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Factors Affecting Peer-to-Peer (P2P) Lending Bad Debts in Java and Sumatra

Zuni Nur Khasanah[1], Hasan Al-Banna[2]
[1,2]Department of Islamic Banking, Faculty of Islamic Economics and Business, UIN Sunan Kalijaga Yogyakarta

Corresponding author: zuninur93@gmail.com

Abstract

Purpose: This study aims to analyse the factors that influence bad debts in Peer-to-Peer (P2P) lending platforms in Jawa and Sumatra. The emergence of fintech as an alternative financing solution for the public and UMKM has created new challenges in the form of high credit risk. This study is motivated by the rapid growth of the fintech industry in Indonesia and the limited academic studies comparing credit risk based on geographical region.
Methodology: This study uses monthly time series secondary data for the period January 2021 – December 2024 obtained from the OJK Fintech Lending Statistics report. This study uses the Autoregressive Distributed Lag (ARDL) method to see the short-term and long-term effects of the variables of loan amount, loan purpose (individual and business entity), and male and female debtors.
Findings: The results showed that the amount of the loan did not have a significant effect on bad debts. Meanwhile, other variables have a significant effect on bad debts.
Novelty: This research has novelty in terms of region; the research focuses on two regions in Indonesia, namely Jawa and Sumatra. These two regions were chosen because they have different economic characteristics of infrastructure and access to financial services.

Keywords: Peer-to-Peer (P2P) lending, bad debts, Jawa Island, Sumatra Island

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Introduction

The development of financial technology (fintech) has revolutionised the global financial system, including Indonesia, with the presence of peer-to-peer (P2P) lending platforms. This platform facilitates access to loans for UMKM and individuals who find it difficult to obtain loans from conventional banks (Nurhayati et al., 2022). The peer-to-peer (P2P) lending industry has grown rapidly, including in Indonesia, which has been active since 2015-2016 (Purwanto et al., 2022). It was marked by the establishment of the Indonesian Fintech Association (AFI) in 2016 (Indofund, 2023).

The fintech industry in Indonesia is growing every year because it is able to provide more inclusive financial access, especially for people who have not been reached by conventional financial institutions (Mukhtar & Rahayu, 2019). Statistical data from the Financial Services Authority (OJK) shows that loan disbursements by peer-to-peer (P2P) lending fintech companies in Indonesia have continued to grow throughout the period from January 2021 to December 2024. In Jawa, the total loan disbursement rose from IDR 7,779 billion in January 2021 to IDR 20,614 billion in December 2024. In Sumatra, loan disbursements also increased from IDR 831 billion to IDR 3,658 billion over the same period. These figures illustrate the continuous expansion of fintech services and their growing contribution to financial inclusion across regions in Indonesia.

Based on data from fintech lending statistics in December 2024, there were 97 fintech lending platforms registered and supervised by the Financial Services Authority (OJK). One of the main challenges in peer-to-peer (P2P) lending services is the risk of bad credit, which in this research is defined based on the TWP90 indicator, referring to the percentage of total outstanding loans with payment delays of more than 90 days, as determined by the Financial Services Authority (OJK). This condition is when loans are not repaid within a period of more than 90 days (Tempo, 2024). This risk is a major concern for lenders due to the uncertainty of the return of funds that have been channelled.

The peer-to-peer (P2P) lending market has a higher level of risk than traditional financial markets. This is due to the lack of transparency (Greiner & Wang, 2009) (Liu & Xia, 2017). The lack of legal and regulatory policies, non-standardised technical operations, imperfect credit systems, and asymmetric information in peer-to-peer (P2P) lending pose various risks, such as legal, technological, management, and credit risks that impact the development and sustainability of the peer-to-peer (P2P) lending industry (Liu & Xia, 2017).

Research related to bad debts on peer-to-peer (P2P) lending platforms has been widely conducted, especially abroad, such as by Emekter et al. (2014) and Serrano-Cinca et al. (2015), who examined the effect of loan amount and demographic characteristics on default risk. However, differences in regulation and market characteristics make these findings less relevant to the Indonesian context. Research by Liu & Xia (2017) and Lin et al. (2017) discusses the importance of information asymmetry in determining default risk.

However, the findings from these international studies cannot be fully applied to the Indonesian context due to differences in regulation, market characteristics, cultural factors, and levels of digital literacy. In Indonesia, borrowing behaviour is often shaped by social and cultural factors, such as taking loans for consumptive purposes or due to pressure from community norms, rather than purely based on financial eligibility. Moreover, the uneven level of digital literacy affects how users understand the risks and responsibilities involved in online borrowing. Most of the existing studies also have not used specific credit risk indicators such as TWP 90, nor have they compared default risk across different regions in Indonesia. This highlights a research gap that needs to be addressed to provide a more relevant and contextual understanding of P2P lending in the Indonesian setting.

