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What Can Big Data Tell Us About Loan Default, Lending Rate and Loan Amount in Financial Technology Peer-to-Peer Lending? Case of Indonesia

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Financial technology Peer-to-Peer Lending (P2PL) is the fastest growing financial sector that will be expected to fill the financing gap left by traditional financial institutions. However, in an emerging economy such as Indonesia, the P2PL industry still faces higher borrowers' default rates and lending rates. Employing a big loan database from 20 platforms that comprise 70% of the total P2PL in Indonesia, our research shows new evidence of factors that impact borrower loan risk, lending rate, and loan amount in the P2P industry. With the new days past due model, we can identify specific loan and borrower characteristics and lending cap policy impact on borrower loan risk in consumption loan, working capital loan, and other kinds of loans from the P2PL industry. Our research outputs have several policy implications for the stakeholders, especially for the P2PL authorities in emerging countries.

Keywords: Financial Technology, Peer-to-Peer Lending, Loan Risk, Lending Rate

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1. Introduction

The development of Financial Technology Peer-to-Peer Lending (P2PL) in Indonesia has enormous potential to grow alongside Indonesia's future economic growth. We Are Social and Hootsuite (2021) reports that Indonesian internet users reached 202.6 million with 345.3 million mobile gadgets and 170 million social media users, the biggest market in the growing Southeast Asia region. The development of the P2PL industry in Indonesia has grown rapidly since Indonesia Financial Services Authority/Otoritas Jasa Keuangan (OJK) has released regulation number 77/POJK.01/2016 concerning Technology-Based Money-Lending Services since the end of 2016. As of September 2021, the number of P2P Lending providers reaches 104 companies with outstanding loans reached Rp27.48 trillion or grew 116.18% from the same period last year. The outstanding loan compromise of 22.88 million active borrower accounts. With that performance P2PL industry in Indonesia and other emerging countries is expected to serve Indonesia's micro, small and medium enterprises that establish around 60% of Indonesia's economy.

However, the growth of the uprising industry in Indonesia has been threatened by several issues, such as relatively high loan default rate and lending rate and the optimal amount that can disburse by the industry to fill the finance gap left by the traditional financial institutions. Another issue faced by the industry is the relatively low disbursement of productive loans. This issue can hamper P2PL's expected performance in serving the domestic economy, especially micro, small, and medium enterprises.

Prior studies that focus on P2PL's borrower probability of default and lending rate are relatively limited, especially in emerging countries (e.g. Chen et al., 2020; Lin et al., 2017). In Indonesia, Santoso et al. (2020) used data from three platforms and found that loan and borrower-specific factors affect borrower failure rates and lending rates. Unlike Santoso et al. (2020), our study focuses on different types of loan failure rates and lending rates. In addition, to our best knowledge, our study is the only study that evaluates factors that determine P2PL loan amount in each type of loan, consumption loan, working capital loan, and other types of loan. Therefore, this research aims to evaluate factors that affect P2PL days past due, lending rate, and loan amount at the industry level and in each type of loan.

Our study has the advantage of using a big loan database from 20 P2PL platforms. Our total sample compromises 70% of the P2PL industry in Indonesia. The big data we gathered from the 20 platforms reached 5.873.689 loan observations. With the enormous observations, we are also to test 17 loan and borrower specific characteristics that potentially affected P2PL's borrower days past due, lending loan, and loan amount. In addition, we also test whether the policy rate in Indonesia affected P2PL borrowers' day past due and lending loan.

To improve the accuracy of our model, we employ Brezigar-Masten et al. (2021) 's new approach to measure borrower loan risk by the number of days in arrears with Tobit regression. Different from the probability of default that only uses borrower default and non-default information. The new approach used the information of number of days from the loan due date to the reporting date. Therefore, the model is expected to predict the borrower loan risk early than the probability of the default model using binary regression.

