[0 \cdot \gamma + r \cdot (1-\gamma)] \;=\; r - (1-\alpha) r\gamma. \tag{3}$$

We assume that γ follows a uniform distribution $U[0,1]$. (Freixas and Ma [11] show that γ follows a uniform distribution between 0 and 1 if entrepreneurs know the exact value of b; moreover, b follows a uniform distribution $(0,B]$; and their utility functions are a specific form of the quadratic function. However, we use the result as an exogenous condition due to the symmetric uninformedness of entrepreneur types in our model, and the negative, deterministic correlation between entrepreneur type and the gross rate of return from a project.) Then, the expected value of the ratio of the non-performing loan to the risky loan, $E(\gamma)$, is $1/2$. (Consequently, the volatility of the cash flow is determined only by the ratio of risk-free loans, α.) and the expected gross rate of return from loans, which is also the expected gross rate of return from investment via P2P lending platforms, is $(1+\alpha)r/2$.

Finally, it should be noted that not all of the entrepreneurs would be able to get a loan from banks regardless of their types without P2P lending for the following reasons. First, the canonical credit rationing problem e.g., ref. [40] can occur: all type of borrowers want to get a loan with a given gross rate of return less than r_L, and some of them are even willing to pay higher rates, but the loan supply is less than the demand. Second, we have assumed that the amount of deposits is not sufficient to cover the entire demand for loans. Note that only one of these two constraints is binding.

4. Comparison of Risks

Following Rochet and Vives [10] and Freixas and Ma [11], we consider only speculative runs by depositors and treat (in)solvency risk and (il)liquidity risk separately. We first use the case wherein only banks exist as a benchmark and compare the result with that of the segmented market case with both banks and P2P lending platforms; furthermore, we investigate how individual risks and total credit risk change under different circumstances.

4.1. Insolvency Risk

4.1.1. Benchmark: Only Banks Exist

Insolvency occurs if the ex-post cash flow θ from the unit loan is smaller than the total amount of bank deposits $F + D$ that must be paid back at $t = 2$. That is if inequality condition,

$$\theta \;=\; r - (1-\alpha)r\gamma \geq F + D, \tag{4}$$

is *not* satisfied, the bank can be considered as insolvent. From Equation (4), the critical level of the loan loss for determining solvency, γ_{SR}, is derived as

$$\gamma_{SR} \;=\; (r - (F + D))/((1-\alpha)r). \tag{5}$$

Note that γ follows a uniform distribution in $[0,1]$. The (in)solvency risk, or the probability that a bank faces the solvency problem, is denoted by ρ_{SR} and derived as $\rho_{SR} \equiv 1 - \gamma_{SR}$. By simple rearrangement in terms of the market gross rate of return from the loan, this is expressed as

$$\rho_{SR} \equiv 1 - \gamma_{SR} \;=\; (F + D - \alpha r)/(1-\alpha)r \tag{6}$$

4.1.2. Co-Existence of Banks and P2P Lending Platforms

Now, we investigate the segmented market case of banks and P2P lending platforms co-existing in the low-credit market segment (Market 1) while only banks exist in the high-credit one (Market 2). Unlike a bank, a P2P lending platform itself does not face the problem of insolvency, as the lenders directly take on the default risk of their loans. The cash flow condition for the bank's soundness is now represented as

$$\hat{\theta} \;=\; \frac{\beta\hat{B}}{B}[r_1 - (1-\alpha_1)r_1\gamma] + \frac{B-\hat{B}}{B}r_2 \geq F' + D' \tag{7}$$

where β is the share of applicants for whom banks provide a loan in Market 1, which satisfies

$$\frac{r_2}{r_1} \;=\; \frac{B-\beta\hat{B}}{B-\hat{B}}\frac{1+\alpha_1}{2}$$

such that the expected cash flows from both a unit loan via banks and via P2P lending are the same. Note that $\alpha_1 \;=\; (\hat{B} - 1/(x - r_1))/\hat{B} < \alpha$, and $\alpha_2 \;=\; 1$.