In Indonesia, research on peer-to-peer (P2P) lending credit risk is still limited. Albanna (2022) found that borrowers outside Jawa are more at risk of default. (Hidajat, 2020) examined the weak regulations that lead to unethical practices. Muhammad et al. (2021) found that factors such as debt level, loan size, and governance have a significant effect on default risk. Meanwhile, Santoso et al. (2020) showed that borrower and lender characteristics affect interest rates and defaults.

This study focuses on non-performing loans in peer-to-peer (P2P) lending platforms in Jawa and Sumatra, given the significant differences in access to finance, digital infrastructure, and economic contribution between the two. Data from the Central Statistics Agency (BPS) shows that in 2024, Jawa contributed 57.02% to the national GDP, while Sumatra accounted for 22.12% (Maheswara, 2025). In addition, according to the Indonesian Internet Service Providers Association (APJII), the internet penetration rate in Jawa at 83.64% is higher than Sumatra at 77.34%, reflecting differences in digital infrastructure that can affect the use of peer-to-peer (P2P) lending services (Ahdiat, 2024).

This study uses the TWP 90 indicator, which is an official measure of non-performing loans employed by the Financial Services Authority (OJK) to monitor the performance of the fintech lending industry in Indonesia. This indicator has not been widely used in previous research. The approach taken in this study not only compares credit risk between Java and Sumatra but also examines how differences in economic conditions and access to financial services in each region may influence the level of non-performing loans. Through this approach, the study is expected to provide relevant insights as input for regulators and P2P lending platforms in formulating policies or strategies that are tailored to the characteristics of each region.

According to data from the Financial Services Authority (OJK) in 2024, there were 97 licensed fintech peer-to-peer (P2P) lending companies, consisting of 90 conventional and 7 sharia. The growth of peer-to-peer (P2P) lending in Indonesia is significant, especially in Jawa and Sumatra. In Jawa, loan disbursements continued to increase from January 2021 to December 2024, with the highest peak in December 2024, amounting to IDR 20,614 billion. Meanwhile, Sumatra Island also showed growth, albeit lower, with the highest disbursement in December 2024, amounting to IDR 3,658 billion.

This increase shows that peer-to-peer (P2P) lending is increasingly being used by the public. Therefore, this study aims to examine the factors influencing bad debts, including loan amount, loan purpose, and borrower demographics, specifically focussing on male and female debtors. This research is expected to contribute to risk management, regulatory policies, and lenders, especially in Java and Sumatra.

Literature Review

Peer-to-peer (P2P) lending is a financial technology innovation that brings together borrowers and lenders through a digital platform. One of the main causes of credit risk in peer-to-peer (P2P) lending is information asymmetry, where borrowers have more knowledge about their ability to repay than the lenders do. This imbalance makes it difficult to assess credit risk and can lead to adverse selection (Serrano-Cinca et al., 2015). In addition, limited transparency and weak audit mechanisms on the platform further exacerbate this risk (Ma & Wang, 2016). Information asymmetry causes inaccurate credit risk assessments, which can increase the potential for default in peer-to-peer (P2P) lending (Suryono et al., 2019). Meanwhile, Santoso et al. (2020) (Dietrich & Wernli found that borrower and borrower characteristics affect interest rates. Albanna (2022) also found that interest rates affect default.

Loan amount is one of the most important risk characteristics in peer-to-peer (P2P) lending (Berger & Gleisner, 2009). Loan amount is a determinant of loan default risk (Y. Jin & Zhu, 2015). Larger amounts generally result in greater perceived default risk from borrowers (J. Jin et al., 2019). Peer-to-peer (P2P) lenders prefer to lend small amounts rather than large amounts because lenders are sensitive to investment risk (Cai et al., 2016). Larger loan amounts tend to increase the risk of default (Yusgiantoro, 2018). Meanwhile, loan amounts play an important role in credit risk analysis, where higher loans tend to increase the risk of default in peer-to-peer (P2P) lending (Vinod Kumar et al., 2016). Loans with high loan amounts are associated with high default risk (Lin et al., 2017). In addition, Sifrain (2023) shows that the larger the loan amount, the higher the probability of default.