First, our study contributes to the literature on loan risk projection in the P2PL industry. To increase the precision of our model, we specifically examine our days past due model in three types of loans. Next, our study also contributes to regulator intervention in determining the lending rate and loan amount in the P2PL industry. Regulators can also use our study to identify which type of loan and platform to focus on the supervision and industry development strategy.

The rest of the paper is organized as follows. In Section 2, we provide the related literature, followed by the institutional setting in Section 3. In Section 4 and 5, we present and discuss the research method and empirical results, respectively. Finally, section 6 provides concluding remarks and policy implications.

2. Related Literature

Loan Failure Rate

One of the main issues faced by the P2P Lending industry is the information asymmetry between borrowers and lenders (Lee and Lee, 2012; Pokorna and Sponer, 2016), where borrowers have far more information about their credit than lenders. Information asymmetry can easily lead to moral hazard (Stiglitz & Weiss, 1981) and adverse selection (Akerlof, 1970; Lee & Lee, 2012) as the theoretical basis for the risk of default on loans or default risk (Balogun and Alimi, 1988). As traditional financial service institutions have begun to do, the P2P Lending industry seeks to reduce information asymmetry by using technological innovations in credit risk assessment as an indicator of loan eligibility (Polena & Regner, 2018).

Iyer et al. (2016) describe two types of information that can describe the risk of loan default: standard hard information and non-standard soft information. Hard information can directly reflect a borrower's financial status or creditworthiness, for example, credit scores and debt-to-income ratios. Meanwhile, soft information is not directly related to the borrower's financial status or creditworthiness, such as photos of the borrower and data on the borrower's demographic characteristics and social relations on the P2P platform (e.g., Galema, 2020).

Using a sample in China, Lin et al. (2017) show evidence that gender, age, marital status, educational level, working years, company size, monthly payment, and loan amount influenced borrowers' defaults. In Indonesia, Santoso et al. (2020) found that in the Indonesian P2P Lending industry, loan and borrower-specific factors play a significant role in loan failure rates and lending rates. They found that loan characteristics such as lending rate, loan amount, loan duration affected the default rate. Meanwhile, borrower-specific factors such as gender, marital status, ownership of residence, education level, age, and income level significantly correlate with loan failure rate, although the impact varies for each platform studied. In line with Santoso et al. (2020), Chen et al. (2020) also found that borrower with higher education level has a lower probability of default. As in the banking industry, previous studies have also found that macroeconomic conditions can also affect loan default rates (e.g., Cerone et al., 2017, Djeundie & Crook, 2018).

Recent studies have attempted to use new models and approaches to complement the previously used binary regression models to improve the accuracy of projected loan default rates. Sigrist and Hirnschall (2019) built a new Gradient Tree-Boosted Tobit (Grabit) model and compared it to the logit and Tobit models. They were able to show that Grabit had more accurate predictions than logit and Tobit. Meanwhile, using the loan credit database in Slovenia, Brezigar-Masten et al. (2021) used a new approach to measure borrower credit risk by the number of days in arrears with Tobit regression. They found that using the number of days in arrears outperformed the commonly used binary regression to predict loan default rates.

Lending Rate and Loan Amount

Factors that affect lending rates and the loan amount have been widely studied. In addition to being influenced by borrowing factors (e.g., Santoso et al., 2020), the market structure also affects lending rates and the size of loans provided by the financial services sector. Specifically, for microfinance institutions, Al-Azzham and Parmeter (2019) show that market concentration does not significantly affect lending rates, but the level of competition can reduce lending rates.

However, studies for the P2P Lending industry are still relatively limited. In the context of Indonesia, Santoso et al. (2020) found a significant and negative relationship between lending rates and loan sizes. The P2P Lending platform tends to provide higher lending to borrowers with small amounts. It can happen because small borrowers are associated with greater credit risk than large borrowers. This is explained because lenders or P2P Lending platforms generally have relatively little information for micro and small borrowers. The findings of Santoso et al. (2019), are consistent with Cai et al. (2016) and Jin et al. (2019). In addition, in line with Lee and Lee (2012), Han et al. (2019), Santoso et al. (2020) found that the loan period affects the given lending rate.