From Equation (7), in the segmented market case, the critical level of loan loss, denoted by $\hat{\gamma}_{SR}$, is derived as

$$\hat{\gamma}_{SR} \;=\; \frac{\beta r_1 + (B-\hat{B})r_2/\hat{B} - B(F'+D')/\hat{B}}{\beta(1-\alpha_1)r_1}. \tag{8}$$

The change in the bank's profit from the benchmark is represented by

$$\delta(r-(F+D)) = \hat{r}-(F'+D') \tag{9}$$

where $\hat{r} = \frac{\hat{B}}{B}\beta r_1 + \frac{(B-\hat{B})}{B}r_2$, which is supposed to be less than r due to competition, represents the bank's gross rate of return, or revenue, on unit loan from both market segments, and $\delta(<1)$ reflects the decrease in the bank's loan–deposit margin compared with the benchmark case. Given the assumptions and Equation (8), the following inequality

$$\hat{\gamma}_{SR} = \frac{\delta(r-(F+D))}{\hat{B}/B(1-\alpha_1)\beta r_1} = \frac{B\delta r(1-\alpha)}{\hat{B}\beta r_1(1-\alpha_1)}\gamma_{SR} = \frac{\delta r(x-r_1)}{\beta r_1(x-r)}\gamma_{SR} < \gamma_{SR}$$

is sufficiently satisfied if β is not sufficiently smaller than δ, implying that the impact of P2P lending on banks' profit reduction is greater than that on their market share in the low-credit segment.

To facilitate comparison with the benchmark results, suppose that $F+D = F'+D' = R$, which means that the future value of the normalized deposit portfolio in the benchmark case and that in the segmented market case are the same. Note that, in this case, the amount of the protected bank deposit, denoted by F', is greater than that in the benchmark case (i.e., $F' > F$) due to the lower rate of return on loan and, consequently, savings deposits. Then, from $\hat{r}-(F'+D') < r-(F+D)+\hat{B}(\beta-1)r_1/B$, Equation (9) leads to the following inequality

$$(1-\delta)(r-(F+D)) > (1-\beta)r_1\hat{B}/B.$$

Given that $\hat{B}r_1/B > 1/2$, and $r-(F+D)$, which is the loan–deposit spread, would not be greater than $1/2$ in any reasonable case, $1-\delta$ must be greater than $1-\beta$, or $\beta > \delta$. Thus, given that $F+D = F'+D' = R$, the insolvency risk of a bank, $\hat{\rho}_{SR} = 1-\hat{\gamma}_{SR}$, is greater than that in the benchmark, ρ_{SR}, which leads to the following proposition.

Proposition 1. *When a loan market is segmented by borrowers' capability and when P2P lending platforms and banks operate simultaneously in the low-credit segment, an individual bank's insolvency risk is greater than that in the benchmark case.*

4.2. Liquidity Risk

4.2.1. Benchmark: Only Banks Exist

We now examine the case of bank failure due to insufficient liquidity caused by depositors' early withdrawal. This situation can occur when a bank is forced to liquidate its long-term assets due to the early withdrawal of many depositors at $t = 1$, even though in the absence of early withdrawals, the bank would not face a soundness problem and it could repay the debt sufficiently at $t = 2$.

Let q be the proportion of a deposit that one can recover from early withdrawal at $t = 1$, and let λ, satisfying $1/(1+\lambda) < q$ as assumed above, be the discount rate applied to a bank's (long-term) loan sold at $t = 1$, which would generate cash flow θ without the early withdrawal request. The condition that the liquidity problem never occurs at $t = 1$ is expressed as

$$\theta/(1+\lambda) > qD,$$

implying that the present value of cash flow θ discounted by $1+\lambda$ is greater than the highest possible recovered amount in early withdrawal.

Let L be the ratio of depositors who take early withdrawals, or run, at $t = 1$. In this case, the level of L at which the bank can survive at $t = 1$ but experiences failure at $t = 2$ is determined by the following inequality

$$(1 - L)D > \theta - F - L(1 + \lambda)qD. \tag{10}$$

The liquidity risk arises when the deposit to be returned at $t = 2$ is greater than the remaining liquidity from the cash flow θ, deducted by the protected deposit F, and by the liquidity that has flowed out due to early withdrawal at $t = 1$, $L(1 + \lambda)qD$. The probability of each depositor's belief that a bank will *not* fail at $t = 2$ due to illiquidity is the probability that L *does not satisfy* Equation (10), which is

$$\Pr\left(L \leq \frac{\theta - F - D}{[(1 + \lambda)q - 1]D} = L^*\right). \tag{11}$$

Whether a depositor i chooses to withdraw early at $t = 1$ or not is influenced by his/her private signal, $s_i = \theta + \epsilon_i$, and his/her forecasts about other depositors' behavior, which are reflected by L. Note that depositor i's strategy is influenced by other depositors' *belief* on L upon observing his/her private signal s_i. Then, ultimately, this depositor must consider the *belief on other depositors' beliefs*, which violates the common knowledge assumption and corresponds with the setting of a global game [28].