Loan purpose is a factor that explains defaults, such as loan size, loan purpose, and borrower characteristics such as annual income, debt, and credit history (Serrano-Cinca et al., 2015). The purpose of a loan is regarded as one of the factors that can explain the likelihood of default (Baesens et al., 2005). On the other hand, Lin et al. (2017) found that borrower demographics such as age, gender, education level, and marital status also affect credit risk in peer-to-peer (P2P) lending. However, their study was conducted in China, which may have different cultural, regulatory, and behavioural characteristics compared to Indonesia or Southeast Asia. As a result, the extent to which these demographic factors affect credit risk in the Indonesian peer-to-peer (P2P) lending context remains unclear and requires further investigation. In addition, borrower gender also affects credit risk. Differences in payment behaviour between men and women affect the level of bad credit (Cai et al., 2016). In addition, Ma & Wang (2016) found that the moral level of the borrower and the stability of the borrower affect credit default in peer-to-peer (P2P) lending.

Methodology

This study uses a monthly data time series. The data used is from the fintech lending statistical report published by the Financial Services Authority (OJK). The data is presented in an aggregated format by region, and this research focuses specifically on regional-level data from Jawa and Sumatra. This regional presentation allows for a comparative analysis of credit risk between areas with differing economic conditions and levels of access to financial services.

The study period spans from January 2021 to December 2024. This timeframe was chosen because it reflects the most recent and complete data available from the Financial Services Authority (OJK), as well as the latest developments in Indonesia's peer-to-peer (P2P) lending industry. The purpose of this study is to analyse the factors influencing bad debts on P2P lending platforms by comparing two regions, namely Jawa Island and Sumatra Island. Therefore, the analysis is conducted separately for each region to observe differences in credit risk factors.

The time span was chosen due to the availability of peer-to-peer (P2P) lending data from the Financial Services Authority (OJK). The purpose of this study is to analyse the factors affecting bad debts in the peer-to-peer (P2P) lending platform by comparing two regions, namely Jawa Island and Sumatra Island. Thus, the analysis is conducted separately for each region in order to observe differences in credit risk factors.

The model used in this research is Autoregressive Distributed Lag (ARDL). This model is a combination of Auto Regressive (AR) and Distributed Lag (DL) models used to analyse the short-term and long-term relationships between independent and dependent variables, even though the variables have different levels of stationarity. The ARDL model is flexible, suitable for small sample sizes, and doesn't require all variables to be at the same level of stationarity. Therefore, this model is considered the most appropriate for analysing the data structure in this study. The ARDL model used in this study is formulated as follows:

$$\Delta Y_t = \beta_0 + \sum_{i=1}^{n} \beta_i \Delta y_{t-i} + \sum_{i=0}^{n} \delta_i \, \Delta x_{t-i} + \varphi_1 y_{t-1} + \varphi_2 x_{t-1} + \mu_t$$

To examine the differences between regions, ARDL estimation is carried out separately for Jawa Island and Sumatra Island. The regional division is based on the aggregation of provincial-level data, where loan data from each province within Jawa and Sumatra is grouped accordingly based on its geographic location. The equation for the ARDL model is presented below:

1. Autoregressive Distributed Lag (ARDL) model equation for Jawa Island:

$$\Delta Y_{Jawa,t} = \beta_{0J} + \sum_{i=1}^{n} \beta_{iJ} \Delta Y_{Jawa,t-i} + \sum_{i=0}^{n} \delta_{iJ} \Delta x_{Jawa,t-i} + \varphi_1 Y_{Jawa,t-1} + \varphi_2 x_{Jawa,t-1} + \mu_t$$

2. Autoregressive Distributed Lag (ARDL) model equation for Sumatra Island:

$$\Delta Y_{Sumatra,t} = \beta_{0S} + \sum_{i=1}^{n} \beta_{iS} \Delta Y_{Sumatra,t-i} + \sum_{i=0}^{n} \delta_{iS} \Delta x_{Sumatra,t-i} + \varphi_{1S} Y_{Sumatra,t-1} + \varphi_{2S} x_{Sumatra,t-1} + \mu_t$$

This approach is to see if there are differences in the characteristics of bad debts on peer-to-peer (P2P) lending platforms between two regions that have different economic conditions and digital infrastructure. Different economic conditions and digital infrastructure. The following variables are used in this study:

Table 1. Explanatory Variables

Variable	Data Used
Bad Debt	Loan Default Rate (TWP 90)
Total Loan	(Log) Accumulated loan disbursement to loan recipients by location
Purpose of Individual Loan	(Log) Outstanding loan (billion IDR) for individuals
Business Entity Loan Purpose	(Log) Outstanding loans (billion IDR) of business entities
Male Debtors	Outstanding loan (billion IDR) male Outstanding loan (billion Rp) (individual loan (>90 days))
Female Debtors	Outstanding loans (billion IDR) female Outstanding loans (billion IDR) (individual loans (>90 days))

