Journal of Electronic Business & Digital Economics

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Preliminary research of P2P lending bankruptcy in emerging country: the role of financial literacy

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Received 17 December 2024
Revised 23 January 2025
2 June 2025
Accepted 24 September 2025

Abstract

Purpose – There is a significant drop in the number of registered peer-to-peer (P2P) lending in Indonesia roughly 63% from 2020 to 2024. On the other hand, the failure of P2P lending influences the stability of the financial system, while financial literacy influences financial stability. Therefore, the study aims to evaluate the role of financial literacy on P2P lending bankruptcy in Indonesia.

Design/methodology/approach – The autoregressive distributed lags (ARDL) are applied to measure the cointegration. Monthly time series data are used from April 2021 to April 2024.

Findings – The findings show that lender financial literacy, return on equity, outstanding loans and loan disbursement negatively influenced P2P lending bankruptcy in short-term periods. Moreover, the stability of P2P lending in the past periods has negatively influenced the stability of P2P lending in recent times. In contrast, borrower financial literacy and the funds provided by the lender positively influenced the bankruptcy of P2P lending in short-term periods. Meanwhile, the fund provided by the lender is the only construct that positively influences the P2P lending stability in short- and long-term periods. Further policy discussion and policy recommendations are available in the paper.

Originality/value – This article is the first study to evaluate the P2P lending bankruptcy in Indonesia using ARDL model.

Keywords Zscore, P2P lending bankruptcy, Financial literacy

Paper type Research article

1. Introduction

Fintech lending, or peer-to-peer (P2P) lending, proves that technology changes human life, including in financial aspects. The value of P2P lending globally will reach USD1000bn in 2005 [1]. Moreover, P2P lending helps small- and medium-sized businesses and unbankable individuals to get loans directly from investors (Albanna, 2022; Gopal & Schnabl, 2022). Unlike traditional financial intermediaries such as banks, P2P lending connects the lender and borrower on the platform where the lender evaluates the candidates who will get the loans (Danisewicz & Elard, 2023). Thus, P2P lending is justified as being more efficient than banks.

Despite the rapid growth of P2P lending in both developed and developing countries, however, Indonesia experienced a decline in the number of P2P lending platforms over time. Following the introduction of fintech regulation Peraturan Otoritas Jasa Keuangan (POJK) No. 77 in 2016 regarding fintech lending, there were 161 registered P2P lending platforms in 2020. However, the number dramatically declined in April 2024 by roughly 63% to 101 registered P2P lending in Indonesia [2]. The fall is out of concern as to why this phenomenon is occurring. The bankruptcy of P2P lending must be addressed because the advantages outweigh the disadvantages, particularly in developing countries such as Indonesia (Albanna, 2022).

JEL Classification — G01, G23

Journal of Electronic Business & Digital Economics
Vol. 5 No. 1, 2026
pp. 69-89
Emerald Publishing Limited
e-ISSN: 2754-4222
p-ISSN: 2754-4214
DOI 10.1108/JEBDE-12-2024-0055

Moreover, the stability of P2P lending influences the stability of the financial system (Braggion, Manconi, & Zhu, 2017; Elsinger *et al.*, n.d.; Fung, Lee, Yeh, & Yuen, 2020; Haddad & Hornuf, 2023). Thus, preventing the bankruptcy of P2P lending is crucial to maintaining the financial system's stability.

Nevertheless, myriad studies have been done by academicians relating to P2P lending such as the disruption of P2P lending on bank's credit channel (Cuadros-Solas, Cubillas, Salvador, & Suárez, 2024; Gopal & Schnabl, 2022; Junarsin, Pelawi, Kristanto, Marcelin, & Pelawi, 2023), P2P lending credit default (Albanna, 2022; Croux, Jagtiani, Korivi, & Vulanovic, 2020; Di *et al.*, 2022), P2P lending and financial stability (Braggion *et al.*, 2017; Fung *et al.*, 2020; Koranteng & You, 2024; Ramlall, 2018) and personal bankruptcy (Danisewicz & Elard, 2023). However, none of the previous studies evaluate the stability or the bankruptcy of P2P lending companies. Therefore, the study is critical to evaluate the business sustainability of P2P lending in Indonesia.

The paper aims to examine the bankruptcy drivers of P2P lending in Indonesia since the number significantly dropped recently. To the best of the author's knowledge, this is the first paper to discuss the antecedents of the P2P lending failure. Due to the lack of empirical research on P2P lending failure, we use Zscore (Hesse, 2010) as a proxy for P2P lending bankruptcy. It was widely used to measure the bankruptcy (stability) of the banking industry (Azmi, Ali, Arshad, & Rizvi, 2019; Ferhi, 2017; Hesse, 2010; Tarazi & Abedifar, 2022). Since P2P lending has a similar function as the banking industry in financial intermediation.

Moreover, we use financial literacy as the main driver of P2P lending failure. Financial literacy means the ability of the individual to process economic information and make effective and efficient financial decisions (Gonzalez, 2023). It is crucial for financial well-being in the fintech era because it prevents financial fraud and encourages financial planning and social welfare (Panos & Wilson, 2020). Elsinger *et al.* (n.d.) and Soekarni *et al.* (2024) stated that the level of financial literacy determines the efficiency and soundness of financial institutions. In addition, financial literacy is critical for both lender and borrower in P2P lending (Ran, Tan, Phan, & Keppo, n.d.). Thus, putting it as the fundamental determinant of P2P lending failure is acceptable. We use the accumulated number of lender lending transactions and the accumulated number of borrower credit transactions as proxies for financial literacy, which much previous research uses survey data. Other determinants are included in the model to gain comprehensive results.

Furthermore, the study contributes to several aspects: the first is for regulators and authorities to evaluate the recent policies and encourage the stability of P2P lending industries. The second is for the investors to increase their level of financial literacy and risk management in P2P lending investment, while for borrowers to use P2P lending as their alternative capital to scale up their business. The third is for the researcher and academicians that the result of the study fills the blank of the current literature on the bankruptcy of P2P lending, which is scarce. The article is divided into five sections, which are the introduction, the literature review, the data and methodology, the results and discussion and the conclusion and policy recommendations, respectively.