Following convention, we first apply the *Laplacian property* [28] to our setting: any investor i's *belief* about the ratio of early withdrawal L follows $U[0, 1]$. Depositors are supposed to use the switching strategy, which is proven to be optimal if the Laplacian Property is satisfied [28]. If depositor i chooses a switching strategy, he/she chooses either to run if the signal is below a certain threshold level or to wait until maturity.

The threshold level of the cash flow for an early withdrawal decision, referred to as s^*, is determined when the expected value of the early withdrawal at $t = 1$ equals that of the maturity withdrawal at $t = 2$, or

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

given that $\Pr(\text{survive at } t = 1 | s = s^*) = 1$, or $\alpha r > (1 + \lambda)qD$. Given that the Laplacian Property is satisfied, in a Perfect Bayesian Equilibrium, the likelihood of other investors' decision to run would behave like a random variable drawn from the uniform distribution of $U[0, 1]$. (Moving away from the switching point, this belief may not actually be uniform. However, according to Morris and Shin [28], as long as the payoff advantage of running on the bank is decreasing in θ, the Laplacian action coincides with the equilibrium action.) From the Equation (11), we can infer that

$$\Pr(\text{survive at } t = 2 | s = s^*) = \Pr(L \leq L^*) = (\theta - F - D)/([(1 + \lambda)q - 1]D)$$

as L follows $U[0, 1]$. Note that the probability of solvency at $t = 2$ is continuous. Thus, the expected payoff from waiting is also continuous and monotone decreasing in L, and thus, monotone increasing in θ. The threshold cash flow level θ^*, under which a bank run may occur, is derived as

$$\theta^* = F + D + q[(1 + \lambda)q - 1]D. \tag{12}$$

Note that s^* is *uniquely* determined, $s^* = \theta^*$. Let $\underline{\theta} = F + D$, and $\bar{\theta} = F + (1 + \lambda)qD$, which satisfy $\underline{\theta} < \theta^* < \bar{\theta}$. Then, a depositor has to run for any $L \in [0, 1]$ if $\theta < \underline{\theta}$ and wait if $\theta > \bar{\theta}$, which means that the *limit dominance property* [28] is satisfied. Thus, we can conclude that our setting of the global game satisfies all the required properties in Proposition 2.1 of Morris and Shin [28] for the existence of a unique switching strategy $s^* = \theta^*$. (While not incorrect, the explanation of the global game model in Freixas and Ma [11] uses the setting of Carlsson and Van Damme [27], where the state variable is an unbounded real number (i.e., $\theta \in \mathbf{R}$) and neither upper nor lower dominance exists.)

Let $\mu = 1 + q[(1+\lambda)q - 1] > 1$ for simplicity of notation. If the bank becomes illiquid, despite it being solvent at $t = 2$, and a run on the bank would occur, the range of cash flow would be

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

Similar to ρ_{SR}, we can define the probability of (il)liquidity risk, ρ_{LR}, as

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

The total credit 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

$$\rho_{TR} = \frac{(F + \mu D) - \alpha r}{(1-\alpha)r}. \tag{14}$$

4.2.2. Co-Existence of Banks and P2P Lending Platforms

Again, we investigate the segmented market case, in which P2P lending platforms enter and operate in the low-credit market segment (Market 1). Considering that loans in the high-credit segment (Market 2) are supposed to be riskless and early withdrawal is not likely to occur, we focus only on Market 1.

Note that the trades of notes in the associated aftermarket at $t = 1$ do not influence depositors outside P2P lending platforms. Then, we can adapt Equation (10), which describes the condition for the illiquidity problem for an otherwise solvent bank, for the segmented market case as

$$(\hat{B}/B)(1-L)D' \geq \hat{\theta} - F' - L(\hat{B}/B)(1+\lambda)qD'.$$

The threshold cash flow that makes early withdrawal and waiting indifferent without actual insolvency, $\hat{\theta}^*$, is then derived as

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

Given the assumptions, we find that the cash flow threshold level $\hat{\theta}^*$ is lower than θ^*, derived from the benchmark case. The liquidity risk in the segmented market case is derived as

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

In the worst case, the cash flow would be generated only from risk-free loans. Given that $B > \hat{B}$, $D' < D$, $\alpha_1 < \alpha$, and $r < r_1$, we derive the following proposition.