Results and Discussion

Results

Descriptive statistics

Descriptive statistics provide an overview of the data characteristics of the research variables. The results of the analysis show that the average level of bad debts in Jawa Island reached 2.69%, higher than that in Sumatra Island at 1.79%. In addition, the amount of loan disbursement in Jawa, of Rp 14.43 billion, was greater than that in Sumatra, of Rp 13.55 billion. The high loan disbursement in Jawa reflects the region's role as the centre of national economic growth as well as more equitable fintech growth. However, this also comes with a higher risk of bad debts.

Individual loan purposes tend to be higher than business entities in both regions, although the difference is not significant. In terms of borrower gender, the distribution of loans between men and women is almost the same, but there is an imbalance in bad debts, with some borrowers having a higher proportion of bad debts. There is inequality in bad debts, where some borrowers experience a large amount of bad debts while others experience almost none.

Table 2. Descriptive Statistics in Jawa Island

Descriptive Statistics	Bad Debt in Java	Total Loans in Jawa	Purpose of Individual Loan	Business Entity Loan Purpose	Male Debtors	Female Debtors
Mean	0.026921	14.42854	4.580833	3.723542	2.230310	1.969877
Maximum	0.037600	14.91000	4.860000	3.900000	54.78600	45.21400
Minimum	0.014000	13.16000	4.130000	3.420000	0.039200	0.004600

Table 3. Descriptive Statistics in Sumatra Island

Descriptive Statistics	Bad Debt in Sumatra	Total Loans in Sumatra	Purpose of Individual Loan	Business Entity Loan Purpose	Male Debtors	Female Debtors
Mean	0.017927	13.55021	4.580833	3.723542	2.230310	1.969877
Maximum	0.026100	14.04000	4.860000	3.900000	54.78600	45.21400
Minimum	0.008800	12.20000	4.130000	3.420000	0.039200	0.004600

Multicollinearity Test

Based on the results of correlation analysis in Java and Sumatra, it is found that bad debts in Java are more influenced by the purpose of individual loans, while in Sumatra they are more influenced by the purpose of business entity loans. The number of loans in both regions has a stronger relationship with personal loans than business loans, but the effect is greater in Sumatra. Gender does not have a significant relationship with bad debts. In addition, there is a strong relationship between the purpose of individual and business entity loans, meaning that any increase in bad debts in the purpose of individual loans tends to be followed by the purpose of business entity loans.

Table 4. Multicollinearity Test Results in Jawa Island

Correlation	Bad Debt in Java	Total Loans in Jawa	Purpose of Individual Loan	Business Entity Loan Purpose	Male Debtors	Female Debtors
Bad Debt	1.000000					
Total Loan in Java	0.463915	1.000000				
Purpose of Individual Loan	0.813523	0.588097	1.000000			
Business Entity Loan Purpose	0.746287	0.284520	0.714965	1.000000		
Male Debtors	0.152026	0.125417	0.128164	0.052618	1.000000	
Female Debtors	0.132562	0.117569	0.116321	0.029537	0.998524	1.000000

Table 5. Multicollinearity Test Results in Sumatra Island

Correlation	Bad Debt in Sumatra	Total Loans in Sumatra	Purpose of Individual Loan	Business Entity Loan Purpose	Male Debtors	Female Debtors
Bad Debt	1.000000					
Total Loan in Sumatra	0.383023	1.000000				
Purpose of Individual Loan	0.461716	0.745429	1.000000			
Business Entity Loan Purpose	0.795718	0.491318	0.714965	1.000000		
Male Debtors	-0.007119	0.090109	0.128164	0.052618	1.000000	
Female Debtors	-0.027883	0.071084	0.116321	0.029537	0.998524	1.000000

Stationarity Test

The Augmented Dickey-Fuller (ADF) unit root test is used to determine data stationarity. The results indicate that some variables require a differentiation process to achieve stationarity. Bad credit variables in Java and Sumatra and the purpose of business entity loans are not stationary at the data level. Thus, it is necessary to conduct further differentiation tests and stationing at the first different level. On the other hand, the variables of total loans in Jawa and Sumatra and the purpose of individual loans and male and female debtors are stationary at the level.