2. Literature reviews

The study relating to the bankruptcy of P2P lending is scarce in the works of literature. However, the emergence of P2P lending is crucial to the stability of the financial system as a whole (Koranteng & You, 2024). The emergence of P2P lending becomes an alternative to credit channelling for borrowers (individuals or small- and medium-sized businesses) and becomes an alternative investment for investors (Braggion *et al.*, 2017; Gopal & Schnabl, 2022). In addition, unlike the banking industry, P2P lending is mostly a broker that connects the lender and the borrower. By matching the lender and borrower directly, P2P lending bypasses the role of traditional banks (Braggion *et al.*, 2017). However, the failure of P2P lending companies disrupts the financial stability as a whole, because sometimes banking

diversifies their credit risk through P2P lending (Elsinger *et al.*, n.d.; Fung *et al.*, 2020). Thus, preventing the bankruptcy of P2P lending is crucial to maintaining the financial system stability.

Nevertheless, the incapability of lenders to predict the credit risk of the borrowers makes the decision ineffective and threatens the stability of P2P institutions (Mild, Waitz, & Wöckl, 2015). Unlike this, banks possess the resources to evaluate the credit risk of borrowers. In contrast, the creditworthiness in P2P lending is determined by the lender's ability to assess the credit. Therefore, the lender must have a high level of financial literacy to ensure a return on P2P investment. Financial literacy reflects the capabilities of individuals to process economic information. Gonzalez (2023), Hasan, Le, and Hoque (2021), Li, Li, Su, Wang, and Wang (2020) and Panos and Wilson (2020) argued that financial literacy has a stronger impact on the penetration of financial technology. Thus, both lender and borrower must have a higher degree of financial literacy. AlSuwaidi and Mertzanis (2024), Ran *et al.* (n.d.) and Quang Trinh (2020) found that financial literacy influences the adoption of fintech in emerging countries. This implies that the level of financial literacy increases the probability of fintech adoption by either borrowers or lenders.

Moreover, financial literacy in the context of fintech (including P2P lending) contains an understanding of financial literacy and digital platforms (Setiawan, Effendi, Santoso, Dewi, & Sapulette, 2022). This means that borrowers and lenders need a good understanding of the platform. According to Lyons and Kass-Hanna (2021), digital financial literacy measures the level of digital financial literacy including basic financial and digital knowledge, awareness of positive financial attitudes and behaviour, ability to make digital financial transactions, ability to make appropriate financial decisions and ability to detect and avoid online scam and fraud. However, the challenge remains the same when lenders have limited information about borrowers (i.e. asymmetric information), while borrowers know about their own financial status and repayment capabilities (Riggins & Weber, 2017; Xu & Chau, 2018). Thus, lenders only give loans to borrowers recommended by other lenders (Gonzalez, 2023). Therefore, digital financial literacy on the lender's side is necessary to make good financial decisions on the fintech platforms while avoiding fraud from borrowers (Luo & Lin, 2013). Luo and Lin (2013) stated that lenders tend to have herding behaviour in their activities on P2P lending platforms, which reduces their return on investment. Meanwhile, borrowers, only those who have better debt literacy, do not default in P2P lending (Hidajat, 2021). Thus, the lack of financial literacy impossibly fully utilized the fintech's benefit neither as a medium of investment nor as a capital resource (Al-Banna & Berakon, 2024; Khan, Liew, & Lee, 2023). The higher the digital financial literacy, the better the financial decision-making (Kumar, Pillai, Kumar, & Tabash, 2023).

In Indonesia, the establishment of P2P lending is based on regulation POJK No.77 2016 about fintech lending, followed by regulation POJK No. 10 2022 about fintech lending and Surat Edaran Otoritas Jasa Keuangan (SEOJK) No.19 2023. The law has been reviewed over time by the Financial Service Authority (OJK) to maintain the environment of fintech lending. The significant difference in the policy is in the contributed capital where in 2016 (POJK No.77 2016) stated that every P2P lending company must provide Rp 1.000.000.000 (one million rupiahs); however, in POJK No. 10 2022, the capital paid has a dramatic increase to Rp 25.000.000.000 (25 million rupiahs). The capital changes in P2P lending suggest that regulators aim to enhance the stability of P2P lending by strengthening its capital base. However, since P2P lending acts as financial intermediation, it is argued that policymakers (OJK) treat P2P lending similarly to banks by reinforcing their capitalization.

Several studies have been done by academicians relating to P2P lending such as the disruption of P2P lending on bank credit channel (Cuadros-Solas *et al.*, 2024; Gopal & Schnabl, 2022; Junarsin *et al.*, 2023), P2P lending credit default (Albanna, 2022; Croux *et al.*, 2020), P2P lending and financial stability (Braggion *et al.*, 2017; Fung *et al.*, 2020; Koranteng & You, 2024; Ramlall, 2018) and personal bankruptcy (Danisewicz & Elard, 2023). However, the discussion of the bankruptcy of P2P lending is absent in the kinds of literature. Therefore,

in this paper, we attempt to evaluate the role of financial literacy in the bankruptcy of P2P lending. The recent failure of P2P lending in Indonesia signalled the authorities to evaluate the current conditions and regulations. Thus, this paper is crucial to be conducted.

3. Data and methodology

3.1 Data

This paper uses monthly time series data from April 2021 to April 2024. The data are taken from the fintech lending statistics of the Financial Service Authority (OJK) website [3]. The given period is selected because of the data availability on the website and the consistency of data reports. However, the report is inconsistent before April 2021; thus, we start the period in April 2021. In advance, 37 observations are gathered and ready to be estimated.

3.2 Methodology

The article aims to evaluate the bankruptcy drivers of P2P lending in Indonesia. We use the Zscore as a dependent variable from Hesse (2010) that represents the bankruptcy level. Zscore is widely used for measuring the bankruptcy (stability) of the banking industry (Ahamed & Mallick, 2017; Azmi *et al.*, 2019; Bilgin, Danisman, Demir, & Tarazi, 2021; Karim, Alhabshi, Kassim, & Haron, 2018). The higher the Zscore value, the lower the probability of default in P2P lending and vice versa. Since P2P lending functions similarly to the banking industry by acting as an intermediary.

Moreover, financial literacy is proxied by the accumulated number of lender lending transactions and the accumulated number of borrower credit transactions. The rationale for using proxies is that P2P lending involves direct interactions between lenders and borrowers. In addition, financial literacy is the knowledge, attitude and behaviour of an individual to make financial decisions (OECD, 2014). Therefore, the number of transactions between lenders and borrowers reflects the level of financial literacy on both sides. People who have a P2P lending account and make a transaction, regardless of a lender or a borrower, have a high level of financial literacy. Furthermore, return on equity (ROE), non-performing loans (NPL), total funds provided by the lender, total loan disbursement to the borrower, productive lending to total lending and outstanding loans are included as bankruptcy drivers.