Proposition 2. *The probability of a bank's (il)liquidity risk is lower when the market is segmented by borrower types and banks compete with P2P platforms than that in the benchmark case, or when* $\hat{\rho}_{LR} < \rho_{LR}$.

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

$$\begin{aligned}\hat{\rho}_{TR} &= \hat{\rho}_{SR} + \hat{\rho}_{LR} = 1 - \frac{\delta B(r - (F+D))}{\beta\hat{B}(1-\alpha_1)r_1} + \frac{(\mu - (B/\hat{B}))D'}{(1-\alpha_1)r_1} \\ &< 1 - \frac{B(r - (F'+D'))}{\hat{B}(1-\alpha_1)r_1} + \frac{(\mu-1)D'}{(1-\alpha_1)r_1} = \frac{(1-\alpha_1)r_1}{(1-\alpha_1)r_1} - \frac{B(r - (F'+D'))}{\hat{B}(1-\alpha_1)r_1} + \frac{(\mu-1)D'}{(1-\alpha_1)r_1},\end{aligned} \tag{17}$$

by assuming $\beta > \delta$. The right-hand side of Equation (17) is less than $\rho_{TR} = (F + \mu D - \alpha r)/((1-\alpha)r)$ if the inequality

$$\frac{\hat{B}}{B}(1-\alpha_1)r_1 + F' + D' - r + \frac{\hat{B}}{B}(\mu - 1)D' < \frac{r_1(x-r)}{r(x-r_1)}(F + \mu D - \alpha r)$$

is satisfied, which can be rewritten as

$$\frac{r_1}{B(x-r_1)} + F' + D' - r + \frac{\hat{B}}{B}(\mu-1)D' < \frac{r_1(x-r)}{r(x-r_1)}(F + D - r + (\mu-1)D) + \frac{r_1}{\hat{B}(x-r_1)} \tag{18}$$

Given A3, $D' < D$ and $\hat{B} < B$, we can conclude that the inequality condition of Equation (18) is always satisfied, which leads to Proposition 3

Proposition 3. *Given the assumptions, the total credit risk of a bank is lower when the loan market is segmented by borrower types and P2P lending platforms operate in the low-credit market segment than that in the benchmark case.*

The insolvency risk rises when the loan market is segmented by credit ratings because banks as well as P2P lending platforms charge higher interest rates in the low-credit segment than they would in the benchmark case, which leads borrowers to choose high-risk, high-return projects, as in Boyd and De Nicolo [15]. In contrast, the decrease in illiquidity risk occurs because the ratio of protected deposits in a bank's portfolio would be higher in the segmented market case. Then, the effect of lowering the cash flow threshold that would trigger a bank run would dominate the effect from the increase in the ratio of risky loans in the low-credit market segment. Note that our model is mainly designed for analyzing the risks of individual institutions; it is not suitable for contagion or systemic risk. Still, our result implies that expecting a minimal impact from P2P lending on contagion and systemic risk in the banking sector is not overstretching. (Freixas and Ma [11] used the same global game approach for the analysis of system risk with strong assumptions about the contagion; it is a simultaneous, non-sequential event that affects only the discount rate.)

Note that our results are mainly derived from the assumptions that (i) P2P lending platforms operate only in the segmented market for borrowers with low-credit ratings while banks operate in both the low- and high-credit market segments; (ii) lending is direct and loans are treated as split notes (non-secured mini-bonds); (iii) only lenders can trade split notes in the associated aftermarket.

5. Extension

5.1. Competition Effects

Two common effects of competition on the soundness of banks are (i) the risk-shifting effect, which is the result of lower risk-seeking tendencies among borrowers as loan rates decline with intensified competition, and (ii) the buffer-reduction effect, which is the lowered capacity of banks to absorb loan loss as loan–deposit margins decline with intensified competition and deteriorating profitability. The effect of competition on the soundness of banks mainly depends on which effect dominates. As the benchmark for this discussion, we again adopt the results of Freixas and Ma [11], which we summarize as follows.