In addition to the loan factor itself, the borrower's characteristics also affect the P2P Lending lending rate. Gender (e.g., Santoso et al., 2020, Jin et al., 2019), marital status (Santoso et al., 2020), homeownership (e.g., Santoso et al., 2020, Greiner & Wang, 2009), and age affect the lending rate provided by P2P Lending (Santoso et al., 2020). However, Santoso et al. (2020) stated that the influence of these factors on lending rates and loan sizes could also be influenced by the characteristics of the P2P Lending platform used by borrowers. This is partly due to the data processing carried out by Santoso et al. (2020) being performed separately for each platform sample.

3. Institutional Settings: Lending Rate Cap Policy in Indonesia

Indonesia Financial Services Authority/Otoritas Jasa Keuangan (OJK)'s regulation number 77/POJK.01/2016 regulates the platform to provide input on the lending rates offered by lenders and borrowers by considering the fairness and development of the national economy. In the regulation, the amount of lending and fees for P2P Lending loans are not regulated.

The P2PL Association Code of Conduct set in 2020 regulates the amount of borrowing costs, including lending and other fees. Determination of the total amount of lending, borrowing costs, and other costs on P2P Lending does not exceed a flat lending rate of 0.8% per day, calculated from the borrower's actual loan amount. For example, the organizer sets the lending rate, borrowing fees, and other fees at 0.8% per day, while late fees (either in the form of fines or otherwise) that can be charged are a maximum of 0.8% per day. So that in the event of a delay, the total amount of lending, borrowing costs, and other costs plus late fees is a maximum of 1.6% per day. For loans with tenors of up to 24 months, the determination of the total amount of lending, loan fees, and all other costs, along with late fees, is a maximum of 100% of the value loan principal. For loans with a tenor of more than 24 months, the total amount of lending, loan fees, and all other costs, along with late fees per year, is a maximum of 100% of the principal value of the loan. On October 22, 2021, to establish a more conducive industrial ecosystem and positively impact the entire community, the P2PL association sets a maximum level of total service fees (other than late fees) of 0.4% flat per day. These provisions are specifically regulated which will be reviewed monthly.

4. Methodology

4. 1. Data

Data used in this research are directly from 20 P2PL providers who send their loan database to Indonesia Financial Services Authority/Otoritas Jasa Keuangan (OJK). The 20 providers represent 71.10% of the portion of the outstanding loan of the industry. The loan-level data are from December 2017 to April 2021 and consist of 5.873.689 loan observations. The data loan data can be classified based on the loan type: consumption loan, working capital loan, and other loans.

4. 2. Empirical Strategy

To evaluate the determinants of the loan risk, this research follows Brezigar-Masten et al. (2021) and using a tobit regression model (Sigrist & Hirnschall, 2019):

Model 1

$$DPD_{it} = c_1 + r_{it}\varphi_1 + L_{it}\omega_1 + X_{it}\beta_1 + D_t\gamma_1 + M_t\delta_1 + \varepsilon_{1,it}$$

DPD is days past due which is calculated from how many days left from the payment maturity date to the reporting date, r is loan lending rate in percentage, L is the amount of loan in million IDR, X is covariates, D is dummy regulatory variable (lending cap policy), and M is macroeconomic variable which is using benchmark lending rate (Bank Indonesia 7-day repo rate) in percentage per annum. The subscript i indicates the loan identification number and t is month observation. The covariates X consist of term loan, gender, marital status, age, education, income, residential ownership, financial institution loan, default loan, authentication, loan purpose (multi), loan purpose (financing), insurance, and collateral. The details of variables used in the model, table 1 provides information how each variable is defined and constructed from raw data.