Then, we use the autoregressive distributed lag (ARDL) model to estimate the time series data. We use the ARDL model because it is suitable for analysing time series data that exhibit different levels of stationarity. This flexibility makes the ARDL approach particularly useful for handling data that may be a mixture of stationary and non-stationary series (Nkoro & Uko, 2016). In addition, the ARDL model is also suitable for small data sizes (Baharumshah, Mohd, & Mansur, 2009; Kripfganz, Schneider, Kripfganz, & Schneider, 2016).

Before running the ARDL model, a unit root test is applied to identify the stationary data, even though ARDL is suitable for both the level and the first difference. After that, ordinary least squares (OLS) regression is tested to see the cointegration of the model. Then, the lags estimation test also implied to seeing the lags involved in the ARDL model in each variable. Moreover, error correction (EC) is also included in the ARDL model to see the short- and long-run (LR) cointegration (Pesaran, Shin, & Smith, 2001). Pesaran *et al.*'s (2001) bound test is implied to explain the LR cointegration in the value of the F-statistic to its critical values. The general model of ARDL is as follows (Wolters, 2006):

$$yt = \alpha + \sum_{i=1}^{p} ai\, yt - i + \sum_{i=0}^{n} ci\, xt - i + \epsilon t \tag{1}$$

The model (1) is an OLS regression, which is applied to see the cointegration between dependent and independent variables to determine the joint significance of lagged levels of the

variables involved. After that, we test the ARDL model with lags involved and EC in the model (see 2), where Δyt is the first difference of the dependent variable, $ci\,\Delta xt$ is the vector of dependent variables, EC is the EC and ϵt is the residual.

$$\Delta yt = \alpha + \sum_{i=1}^{p} ai\,\Delta yt - i + \sum_{i=0}^{n} ci\,\Delta xt - i + \sum_{i=0}^{n} ci\,xt - i + ECt + \epsilon t \tag{2}$$

$$\begin{aligned}\Delta ZSCORE = {} & \alpha + \beta\Delta Zscore_t + \beta\Delta ROE_t + \beta\Delta NPL_t + \beta\Delta LNDYB_t + \beta\Delta LNPP_t + \beta\Delta OUT_t \\ & + \beta\Delta PRO_t + \beta\Delta FLLENDER_t + \beta\Delta FLBOR_t + \beta ROE_t + \beta NPL_t + \beta LNDYB_t \\ & + \beta LNPP_t + \beta OUT_t + \beta PRO_t + \beta FLLENDER_t + \beta FLBOR_t + ECt + \epsilon t\end{aligned} \tag{3}$$

Model 3 above is the model of ARDL in this article where the dependent and independent variables are defined. Further variable definitions are available in Table 1 below.

4. Result and discussion

4.1 Result

In this section, the results of the data estimation are provided. Starting with the descriptive statistic in Table 2, the result illustrates that the mean value of ZSCORE is 15.525, with a 3.45 standard deviation and min and max values at 12.461 and 26.665, respectively. The value of standard deviations is below its mean value, indicating that the bankruptcy level of P2P lending in Indonesia is similar in aggregate. In addition, the distance of the min and max values is also close. However, the mean value of ROE is lower than its standard deviation at 0.38 and 0.71, respectively. This shows the variability of ROE in P2P lending in Indonesia aggregately.

Table 1. Variables definitions

Variable	Proxies	Definitions	Reference
Dependent variable			
Bankruptcy	ZSCORE	$Zscore = \frac{(k+ROA)}{\sigma ROA}k$ = total equity to total asset σROA = standard deviation of return on assets	Hesse (2010)
Independent variables			
Financial literacy	FLLENDER	The number of lender lending transactions	Author calculation
	FLBOR	The number of borrower credit transactions	Author calculation
Other drivers	OUT	Natural logarithm of total outstanding loan	Author calculation
	PRO	Total productive lending to total lending	Author calculation
	LNDYB	Natural logarithm of total funds provided by the lender	Author calculation
	LNPP	Natural logarithm of total loan disbursement to the borrower	Author calculation
	ROE	Return on equity	Author calculation
	NPL	Percentage of non-performing loan	Author calculation

Source(s): Table by author

Table 2. Descriptive statistic

Variable	Obs	Mean	Std. dev.	Min	Max
ZSCORE	36	15.525	3.453	12.461	26.655
ROE	37	0.038	0.071	−0.066	0.174
NPL	37	0.026	0.005	0.014	0.035
LNDYB	37	4.251	0.094	4.034	4.36
LNPP	37	4.257	0.08	4.086	4.363
PRO	37	0.449	0.104	0.294	0.685
OUT	37	4.626	0.146	4.314	4.798
FLLENDER	37	3.354	1.083	1.592	4.978
FLBOR	37	6.767	1.599	3.649	9.138

Source(s): Table by author

In addition, the distance between the min and max values had a huge gap at −0.066 and 0.174, respectively.

On the other hand, the mean value of NPL is 0.026 with a 0.005 standard deviation, while the min and max values are 0.014 and 0.35, respectively. The finding proves that the non-performing loan in P2P lending is relatively low at 3.5% maximum. Meanwhile, LNDYB (total fund provided by the lender) and LNPP (total loan disbursement to the borrower) have similar mean values at 4,251 and 4,257, respectively. Following the standard deviation values, min and max values are identical at 0.094 and 0.08, 4,034 and 4,086, 4.36 and 4.363 in order. Moreover, the mean value of the PRO variable (total productive lending to total lending) is at 0.449, with the standard deviation value lower than its mean at 0.104. This illustrates that P2P lending in Indonesia channels their lending to productive sectors aggregately. In addition, the min and max values are 0.294 and 0.685, respectively.

Furthermore, the mean value of the OUT variable (total outstanding loan) is 4.626, and the standard deviation value is lower than the mean value at 0.146, which indicates the variability of the outstanding loan is close. Meanwhile, the min and max values are 4.314 and 4.798 in order. Nevertheless, the FLLENDER (number of lender lending transactions) is more than half compared to FLBOR (number of borrower credit transactions) in mean, min and max values at 3.354 and 6.767, 1,592 and 3.649 and 4.978 and 9.138, respectively. However, the standard deviation value between FLLENDER and FLBOR is 1.083 compared to 1.599. The details of descriptive statistics are in Table 2 as follows.