Considering that the risk-free loan ratio α is also a function of the gross rate of return from a loan r, the first derivative of the benchmark insolvency risk ρ_{SR} is as follows:

$$\frac{\partial \rho_{SR}}{\partial r} = \frac{-1}{(1-\alpha)^2 r^2}\frac{\partial \alpha}{\partial r}(r^2 - x(F+D)). \tag{19}$$

Equation (2) shows that α is monotonically decreasing in r. Thus, the insolvency risk ρ_{SR} increase in r, or declines as the competition intensifies, only when $r^2 - x(F+D) > 0$, which is a necessary and sufficient condition. In other words, given that all other conditions remain the same, competition in the loan market initially reduces banks' rates of return on loans and contributes to the reduction of insolvency risk. However, once the rate falls below a threshold (or $r^2 - x(F+D) < 0$), it leads to decreased buffering capital and increased insolvency risk. The first derivative of the illiquidity risk ρ_{LR} with respect to r in the benchmark case is as follows:

$$\frac{\partial \rho_{LR}}{\partial r} = (\mu - 1)\frac{-D}{(1-\alpha)^2 r^2}\left(\frac{\partial(1-\alpha)}{\partial r} r + (1-\alpha)\right) < 0. \tag{20}$$

As competition intensifies, the rate of return on loan r decreases and, consequently, the illiquidity risk increases.

Finally, from Equation (14), we conclude that the total credit risk ρ_{TR} increases with respect to r if and only if $r^2 - x(F+\mu D) > 0$. In other words, under the threshold level, $\tilde{r} = \sqrt{x(F+\mu D)}$, the risk-shifting effect no longer dominates the buffer reduction effect, or competition causes the total credit risk to be higher.

Now, we examine the segmented market case. Suppose the rate of return on a loan in Market 2, r_2, is fixed, and we focus on the rate of return on a loan in Market 1, r_1, and the competition effects in the low-credit market segment between banks and P2P lending platforms. Equation (8) implies that $\hat{\gamma}_{SR}$ monotone decreases in r_1 in a way that is similar to the benchmark case. That is, the insolvency risk of a bank, $\hat{\rho}_{SR} = 1 - \hat{\gamma}_{SR}$, decreases, and competition reduces the insolvency risk until r_1 reaches the threshold level. However, the risk then increases if the interest rate further decreases below the threshold level. From Equation (16), we conclude that competition in Market 1 reduces the illiquidity risk of a bank.

The effect on a bank's total credit risk is similar to that observed in the benchmark case. Instead of the exact threshold rate of return from a loan, we use the approximation derived from Equation (18) to determine the threshold level as

$$r_1^2 > x_1(F' + (1 + \hat{B}/B(\mu-1))D').$$

Given that $x_1 > x$, and $F' + (1+\hat{B}/B(\mu-1))D' < F + \mu D$, whether the threshold value of r_1, $\tilde{r_1} = \sqrt{x_1(F' + (1+\hat{B}/B(\mu-1))D')}$, is greater or not than that of the benchmark case $\tilde{r}$ depends on the values of these variables.

Proposition 4 shows that the threshold rate of return on a loan in Market 1 is likely to be lower than that in the benchmark case. That is, the risk-shifting effect—the upside—is likely to dominate the buffer-reduction effect—the downside—for a lower level of threshold rate in the segmented market case than in the benchmark case.

Proposition 4. *Given $F + D = F' + D'$, the threshold rate of Market 1 in the segmented market case, $\tilde{r_1}$, is lower than $\tilde{r}$, the threshold rate in the benchmark case (i.e., $\tilde{r_1} < \tilde{r}$).*

Proof. We want to show that $x_1(F' + (1+\hat{B}/B(\mu-1))D') < x(F+\mu D)$. Given that $x_1 \approx x$, we can rewrite the inequality as

$$F' - F' = D - D' < \mu D - D' - \hat{B}(\mu - 1)D'/B,$$

which leads to

$$\hat{B}(\mu-1)D'/B < (\mu-1)D.$$

As $\hat{B}/B < 1$ and $D' < D$, we conclude that the inequality holds true. □

Proposition 4 also implies that competition is more likely to reduce the combined credit risk in the segmented market case than in the benchmark case.

5.2. Implication for the Separation of P2P Lending and Banking

So far in our analysis, we have strictly limited bank participation in P2P lending and assumed that only individual lenders can buy split notes and trade them in an associated aftermarket. Given the stringent regulations that prohibit shadow banking that includes P2P lending, it is doubtful that P2P lending platforms would be allowed to take deposits or mediate loans for borrowers with high credit ratings. In contrast, banks could use their subsidiaries and invest in and/or trade payment-dependent notes via P2P lending platforms, (For example, as stated in Vallee and Zeng [25], financial institutions like banks could combine their information with that of P2P lending platforms and use this higher-quality information to purchase split notes) or they could even operate their own P2P lending platforms.