Following Santoso et al. (2020), we estimate the determinant of lending rate a with set of same covariates X, loan amount, dummy lending cap policy, and benchmark lending rate with ordinary least square estimation:

Model 2

$$r_{it} = c_2 + L_{it}\omega_2 + X_{it}\beta_2 + D_t\gamma_2 + M_t\delta_2 + \varepsilon_{2,it}$$

Furthermore, we estimate the determinant of loan amount with same covariates X, dummy lending cap policy, and benchmark lending rate ordinary least square estimation:

Model 3

$$L_{it} = c_3 + X_{it}\beta_3 + D_{it}\gamma_3 + M_t\delta_3 + \varepsilon_{3,it}$$

Table 1. Variable Description

Variable	Definition	Source	Expected Sign
Lending Rate	Total lending loan (including platform fee) paid by borrower in percentage	OJK	+
Loan Amount	Total loan amount borrowed in million IDR	OJK	+
Lending Cap Policy	Dummy variable that indicates implementation of Lending Rate Cap Policy 0.8% per day. The value of this variable is 1 if month observation is after March 2019, and 0 otherwise	OJK	-
Term Loan	Total of loan period in days, measured from loan origination until last due date of payment term	OJK	+
Gender	The dummy variable of gender, the value is 1 if male and 0 is female	OJK	-
Marital Status	The dummy variable of marital status, the value is 1 if married and 0 is not married	OJK	-
Age	Age of borrower in years	OJK	-
Education	The dummy variable of last borrower education. The value is 1 if borrower education at least S1 degree, and 0 otherwise	OJK	-
Income	Income of borrower in million IDR	OJK	-
Residential Ownership	The dummy variable of residential ownership. The value is 1 if borrower has resident, and 0 otherwise	OJK	-
Financial Institution Loan	The dummy variable of having other financial institution loan. The value is 1 if borrower has at least one loan type in other financial institution, and 0 otherwise	OJK	+
Default Loan	The dummy variable of having default loan in P2PL or other financial institution. The value is 1 if borrower has at least one default loan in P2PL or other financial institution, and 0 otherwise	OJK	+
Authentication	The dummy variable of authentication process. The value is 1 if there is authentication process in loan application	OJK	-
Loan Purpose (Multi)	The dummy variable of loan purpose. The value is 1 if loan purpose is multi, and 0 otherwise	OJK	+
Loan Purpose (Financing)	The dummy variable of loan purpose. The value is 1 if loan purpose is financing, and 0 otherwise	OJK	+
Insurance	The dummy variable of having insurance. The value 1 if loan is guaranteed by insurance, and 0 otherwise	OJK	-
Collateral	The dummy variable of loan collateral. The value is 1 if there is collateral in loan application, and 0 otherwise	OJK	-
Benchmark Lending Rate (BI 7DRR)	Benchmark lending rate in percentage (Bank Indonesia 7 days repo rate)	BI	+

Variable definition and source used in the research. Expected sign refers to coefficient sign of DPD regression.

5. Results

5.1 Descriptive Statistics

Table 2 shows descriptive statistics of loan-level data for 20 providers. For the ceiling value, the average value is around IDR 454.63 million, with the lowest value of IDR 5 and the highest of IDR 2 billion or in line with the maximum loan amount regulation from the association. The minimum value in the observation is IDR 5 or an outlier less than 1% of the data percentile, which is estimated to be due to data input or reporting errors. Meanwhile, the remaining loan/debit balance has an average IDR 355.61 million or 78.2% of the ceiling, with a minimum value of zero IDR and a maximum of IDR 2 billion.

The average lending rate is 0.71% per day, with the highest rate being 1.27% per day. This highest value comes from the period prior to the implementation of lending rate restrictions. For day past due, or the number of days in arrears, the average value is around 18.47 days, with the lowest value being zero-days or not being late/overdue, with the highest value being 553 days. Compared to other financial services sector lending rates, these data indicate that the average lending rate during the observation period is still quite high.