Before testing the ARDL model, we deploy the stationary test in two different degrees, which are stationary in level and first difference. As mentioned in the table below, all variables are stationary in the first difference, while OUT and FLBOR variables are stationary both in the level and the first difference at 1%. The results show that the ARDL model can be implemented in the observed data because all the variables have different stationary levels, whether in the level or the first difference. Further stationary tests are available in Table 3.

After the stationary test, we employ the OLS regression to capture the cointegration between dependent and independent variables. Then, the lags estimation model for ARDL is tested, which will be involved in the ARDL model. The result shows that ZSCORE, LNDYB and OUT variables have 1 lag, while others have 0 lags. Moreover, the lags estimation model is available in Table 4.

Table 5 describes the ARDL model including the ARDL-based model with maximum lags of 1 in column 1. Meanwhile, columns 2, 3 and 4 are the ARDL model with lags and EC models. In addition, column 2 describes the adjustment (ADJ) of ZCSORE variable, while columns 3 and 4 explain the LR cointegration and short-run (SR) cointegration in the ARDL model. Moreover, the results will be discussed from the base model to the model with the EC

Table 3. Stationarity test

Variables	Level	1st difference
Zscore	0.9589	0.0001***
ROE	0.4097	0.0001***
NPL	0.1190	0.0000***
LNDYB	0.1122	0.0000***
LNPP	0.1787	0.0000***
PRO	0.2878	0.0000***
OUT	0.0023***	0.0002***
FLLENDER	0.5017	0.0032***
FLBOR	0.0000***	0.0002***

Note(s): Significant level: *1%, **5% and ***1%
Source(s): Table by author

Table 4. Lags estimation model

	ZSCORE	ROE	NPL	LNDYB	LNPP	PRO	OUT	FLLENDER	FLBOR
r1	1	0	0	1	0	0	1	0	0

Source(s): Table by author

model. The results of the ARDL-based model (column 1) show that the probability of bankruptcy (L.ZSCORE) in P2P lending industries is positively influenced by its stability in the period before. This indicates that the bankruptcy of P2P lending is predictable historically.

Meanwhile, ROE, the fund provided by the lender (L.LNDYB) lag 1, and the accumulated number of lender lending transactions in a unit of account (FLLENDER) negatively influenced the bankruptcy of P2P lending enterprises. This explains that the smaller the number of those variables, the higher the stability of P2P lending enterprises. Nevertheless, the fund provided by the lender (LNDYB) and the accumulated number of borrower credit transactions in a unit of account (FLBOR) positively influence the bankruptcy of P2P lending companies. This means that the higher the number of those variables, the higher the stability of P2P lending in Indonesia.

On the other hand, the results of the ARDL model with EC (columns 2, 3 and 4) show that Zscore in the previous period (L.ZCSCORE), ROE, total loan disbursement to the borrower (LNPP), total outstanding loan (OUT) and the number of lender lending transactions (FLLENDER) negatively influence the bankruptcy of P2P lending in Indonesia in the ADJ coefficient and LR cointegration. However, the number of borrower credit transactions (FLBOR) and the fund provided by the lender (LNDYB) positively influences the stability of P2P lending in LR cointegration, while in the short-term cointegration the lag of the fund provided by the lender (D.LNDYB) positively influences the bankruptcy of P2P lending in Indonesia (see Figure 1).

Finally, we employ post-estimation in ARDL with the bound test. The bound test result shows that the F-statistic value is 4.927, higher than its critical values I(0) and I(1) at the 10%, 5%, 2.5% and 1% levels. This means that there is a LR relationship in the model. The details of the bound test are available in Table 6.

The line graph in the chart represents the cumulative sum (CUSUM) of the deviations of the sample values from a target value or mean. In a CUSUM squared test, this line tracks the CUSUM of squared deviations, making it sensitive to changes in variability. However, if the CUSUM line crosses these limits, it indicates a significant change in the process that may require investigation. Even though the CUSUM square test crosses the line in the middle of the period, it is back to its stability at the end of the period. This indicates that the model is quite stable.

Table 5. ARDL estimation

Variables	(1) Model 1 ARDL (Lags)	(2) Model 2 ARDL EC (ADJ)	(3) Model 2 ARDL EC (LR)	(4) Model 2 ARDL EC (SR)
L.ZSCORE	0.2633*	−0.7367***		
	(0.1496)	(0.1496)		
ROE	−47.6855***		−64.7246***	
	(8.0905)		(8.1402)	
NPL	−64.5863		−87.6644	
	(140.9151)		(193.7621)	
LNDYB	35.2848***		34.0466**	
	(11.5048)		(13.2528)	
L.LNDYB	−10.2011*			
	(5.6833)			
LNPP	−40.9007**		−55.5155**	
	(15.8286)		(20.8419)	
PRO	5.8309		7.9144	
	(7.5290)		(9.7083)	
OUT	−35.6032		−107.7556***	
	(31.7454)		(19.8269)	
L.OUT	−43.7852			
	(26.5948)			
FLLENDER	−0.0139***		−0.0189***	
	(0.0049)		(0.0066)	
FLBOR	0.0189***		0.0257***	
	(0.0043)		(0.0053)	
D.LNDYB				10.2011*
				(5.6833)
D.OUT				43.7852
				(26.5948)
Constant	364.9361***			364.9361***
	(71.1887)			(71.1887)
Observations	35	35	35	35
R-squared	0.8990	0.6682	0.6682	0.6682

Note(s): Standard errors in parentheses ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$
Source(s): Table by author

4.1.1 Robustness test. Furthermore, to gain a comprehensive result, a robustness test is applied using an alternative measure of bankruptcy with a natural logarithm of Zscore. The use of the natural logarithm of Zscore (LNZSCORE) is commonly used by several previous studies regardless of the robustness check or main dependent variable (Abedifar, Molyneux, & Tarazi, 2011; Bilgin *et al.*, 2021; Chiaramonte, Croci, & Poli, 2015). The specific ARDL model for the robustness check is below:

$$\begin{aligned}\Delta LNZSCORE = {} & \alpha + \beta\Delta LNZscore_t + \beta\Delta ROE_t + \beta\Delta NPL_t + \beta\Delta LNDYB_t + \beta\Delta LNPP_t \\ & + \beta\Delta OUT_t + \beta\Delta PRO_t + \beta\Delta FLLENDER_t + \beta\Delta FLBOR_t + \beta ROE_t \\ & + \beta NPL_t + \beta LNDYB_t + \beta LNPP_t + \beta OUT_t + \beta PRO_t + \beta FLLENDER_t \\ & + \beta FLBOR_t + ECt + \epsilon t\end{aligned} \tag{4}$$