Table 6. Stationary Test Results in Jawa Island

Variable	*Level*		*First Different*	
	ADF	**Prob**	**ADF**	**Prob**
Bad Debt	-1.427979	0.5607	-6.064802	0.0000
Total Loan in Java	-4.811483	0.0003	-	-
Purpose of Individual Loan	-4.290319	0.0013	-	-
Business Entity Loan Purpose	-2.641762	0.0922	-4.150433	0.0021
Male Debtors	-6.969969	0.0000	-	-
Female Debtors	-7.014504	0.0000	-	-

Table 7. Stationary Test Results in Sumatra Island

Variable	*Level*		*First Different*	
	ADF	**Prob**	**ADF**	**Prob**
Bad Debt	-2.636221	0.0931	-7.929184	0.0000
Total Loan in Sumatra	-3.880470	0.0044	-	-
Purpose of Individual Loan	-4.290319	0.0013	-	-
Business Entity Loan Purpose	-2.641762	0.0922	-4.150433	0.0021
Male Debtors	-6.969969	0.0000	-	-
Female Debtors	-7.014504	0.0000	-	-

Cointegration Test

The F-Bounds test results indicate the existence of a cointegration relationship in both regions; on Jawa Island the F-statistic value is 9.153412, and on Sumatra Island the F-statistic is 5.056749. Both values exceed the upper bound critical value at the 5% significance level. This indicates the existence of a long-run relationship between bad debts and the independent variables.

Table 8. Cointegration Test Results in Jawa Island

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Significant	I(0)	I (1)
		Asymptotic: n=1000		
F-statistic	9.153412	10%	2.26	3.35
k	5	5%	2.62	3.79
		2.5%	2.96	4.18
		1%	3.41	4.68
Actual Sample Size	44	Finite Sample: n=45		
		10%	2.458	3.647
		5%	2.922	4.26
		1%	4.03	5.598
		Finite Sample: n=40		
		10%	2.483	3.708
		5%	2.962	4.338
		1%	4.045	5.898

Table 9. Cointegration Test Results in Sumatra Island

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Significant	I(0)	I (1)
		Asymptotic: n=1000		
F-statistic	5.056749	10%	2.26	3.35
k	5	5%	2.62	3.79
		2.5%	2.96	4.18
		1%	3.41	4.68
Actual Sample Size	44	Finite Sample: n=45		
		10%	2.458	3.647
		5%	2.922	4.268
		1%	4.03	5.598
		Finite Sample: n=40		
		10%	2.483	3.708
		5%	2.962	4.338
		1%	4.045	5.898

Table 10. Levels Equation in Jawa Island

Variable	Coefficient	t-Statistic	Prob.	Description
JP_JAWA	-5.15E-05	-0.021980	0.9827	Not Significant
TP_PEROR	-0.017266	-1.806594	0.0859	Not Significant
TP_BU	0.066017	4.221868	0.0004	Significant
DEB_MALE	-0.021577	-3.251938	0.0040	Significant
DEB_FEMALE	0.026585	3.290370	0.0037	Significant

Notes: 1) KM_JAWA/SUMT = Bad Debt in Jawa/Sumatra
2) JP_JAWA/SUMT = Total Loans in Jawa/Sumatra
3) TP_PEROR = Purpose of Individual Loan
4) TP_BU = Business Entity Loan Purpose
5) DEB_MALE = Male Debtor
6) DEB_FEMALE = Female Debtor

Table 11. Levels Equation in Sumatra Island

Variable	Coefficient	t-Statistic	Prob.	Description
JP_SUMT	0.003228	0.878527	0.3874	Not Significant
TP_PEROR	-0.008822	-1.069904	0.2941	Not Significant
TP_BU	0.021729	3.186097	0.0036	Significant
DEB_MALE	-0.004795	-2.060295	0.0491	Significant
DEB_FEMALE	0.005790	2.052323	0.0499	Significant

Notes: 1) KM_JAWA/SUMT = Bad Debt in Jawa/Sumatra
2) JP_JAWA/SUMT = Total Loans in Jawa/Sumatra
3) TP_PEROR = Purpose of Individual Loan
4) TP_BU = Business Entity Loan Purpose
5) DEB_MALE = Male Debtor
6) DEB_FEMALE = Female Debtor

Based on tables 10 and 11 of the Levels Equation in Jawa and Sumatra above, it shows that the variables of business entity loan purpose, male debtors, and female debtors have a significant influence in the long run.

ARDL Estimation

Autoregressive Distributed Lag (ARDL) testing considers lags in the analysis process. This testing process uses EViews 12 software to analyse and determine the best model based on the Akaike Information Criterion (AIC).