Once banks begin purchasing split notes via P2P lending platforms, they would replace the "loans" that the banks would otherwise provide. These could also be used as another source of interim liquidity in the aftermarket, which would be less conspicuous to monitoring authorities than the money market. From the analysis of competition effects in the previous subsection, however, we expect that reduced competition in the low-credit market segment, along with the lax separation of P2P lending and banking, would lead to a higher rate of return on loan r_1. It would also increase an individual bank's liquidity and total credit risk.

Another possibility is the banks' direct participation in P2P lending. From the perspective (and within the limitations) of our model, unlike banks purchasing split notes via P2P lending platforms, competition in the low-credit market segment (Market 1) would not decrease, although banks would now hold more payment-dependent split notes. If banks choose to buy more notes in the aftermarket after observing their private signals, their liquidity reserves would decrease, which would lead to a higher rate of the haircut in the money market, as suggested by the higher discount rate λ. If a bank chooses to sell more notes in the aftermarket, the sales themselves would decrease the expected value of the split notes. This would be bad news for the bank, which could, in turn, lead to an increase in the probability of a run on an otherwise solvent bank. In all, allowing banks to participate in P2P lending would counter the purpose of Basel III, which requires stronger prudential regulation of bank liquidity.

6. Concluding Remarks

Since the global financial crisis of 2007–2008, direct finance via P2P lending has emerged and rapidly grown as a new vehicle for borrowers without high credit ratings, especially among households and small- and mid-sized enterprises. The growth of P2P lending may have two countervailing effects on banking. One is that banks are less exposed to risky loans and interim liquidity needs, which tend to be better served by P2P lending platforms and their associated aftermarkets. The other is that banks must compete against P2P lending platforms, reducing the liquidity buffers that they need to maintain solvency.

In this study, we investigated the effects of P2P lending on major bank risks: (in)solvency risk and (il)liquidity risk. Specifically, considering the characteristics of direct investments through P2P lending platforms, we compared two cases: (i) the benchmark case, in which only banks exist in a single loan market, and (ii) a segmented market case in which the loan market is segmented by borrowers' creditworthiness, P2P lending platforms operate only in the low-credit segment, and banks operate in both low-and high-credit segments. For the segmented market case, as compared with the benchmark one, we find that while banks' insolvency risk increases, their illiquidity risk decreases such that their overall risk also decreases.

We also find that competition between banks and P2P lending platforms is more likely to reduce the combined credit risk, the sum of (in)solvency, and (il)liquidity risks, in the segmented market case than in the benchmark one. This result implies that once banks begin to participate in P2P lending either directly or indirectly, it would create an adverse effect on the combined risk because it would lessen the competition in the segmented market case. In all, sustainable P2P lending requires an appropriate differentiation of roles between the banking sector and P2P lending so that P2P lending platforms focus more on borrowers with low-credit ratings, while banks focus more on the high-credit market segment and protected deposits.

To the best of our knowledge, this study is one of the first works, if not the first, to implement a full theoretical analysis of the effects of the competition between P2P lending platform and banks on bank failure risks, specifically in the strand of microeconomic banking literature such as Rochet and Vives [10], Freixas and Ma [11], Goldstein and Pauzner [29].

Note that our results are valid only if P2P lending platforms adhere to more primitive, direct forms of financing (e.g., issuing and circulating payment-dependent notes), without handling shadow deposits, derivatives or secured loans. If these platforms expand their business scope and develop more highly leveraged or complex products strongly linked to and affected by other markets and tradings, the implications of the results would be investigated. This is because our assumption that the effects of aftermarket trades of notes stay within the scope of P2P lending platforms would be no longer valid. Finally, we do not fully examine the strategic behaviors of P2P lending platforms in this study. Apart from filling this gap, future studies can (i) empirically investigate how P2P lending platforms affect bank risks under different regulatory frameworks in different economies, and (ii) explore how the role of P2P lending platforms differs from that of banks in advanced economies.

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Abbreviations

The following abbreviations are used in this manuscript:

P2P	Peer-to-Peer
BDD	Bryant–Diamond–Dybvig

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