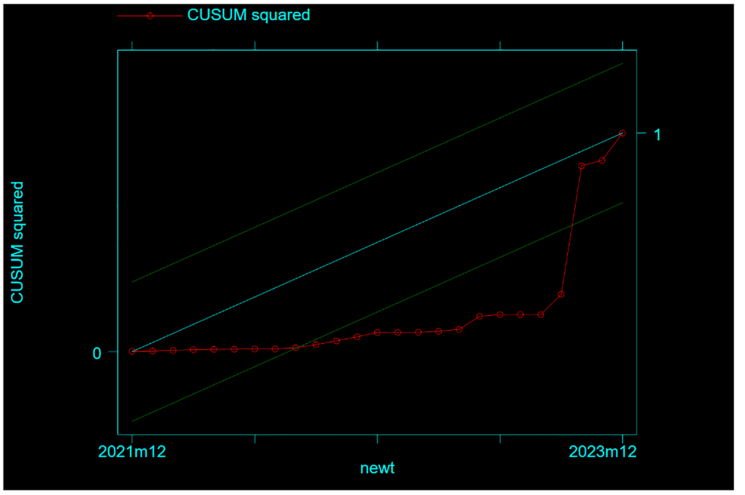

Figure 1. Cumulative sum (CUSUM) test. Figure by author

Table 6. Bound test

	Critical values							
F-statistic	10% I(0)	10% I(1)	5% I(0)	5% I(1)	2.5% I(0)	2.5% I(1)	1% I(0)	1% I(1)
4.927	1.95	3.06	2.22	3.39	2.48	3.70	2.79	4.10

Source(s): Table by author

Where Δ*LNZSCORE* is the natural logarithm of Zscore as the dependent variable. Meanwhile, the independent variables remain the same. Detailed results are in the table below.

Table 7 shows the results of the robustness test of the ARDL model. The findings illustrate that lender financial literacy has a negative influence on the bankruptcy of P2P lending, while borrowers' financial literacy has a positive influence in a LR relationship. This implies that the results of the study are robust, even though the R-squared value is lower compared to its baseline model (see Table 5).

Table 8 above describes the additional ARDL test, which, in the new model, uses the other financial literacy proxy. We develop the new financial literacy proxies for both the lender and borrower sides. The new proxy is generated from the number of lender lending transactions to the number of lender accounts for the proxy of the lender's financial literacy. Meanwhile, for the borrowers, the use the number of borrower credit transactions to the number of borrower accounts. The use of the proxies is capturing the number of lender and borrower transactions in a single account, which represents how often the lender agrees with the borrower's credit proposal and how often the borrower's proposal is agreed to by the lenders. The results show that borrower financial literacy (NEWFBOR) positively influenced the stability of P2P lending in Indonesia in the SR. In contrast, the lender's financial literacy (NEWFLENDER) shows insignificant influence, although it has a negative direction. Thus, the results remained robust.

Moreover, to ensure the new model is free from multicollinearity, we eliminated several variables that possibly have multicollinearity effects. The deleted variables are NPL, LNDYB and OUT. Therefore, the pairwise correlation matrix test and variance inflation factors are

Table 7. ARDL robustness test

Variables	(1) Model 1 ADJ	(2) Model 2 LR	(3) Model 3 SR
ROE		−3.3913***	
		(0.5165)	
NPL		−4.8456	
		(12.9006)	
LNDYB		1.4151*	
		(0.8265)	
LNPP		−2.4404**	
		(1.1378)	
PRO		0.3644	
		(0.6300)	
OUT		−5.8559***	
		(1.2704)	
FLLENDER		−0.0000**	
		(0.0000)	
FLBOR		0.0000***	
		(0.0000)	
L.LNZSCORE	−0.6674***		
	(0.1649)		
D.LNDYB			0.6086*
			(0.3399)
Constant			18.9752***
			(4.5257)
Observations	35	35	35
R-squared	0.5715	0.5715	0.5715

Note(s): Standard errors in parentheses ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$. The dependent variable is the natural logarithm of Zscore (LNZSCORE) and the independent variables are the same as the baseline model (see Table 5). The maximum lag used in the robustness check is (100100000). Model (1) describes the error correction model of the dependent variable. Meanwhile, models (2) and (3) describe the long-run and short-run relationship of independent variables

Source(s): Table by author

conducted. The results in the table below (see Tables 9 and 10). The results illustrate that the variable used in the model is far from multicollinearity, with the pairwise correlation values below 0.9 and VIF below 10 (Das, 2019; García, García, López Martín, & Salmerón, 2015).

Furthermore, we employ the vector autoregressive correction model (VECM) to capture the dynamic change in the model. LNZSCORE is used as a dependent variable, and then ROE, LNPP, NEWFLENDER, NEWFBOR and PRO are the independent variables. The results illustrate that there was a LR relationship in the zscore, which means that the stability of P2P lending is influenced by the past stability. Unlike the ARDL model (Table 7), the financial literacy of borrowers (NEWFBOR) has a significant negative influence in the LR in the VECM model. In contrast, the lenders' financial literacy (NEWFLENDER) has a negatively but insignificant to the stability of P2P lending. This indicates that in the LR, borrowers' decisions worsen the stability of the P2P lending. The results of the VECM model are in Table 11 below.

4.2 Discussion

The study aims to evaluate the role of financial literacy in P2P lending bankruptcy in Indonesia. In this section, the discussion is based on the results in columns 2, 3 and 4 in Table 5, beginning with the justifications of financial literacy and followed by other significant determinants.