Based on table 12 below, it indicates that there are ARDL model selection results in Jawa Island, namely (3, 1, 4, 4, 3, 3). This means that the variables of bad credit, male debtors, and female debtors are on lags of up to 3 periods. The number of loans is on a lag up to 1 period, and the purpose of individual and business entity loans is on a lag up to 4 periods. R-squared in this test shows a value of 0.976793, or 97.67%, of bad credit variables in Jawa Island are influenced by the number of loans in Jawa Island, the purpose of individual loans, the purpose of business entity loans, male debtors, and female debtors. Meanwhile, 2.32% is influenced by other variables outside the model.

Table 12. ARDL Model Estimation Results in Jawa Island

Variable	Coefficient	t-Statistic	Prob.*	Description
KM_JAWA (-1)	0.521922	3.335317	0.0033	Not Significant
KM_JAWA (-2)	0.273195	1.270815	0.2184	Not Significant
KM_JAWA (-3)	-0.198864	-1.386461	0.1809	Not Significant
JP_JAWA	0.001105	1.377634	0.1835	Not Significant
JP_JAWA (-1)	-0.001126	-1.874036	0.0756	Not Significant
TP_PEROR	0.017906	0.811105	0.4269	Not Significant
TP_PEROR (-1)	-0.105058	-3.940628	0.0008	Significant
TP_PEROR (-2)	-0.009202	-0.375982	0.7109	Not Significant
TP_PEROR (-3)	-0.023492	-0.947374	0.3548	Not Significant
TP_PEROR (-4)	0.112875	5.351567	0.0000	Significant
TP_BU	0.011205	1.075610	0.2949	Not Significant
TP_BU (-1)	-0.007529	-0.514184	0.6128	Not Significant
TP_BU (-2)	0.012777	0.929231	0.3638	Not Significant
TP_BU (-3)	0.041889	2.813497	0.0107	Significant
TP_BU (-4)	-0.031688	-2.929579	0.0083	Significant
DEB_MALE	-0.001418	-1.615005	0.1220	Not Significant
DEB_MALE (-1)	-0.001712	-2.517082	0.0205	Significant
DEB_MALE (-2)	-0.002705	-4.037099	0.0006	Significant
DEB_MALE (-3)	-0.002876	-3.576683	0.0019	Significant
DEB_FEMALE	0.001825	1.716910	0.1014	Not Significant
DEB_FEMALE (-1)	0.002152	2.606240	0.0169	Significant
DEB_FEMALE (-2)	0.003272	4.032124	0.0007	Significant
DEB_FEMALE (-3)	0.003485	3.584026	0.0019	Significant
C	-0.053497	-2.742292	0.0126	
R-squared		0.976793		
F-statistic		36.60019		

Notes:
1) KM_JAWA/SUMT = Bad Debt in Jawa/Sumatra
2) JP_JAWA/SUMT = Total Loans in Jawa/Sumatra
3) TP_PEROR = Purpose of Individual Loan
4) TP_BU = Business Entity Loan Purpose
5) DEB_MALE = Male Debtor
6) DEB_FEMALE = Female Debtor

Table 13 below presents the results of the ARDL model applied to Sumatra Island, specifically (1, 3, 3, 4, 0, 0). This means that bad debts in Sumatra Island are on a lag of up to 1 period, and the number of loans and the purpose of individual loans are on a lag of up to 3 periods. The purpose of the business entity loan is on a lag of up to 4 periods, while the male debtor and female debtor variables are on a lag of up to 0 periods. The R-squared in this test shows a value of 0.808148, or 80.81%, of bad credit variables on the island of Sumatra are influenced by the number of loans on the island of Sumatra, the purpose of individual loans, the purpose of business entity loans, and male debtors and female debtors. Meanwhile, 19.19% is influenced by other variables outside the model.

Table 13. ARDL Model Estimation Results in Sumatra Island

Variable	Coefficient	t-Statistic	Prob.*	Description
KM_SUMT (-1)	0.432279	2.985419	0.0060	Not Significant
JP_SUMT	0.000253	0.250261	0.8043	Not Significant
JP_SUMT (-1)	-0.001445	-1.394533	0.1745	Not Significant
JP_SUMT (-2)	0.001679	1.751877	0.0911	Not Significant
JP_SUMT (-3)	0.001345	1.422401	0.1664	Not Significant
TP_PEROR	-0.032191	-1.251579	0.2215	Not Significant
TP_PEROR (-1)	-0.025056	-0.816862	0.4212	Not Significant
TP_PEROR (-2)	0.022960	0.771012	0.4474	Not Significant
TP_PEROR (-3)	0.029279	1.332477	0.1938	Not Significant
TP_BU	0.038451	2.803390	0.0092	Significant
TP_BU (-1)	-0.032671	-1.708498	0.0990	Not Significant
TP_BU (-2)	0.028702	1.701767	0.1003	Not Significant
TP_BU (-3)	0.023942	1.294751	0.2064	Not Significant
TP_BU (-4)	-0.046088	-3.365403	0.0023	Significant
DEB_MALE	-0.002723	-2.586933	0.0154	Significant
DEB_FEMALE	0.003287	2.578870	0.0157	Significant
C	-0.036455	-1.695285	0.1015	
R-squared		0.808148		
F-statistic		7.108331		