Table 8. ARDL additional test

Variables	(1) Zscore	(2) Zscore ADJ	(3) Zscore SR	(4) Zscore LR	(5) lnZscore	(6) lnZscore ADJ	(7) lnZscore SR	(8) lnZscore LR
L.ZSCORE	0.807***	−0.193						
	(0.114)	(0.114)						
ROE	−24.13***		−37.18		−1.101***		−1.779	
	(6.379)		(23.78)		(0.354)		(1.098)	
L.ROE	16.97**				0.701*			
	(7.205)				(0.392)			
LNPP	−9.790		−50.83		−0.602		−2.675	
	(9.219)		(48.21)		(0.515)		(2.253)	
NEWFLENDER	−0.698		−3.622		−0.0369		−0.164	
	(1.328)		(7.190)		(0.0738)		(0.337)	
NEWFBOR	−0.0504		0.288**		−0.00321		0.0143**	
	(0.0364)		(0.129)		(0.00202)		(0.00564)	
L.NEWFBOR	0.106**				0.00642***			
	(0.0394)				(0.00220)			
PRO	−3.981		−20.67		−0.194		−0.864	
	(5.007)		(29.89)		(0.278)		(1.343)	
D.ROE				−16.97**				−0.701*
				(7.205)				(0.392)
D.NEWFBOR				−0.106**				−0.00642***
				(0.0394)				(0.00220)
L.LNZSCORE					0.775***	−0.225*		
					(0.113)	(0.113)		
Constant	45.55			45.55	3.196			3.196
	(38.90)			(38.90)	(2.254)			(2.254)
Observations	35	35	35	35	35	35	35	35
R-squared	0.876	0.594	0.594	0.594	0.865	0.562	0.562	0.562

Note(s): Standard errors in parentheses ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$. Models 1 and 5 are the results of ARDL base line models. The rest of the model (excluding 1 and 5) are the results of ARDL with error correction and stability test. Models 1 through 4 use Zscore as a dependent variable, while models 5 through 8 use the natural logarithm of zscore (lnzscore) as a dependent variable. All the ARDL models use (110010) lags

Source(s): Table by author

Table 9. Pairwise correlations

Variables	(1)	(2)	(3)	(4)	(5)
(1) ROE	1.000				
(2) LNPP	0.000	1.000			
(3) NEWFLENDER	0.061	0.871	1.000		
(4) NEWFBOR	0.295	0.693	0.742	1.000	
(5) PRO	−0.146	−0.859	−0.753	−0.683	1.000

Source(s): Table by author

Table 10. Variance inflation factor

	VIF	1/VIF
LNPP	7.292	0.137
NEWFLENDER	4.712	0.212
PRO	4.102	0.244
NEWFBOR	2.696	0.371
ROE	1.29	0.775
MEAN VIF	4.019	

Source(s): Table by author

In this paper, we use the accumulated number of lender lending transactions and the accumulated number of borrower credit transactions to represent the financial literacy of lenders and borrowers, respectively. The findings showed that the financial literacy of the lender negatively influenced the bankruptcy of P2P lending in the short term (Table 5 column 3). This implies that the more transactions conducted by lenders, the more likely it is to make P2P lending go bankrupt. The result is in line with Gao, Yen, and Liu (2021) and Mild *et al.* (2015), who stated the inability of lenders to secure a return in the P2P lending market. Unlike banks, all of the credit approvals are made by the lender's decision, while lenders are incapable of assessing the creditworthiness of borrowers due to the lack of financial literacy, particularly in risk management. Even though P2P lending institutions provide the information and credit score of borrowers. Jagtiani and Lemieux (2019) found that credit scores provided by P2P companies are unable to predict the probability of default of the borrower.

The lender's decision in the P2P lending credit market is similar to their decision in investment activities, such as in the capital market. It needs a strong analysis of how their investment will return positively. Because of information asymmetry, to succeed in the P2P credit market, lenders need to equip themselves with strong financial literacy, particularly in areas such as credit analysis, portfolio management and investment decision-making. However, the result is rational when the level of Indonesian financial literacy in fintech is only 10.9% in 2022 and causes bankruptcy of P2P lending. OJK (2022), Hasan *et al.* (2021), Li *et al.* (2020), Panos and Wilson (2020) and Ran *et al.* (n.d.) argued that financial literacy is the fundamental aspect in this digital era. Thus, it prevents online financial fraud, increases digital financial literacy and inclusive finance and has financial planning, risk management and good financial decisions.

Furthermore, regulators, authorities and stakeholders must promote P2P lending as an alternative to investment, not only as an alternative to credit channels. P2P lending has traditionally been promoted as an alternative source of consumer credit, characterized by its straightforward terms and accessible facilities. However, it is important to recognize that P2P lending operates under a distinct business model, wherein borrowers obtain loans directly from

Table 11. VECM model

Variables	(1) D_ LNZSCORE	(2) D_ROE	(3) D_LNPP	(4) D_ NEWFLENDER	(5) D_ NEWFBOR	(6) D_PRO
L._ce1	−1.854***	0.188	−0.627***	0.723	35.35	0.318
	(0.606)	(0.377)	(0.192)	(0.542)	(84.80)	(0.385)
L._ce2	−0.742***	0.249	0.133	−0.155	−21.27	0.344**
	(0.262)	(0.163)	(0.0830)	(0.234)	(36.62)	(0.166)
L._ce3	−2.276	0.0239	−2.136***	3.080**	93.57	0.649
	(1.472)	(0.914)	(0.466)	(1.316)	(205.8)	(0.935)
LD.LNZSCORE	0.791*	0.111	0.454***	−0.932**	−32.42	−0.141
	(0.434)	(0.270)	(0.138)	(0.388)	(60.69)	(0.276)
L2D.LNZSCORE	0.401	−0.0501	0.143	−0.785***	2.425	0.245
	(0.328)	(0.204)	(0.104)	(0.293)	(45.81)	(0.208)
L3D.LNZSCORE	−0.0293	−0.134	0.320***	0.299	−90.70*	−0.129
	(0.347)	(0.215)	(0.110)	(0.310)	(48.47)	(0.220)
LD.ROE	1.652**	−0.159	−0.272	−0.166	−24.57	−1.277***
	(0.679)	(0.422)	(0.215)	(0.607)	(94.94)	(0.432)
L2D.ROE	−0.653	−1.064	−1.107***	−0.415	157.0	−0.0989
	(1.069)	(0.664)	(0.339)	(0.956)	(149.4)	(0.679)
L3D.ROE	−0.415	0.289	−0.965***	1.568*	196.2	0.243
	(1.037)	(0.645)	(0.329)	(0.928)	(145.1)	(0.659)
LD.LNPP	−0.0856	−0.514	0.950***	−2.306***	108.8	−1.058*
	(0.967)	(0.601)	(0.306)	(0.865)	(135.2)	(0.615)
L2D.LNPP	−0.425	0.0644	0.316	−1.165*	59.46	−0.538
	(0.720)	(0.447)	(0.228)	(0.644)	(100.6)	(0.457)
L3D.LNPP	−0.509	0.00385	0.371**	−0.763	68.60	−0.158
	(0.588)	(0.366)	(0.186)	(0.526)	(82.27)	(0.374)
LD.NEWFLENDER	−0.336	−0.0887	−0.241**	0.0469	23.61	0.255
	(0.359)	(0.223)	(0.114)	(0.321)	(50.21)	(0.228)
L2D.NEWFLENDER	0.229	−0.153	−0.177*	0.498*	−40.99	0.0449
	(0.294)	(0.182)	(0.0930)	(0.263)	(41.06)	(0.187)

(*continued*)

Table 11. Continued

Variables	(1) D_ LNZSCORE	(2) D_ROE	(3) D_LNPP	(4) D_ NEWFLENDER	(5) D_ NEWFBOR	(6) D_PRO
L3D.NEWFLENDER	−0.149	−0.210	−0.0435	0.139	10.18	−0.133
	(0.291)	(0.181)	(0.0921)	(0.260)	(40.64)	(0.185)
LD.NEWFBOR	−0.0221***	0.00303	−0.000643	−0.000122	0.503	0.00393
	(0.00620)	(0.00385)	(0.00196)	(0.00554)	(0.866)	(0.00394)
L2D.NEWFBOR	−0.0172***	0.00473	−0.00268	0.00520	−0.537	0.00461
	(0.00537)	(0.00334)	(0.00170)	(0.00481)	(0.751)	(0.00342)
L3D.NEWFBOR	−0.0118*	−8.60e−05	−0.000452	0.00180	0.0117	0.00450
	(0.00626)	(0.00389)	(0.00198)	(0.00560)	(0.875)	(0.00398)
LD.PRO	−0.977*	−0.0246	0.327*	−0.824*	38.94	−0.235
	(0.535)	(0.333)	(0.170)	(0.479)	(74.86)	(0.340)
L2D.PRO	−0.679*	0.133	0.0308	0.286	24.13	0.382
	(0.386)	(0.240)	(0.122)	(0.345)	(53.95)	(0.245)
L3D.PRO	0.125	0.250	0.164	0.447	−38.29	0.0913
	(0.438)	(0.272)	(0.139)	(0.392)	(61.29)	(0.279)
Constant	0.00455	0.0305	0.0285**	0.0140	0.000288	0.000814
	(0.0396)	(0.0246)	(0.0125)	(0.0354)	(5.531)	(0.0251)
Observations	32	32	32	32	32	32

Note(s): Standard errors in parentheses ***$p < 0.01$, **$p < 0.05$ and *$p < 0.1$. The dependent variable is the natural logarithm of zscore (LNZSCORE), while the dependent variables are ROE, LNPP, NEWFLENDER, NEWFBOR and PRO. The VECM model above uses 4 lags and 3 ranks (Johansen Cointegration Test)

Source(s): Table by author

individual investors (lenders), which means that credit risk is borne by the lender. Meanwhile, in developed countries such as the USA and China, where P2P lending is mushrooming, with platforms and third parties developing machine learning and artificial intelligence to give insight to lenders for their investment decisions (Babaei & Bamdad, 2020; Babaei, Giudici, & Raffinetti, 2023; Di Maggio & Yao, 2021; Jagtiani & Lemieux, 2019). However, artificial intelligence is not fully used in emerging countries in managing the risk. Promoting P2P lending as an investment, on the one hand, will change the brand image of P2P lending and encourage people to learn more about portfolio and risk management; on the other hand, it will boost the environment of P2P lending itself by attracting third parties to develop innovative platforms. Investment financial literacy is needed, which has a relatively low level in Indonesia, to encourage the awareness of potential lenders to put their money in P2P lending.

In contrast, borrowers' financial literacy positively influenced the short-term and long-term bankruptcy of P2P lending. This indicates that the number of borrower transactions in P2P lending decreases the probability of default in P2P lending companies. The borrower transaction gives P2P lending a fee to the platform if the lending is performed well. The result is supported by the insignificant influence of the NPL (credit default) variable on bankruptcy P2P lending. These results indicate that borrower loans return positively (see Table 2), where the average non-performing loan is 2.6%. However, lenders must be aware of the factors that determine credit default in P2P lending, such as the borrower's domicile (Albanna, 2022), indebtedness and loan purposes (Croux *et al.*, 2020). In addition, platforms need to pay more attention to new borrowers because the vast majority of new borrowers' transactions default and cause the bankruptcy of P2P lending platforms (Wu & Zhang, 2021). Thus, platforms seriously manage debt collection from the borrower's probability of default. The successful platform in collecting credit from borrowers will gain the lender's trust, which will lead to the new customer adoption, regardless of whether they are borrowers or lenders. In addition, lenders give the loan to the recommended borrowers from another lender (Gonzalez, 2023). This indicates that borrowers with good credit ratings have easy access to borrow money from many lenders. Moreover, a lender's word of mouth means something to the borrower's image. Therefore, authorities and stakeholders have to encourage moral suasion regarding the borrower's responsibility and ethical conduct to minimize credit default due to moral hazard.

The massive campaign of P2P lending as a credit channel alternative is successful not only for individuals but also for small- and medium-sized enterprises (Gopal & Schnabl, 2022; Soekarni *et al.*, 2024). Fast and easy processes are the reason why some people choose P2P lending over a bank. Nevertheless, a higher interest rate is one of the consequences of the ease of use in P2P lending. Moreover, it causes the borrower to scam the loan, which means that borrowers with the same characteristics tend to default on their loans in P2P lending compared to in personal debt (Di Maggio & Yao, 2021). Therefore, providing as much information as possible to reduce credit risk is critical, particularly for new borrowers. Besides, discounts and collaboration with other marketplaces are needed to attract new applicants. Regulators and authorities need to consider the cost of loans for the borrowers to increase the transactions; however, the charge is a concern for the borrowers.

The other significant variable that positively influences the bankruptcy of P2P lending is the funds provided by the lender, regardless of whether short- or long-term. This indicates that the amount of money provided by the investors maintains the stability of P2P lending. The cash from lenders that has not yet been lent to borrowers can serve as an alternative to maintain the stability of P2P lending. To increase the amount of cash deposited by lenders, platforms could offer a form of interest on deposits if lenders withhold their loans to borrowers for a specified period. Subsequently, this cash could be invested in other portfolios with durations aligned with the holding period of the lenders. This approach provides lenders with an alternative investment option beyond direct lending to borrowers, utilizing the idle funds provided by the lenders. For instance, the lenders top up their money to the platform at around $100 dollars. After that, the platforms give the option to the lenders whether the money will all go into lending or one-fifth of the total amount will be invested in other securities. The platforms

provide alternative investment to the lender, not only a credit channel to the borrower. It will attract customers and switch the business model of P2P lending platforms. Platforms will have another source of income in managing lenders' idle cash, and lenders will have portfolio and risk management diversification.