Notes: 1) KM_JAWA/SUMT = Bad Debt in Jawa/Sumatra
2) JP_JAWA/SUMT = Total Loans in Jawa/Sumatra
3) TP_PEROR = Purpose of Individual Loan
4) TP_BU = Business Entity Loan Purpose
5) DEB_MALE = Male Debtor
6) DEB_PR = Female Debtor

Discussion

The results show that the loan amount variable has no significant effect on bad debts, either in Java or Sumatra. All lags of the loan amount variable in both regions have a probability above 5%, so it is not statistically strong enough to explain the relationship between loan size and the risk of bad debts. This finding contradicts Lin et al. (2017) and Sifrain (2023), who found a significant effect of loan size on default risk. The difference is due to factors such as regional borrower characteristics and the credit risk indicator used. This study applies the TWP90 indicator and regional data from Indonesia, while prior studies used data from China and the U.S. This study shows that loan amount is not the only determinant of credit risk. Therefore, for peer-to-peer (P2P) lending companies, these results emphasise the importance of comprehensive risk assessment. For regulators, there is a need for regulations that pay attention to non-financial factors that have the potential to affect bad credit, and for lenders, it is advisable not only to focus on the size of the loan but also to pay attention to the profile of the borrower.

Based on the ARDL model estimation, in Jawa Island, it is found that the purpose of personal loans in the previous one-month period (1st lag) has a significant negative effect on bad debts, meaning that the higher the loan given for the purpose of personal loans in the previous one-month period, the lower the risk of bad debts in the current period. In contrast, loans in the previous four-month period (4th lag) have a significant positive effect. Thus, the higher the loans granted for personal purposes in the previous four-month period, the higher the risk of bad debts in the current period.

Meanwhile, the purpose of personal loans in the current period, two months earlier, and three months earlier shows no significant effect. On Sumatra Island, although all lag periods show no significant effect on bad debts, this may indicate that other factors beyond personal loan purposes, such as business loan purposes or borrower characteristics, play a more dominant role in influencing default risk in this region. The results of this study are in accordance with research by Serrano-Cinca et al. (2015) which states that loan objectives can predict default risk. Implications for peer-to-peer (P2P) lending companies in Jawa Island: they can prioritise funding on one-month loans and tighten supervision for loans with a four-month term. Regulators are expected to strengthen supervision and data transparency, while lenders are advised to pay attention to loan tenure in assessing risk, especially in Jawa.

The ARDL estimation results show that in Jawa Island, the purpose of business entity loans three months earlier (3rd lag) has a significant positive effect on bad debts, while loans four months earlier (4th lag) show a significant negative effect. This means that the higher the enterprise loans in the previous three-month period, the higher the bad debts in the current period. Meanwhile, in the 4th lag, the higher the loans of business entities in the previous four-month period, the lower the bad debts in the current period. In contrast, loans in the current period compared to the previous two months show no significant effect. On Sumatra Island, corporate loans in the current period (0th lag) have a significant positive effect on bad debts, while loans in the previous four-month period show a significant negative effect. However, loans one to three months earlier have no significant effect.

This study is consistent with research (Serrano-Cinca et al., 2015) that states that the purpose of the loan is among the factors that predict default risk. Implications for peer-to-peer (P2P) lending companies in Java: they need to be careful about loans with a period of three months in Java and loans in the current period on the island of Sumatra. Regulators are advised to strengthen supervision and improve data transparency. For lenders, they can improve their funding strategy by being more selective towards loans in the current period in Sumatra Island and prioritising four-month loans in Jawa Island.

The results show that male debtors have an effect on reducing bad debts in peer-to-peer (P2P) lending, although the effect differs depending on the region and time period. On Jawa Island, male debtors from lag 1 to lag 3 have a significant negative effect on bad debts. This means that the higher the loan given to male borrowers in the previous one- to three-month period, the lower the current risk of bad debts. However, in the current period (lag 0), no significant effect is found. On Sumatra Island, male borrowers in the current period also show a significant negative effect on bad debts. This means that the higher the loan given to male debtors in Jawa Island in the current period, the lower the level of bad debts in the same period.