Moreover, this scheme can attract various types of lenders except individual lenders such as banks or other companies. Cuadros-Solas *et al.* (2024) and Junarsin *et al.* (2023) found that the existence of P2P lending disrupts the bank in the lending market. Therefore, rather than competing with banks in the lending market, it would be more beneficial for P2P lending and banks to collaborate in a mutually advantageous manner. Banks can use P2P lending as a means to diversify their credit risk, while the cash from banks can be utilized by P2P lending platforms for direct lending or other investments. Besides, sufficient regulations are needed to bridge this notion, because without sufficient rules and laws, P2P lending default is the price (Wu & Zhang, 2021).

On the other hand, Zscore in the past years, ROE, loan disbursement to borrowers and outstanding loans negatively influence the bankruptcy of P2P lending in the short-term period. These imply that all of these variables increase the bankruptcy level in P2P lending. The negative signs of past Zscore indicate that the bankruptcy in P2P lending was predictable a year before. Since the Zscore is measured by summing the total equity to total assets, it is assumed that the equity of P2P lending comes from leverage. In addition, the higher leverage will increase the cost of capital for P2P lending. The justification is in line with the negative sign of ROE: the higher ROE increases the bankruptcy. In addition, Frank and Shen (2016) and Hasan, Hossain, Cheung, and Habib (2015) found that the higher cost of equity will reduce investment activities and reduce the return on assets. The findings warn that P2P lending reduces the cost of capital and focuses on return on assets. Regulators and authorities need to guide the P2P soundness, similar to the bank soundness, through regulations to maintain the stability of P2P lending in particular and the financial system as a whole.

Furthermore, the loan disbursement and outstanding loans reduce the stability of P2P lending. Even though the NPL is insignificant, the number of outstanding loans and loan disbursements to the borrower tends to increase the probability of default in P2P lending. Platforms need to ensure that outstanding loans end with a return and that the loan is distributed to the responsible borrowers. The coefficient value of an outstanding loan is higher than loan disbursement. This indicates that outstanding loans influence more than loan disbursement. However, these conditions are quite hard regarding the decision of loan disbursement in the lender's hand, while the lender's incapabilities to mitigate the credit risk worsen the situation. Therefore, developing artificial intelligence and machine learning to help the lender in their decision is necessary (Babaei & Bamdad, 2020; Babaei *et al.*, 2023; Di Maggio & Yao, 2021; Jagtiani & Lemieux, 2019). However, other variables are insignificant drivers in P2P lending bankruptcy such as NPL, total productive loans to total loans (PRO) in short-term periods and past loan disbursement in long-term periods. Further policy recommendations are available in the following section.

5. Conclusion

The study aims to evaluate the role of financial literacy in P2P lending bankruptcy. The study is critical since the emergence of P2P lending in the lending market influences the financial system's stability. Therefore, maintaining the stability of P2P lending is equal to preventing the financial crisis. However, the literature regarding bankruptcy in P2P lending is limited.

The findings show that lender financial literacy, ROE, outstanding loans and loan disbursement negatively influenced P2P lending bankruptcy in short-term periods. Moreover, the stability of P2P lending in the past periods negatively influenced the stability of P2P lending in recent times. This implies that the higher value of these variables increases the probability of default in P2P lending. In contrast, borrower financial literacy and the funds provided by the lender positively influenced the bankruptcy of P2P lending in short-term

periods, which means that the higher the value of these variables, the higher the stability of P2P lending. In addition, the fund provided by the lender is the only construct that positively influences the P2P lending stability in both short- and long-term periods.

However, the paper has several limitations. The first is that the data used in this paper are time series data; however, the use of panel data is required to gain more detailed results in individual P2P lending bankruptcy. The second is the short duration of the research period from April 2021 to April 2024; therefore, a longer research time frame is necessary to capture the business cycle of P2P lending over time. The third is that the number of observations is limited due to the availability of the data and the short time period. Thus, using more observed data will yield robust results. The fourth is methodology; it is necessary to test the data by using another methodology, such as the vector autoregressive error correction model (VECM), to capture the causality issues in the model.

6. Policy recommendations

It is essential to reassess several policies in light of the paper's findings. The recommendations are as follows:

(1) Regulators, authorities and stakeholders need to promote (massive campaigns) P2P lending as an alternative investment platform, not only as a credit channel option. However, all this time, P2P lending has been promoted as a platform for borrowing money easily and quickly. The suggestion is based on the negative result of lender financial literacy.

(2) Regulators, authorities and stakeholders need to encourage financial literacy (lender and borrower) in investment aspects, such as portfolio management, risk management and business evaluations, to reduce the bankruptcy of P2P lending, because the lack of financial literacy influences the probability of default in P2P lending.

(3) Regulators and authorities need to regulate P2P lending soundness and risk management practices as the bank does. The current regulation of P2P lending guidelines on P2P lending financial health and risk management is absent in the regulations. Defining the risk inherent in P2P lending and risk management guidelines is critical to ensure the compliance of P2P lending.

(4) Regulators and authorities need to set up the capital adequacy of P2P lending. Since P2P lending has a similar role to banks as financial intermediaries. However, current regulation only sets the paid-in capital, not the capital adequacy. Capital adequacy is critical to buffering the non-performing assets.

(5) To develop the environment of fintech innovation, regulators and authorities necessarily conduct the guidelines for the possibility of P2P lending to manage the funds (individual or companies) to invest in other portfolio investments such as bonds, sukuk or other securities. This will attract funds from banks and other financial institutions and at the same time will increase the profitability of P2P lending.

(6) A platform is necessarily urgent to develop the credit score, especially for the new borrower, based on machine learning and artificial intelligence to generate borrower information to help lender decisions, because lenders are incapable of mitigating the credit risk.

(7) For academicians and researchers, this study can be the path for P2P lending studies and other fintech firms such as crowdfunding, marketplaces and business aggregators. Nevertheless, the study in the fintech industry is limited and needs further future direction regarding the topics, theories and methodology. Discussing the fintech sector from the financial and business perspectives is critical due to its impact on economic growth and financial ecosystem.

Notes

1. https://www.statista.com/statistics/325902/global-p2p-lending/
2. https://www.ojk.go.id/id/kanal/iknb/data-dan-statistik/fintech/Default.aspx
3. https://www.ojk.go.id/id/kanal/iknb/data-dan-statistik/fintech/Default.aspx

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