This finding is different from the research of Lin et al. (2017) and Chen et al. (2017) in China, which states that women have lower default rates than men. This difference may occur because the socio-economic conditions in Indonesia are not the same as in China. In Indonesia, men generally act as the main breadwinner, so they have a more stable income to pay loan obligations. GoodStats data (2024) shows that men dominate formal sector employment at 65.67%, while women are mostly in the informal sector at 43.13%, which generally has an irregular income (Magistravia, 2024). However, this result cannot be generalised to mean that all male debtors are better at managing loans. It is also necessary to look at the regional context, economic conditions, and different social roles. In this study, the use of the ARDL method and a regional approach represents a new contribution, as it allows for the examination of short-term influences specific to each region.

Implications for peer-to-peer (P2P) lending companies: they can utilise these findings to channel loans more selectively, especially to male borrowers in Jawa and Sumatra. Regulators can encourage demographic data-based policies to minimise credit risk. Lenders are also advised to consider gender and regional factors in funding strategies and encourage information transparency from peer-to-peer (P2P) lending platforms.

Based on the ARDL estimation results in Jawa Island, the female debtor variable in lag 1 to lag 3 has a positive effect. The 1st to 3rd lag has a significant positive effect on bad credit. This means that the higher the loan given to female debtors in the previous one to three months, the higher the level of bad debts in the current period. Meanwhile, the 0th lag has no significant effect on bad debts. On Sumatra Island, female debtors at lag 0 also show a significant positive effect on bad debts. This indicates that an increase in loans to female debtors at this time has a direct impact on the increase in bad debts in the same period.

This finding contradicts research by Lin et al. (2017); And Chen et al. (2017), who found that female borrowers tend to have lower default risk than males. This difference may be explained by local socioeconomic conditions. In Indonesia, especially Jawa and Sumatra, women's financial literacy is still low, especially in rural areas. Many women work in the informal sector with unstable incomes, putting them at higher risk of late payments (America, 2025). In peer-to-peer (P2P) lending platforms, this may contribute to the increased risk of bad debts among female borrowers.

Implications for peer-to-peer (P2P) lending companies, it is important to tighten the evaluation of loans to female borrowers to reduce the risk of bad debts. Regulators should encourage digital financial education for women and the reporting of loan data based on gender and region. For lenders, it is recommended to be more selective in providing funding to minimise credit risk.

Conclusions

The results show that the number of loans has no significant effect on the risk of bad debts in Java and Sumatra. This shows that the risk of bad debts is not only influenced by the size of the loan but also other factors such as the purpose of the loan and the characteristics of the debtor. The purpose of an individual loan on Jawa Island is that a loan one month earlier reduces the risk of bad debts, while a loan four months earlier increases the risk. On Sumatra Island, the purpose of the loan has no significant effect. The purpose of business entity loans on Jawa Island is that a loan three months earlier increases the risk, while a loan four months earlier decreases it. On Sumatra Island, the current purpose of a business loan increases risk, while a loan four months prior decreases risk.

In addition, male debtors in Jawa Island in lag 1 to lag 3 and Sumatra in the current period are shown to reduce the risk of bad debts. This indicates that male borrowers on Java reduced their risk of non-performing loans during the previous one to three months, and on Sumatra, male borrowers also reduced their risk of non-performing loans during the current period. In contrast, female borrowers in Jawa in lag 1 to lag 3 and Sumatra increase the risk of bad debts. This difference can be explained by socioeconomic conditions, where men generally have more stable incomes. Meanwhile, women, particularly in the informal or rural sectors, face challenges in financial literacy and income stability. Implications for peer-to-peer (P2P) lending companies: they need to conduct a more comprehensive risk assessment by taking into account the purpose of the loan, debtor profile, and gender and regional factors. Regulators should strengthen supervision, improve financial education, especially for women, and encourage data transparency based on demographics. Lenders are advised to be more selective in funding by considering these factors in order to minimise the risk of bad credit.

However, this study has several limitations, including: First, the data used only covers the period from January 2021 to December 2024. This period was selected based on the availability of more complete, recent data from the Financial Services Authority (OJK), which is considered to best represent the latest developments in the P2P lending industry. Second, the study's scope is limited to the islands of Jawa and Sumatra, given that these two are major contributors to the national economy and have a dominant loan volume. Third, the variables used in the study are limited to the variables of loan amount, individual loan purpose, business entity loan purpose, male debtors, and female debtors. This study has not considered other variables that also have the potential to affect bad credit.

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