Table 2. Descriptive Statistics

	count	Mean	sd	min	max
Lending Rate (daily %)	5.873.689	0,71	0,45	0,02	1,27
Loan Amount	5.873.689	454.627.149	331.245.732	5	2.000.000.000
Outstanding	5.873.689	355.612.457	285.476.483	0	2.000.000.000
Term Loan	5.873.689	1,06	3,09	0,10	58,35
Gender	5.873.689	0,45	0,43	0	1
Marital Status	5.873.689	0,37	0,29	0	1
Age	5.873.689	28,77	6,57	18	60
Education	5.873.689	0,13	0,12	0	1
Income	5.873.689	4,18	3,89	0,00	68,00
Residential Ownership	5.873.689	0,21	0,20	0	1
Financial Institution Loan	5.873.689	0,67	0,54	0	1
Default Loan	5.873.689	0,52	0,47	0	1
Authentication	5.873.689	0,83	0,62	0	1
Loan Purpose (Multi)	5.873.689	0,30	0,28	0	1
Loan Purpose (Financing)	5.873.689	0,59	0,51	0	1

Insurance	5.873.689	0,04	0,20	0	1
Collateral	5.873.689	0,03	0,17	0	1
Benchmark Interest Rate (BI 7DRR)	41	4,84	0,85	3,50	6,00
Days Past Due (DPD)	5.873.689	18,47	14,24	0	553
Platform fee (%)	5.873.689	6,75	3,95	0,2	8,36
Observations	5.873.689				

Descriptive statistic of variables used in this research. Loan lending rate is % daily; loan amount, outstanding, and income are in IDR; term loan, term loan age in months; benchmark lending rate is in % per annum; and the other variables are dummy.

Table 3 presents the correlation matrix of variables used in the regression analysis. The values of correlation among variables are relatively low. Therefore, there is no multicollinearity issue in the estimation.

Table 3. Correlation Matrix

	Lending Rate	Loan Amount	Lending Cap Policy	Term Loan	Gender	Marital Status	Age	Edu.	Income	Resid. Own.	Fin. Ins. Loan	Default Loan	Auth.	Loan Purp. (Multi)	Loan Purp. (Fin.)	Insur.	Collat.	Bench. Interest Rate
Lending Rate	1																	
Loan Amount	-0.108	1																
Lending Cap Policy	-0.213	0.094	1															
Term Loan	-0.007	0.188	0.088	1														
Gender	-0.072	0.124	0.007	-0.053	1													
Marital Status	-0.017	0.083	0.002	-0.062	-0.012	1												
Age	-0.058	0.101	0.030	0.037	0.065	0.113	1											
Education	-0.098	0.046	0.049	-0.097	0.101	0.057	0.046	1										
Income	0.108	0.067	0.099	0.055	0.043	0.078	0.030	0.038	1									
Residential Ownership	0.021	0.065	0.039	-0.109	0.096	0.077	0.070	0.040	0.048	1								
Financial Institution Loan	0.148	0.104	0.092	0.042	0.085	0.085	0.014	0.094	0.099	0.046	1							
Default Loan	0.166	0.029	0.065	0.060	0.065	0.037	0.028	0.022	0.022	0.107	0.069	1						
Authentication	-0.008	0.081	0.056	0.084	0.054	0.068	0.109	0.062	0.048	0.106	0.048	0.072	1					
Loan Purpose (Multi)	0.061	0.027	0.101	0.046	-0.020	0.050	0.062	0.052	0.045	0.059	0.077	0.031	0.061	1				
Loan Purpose (Financing)	0.026	0.064	0.037	0.040	-0.071	0.038	0.061	0.078	0.071	0.106	0.042	0.074	0.035	0.101	1			
Insurance	0.023	0.078	0.046	0.041	0.092	0.056	0.046	0.105	0.108	0.018	0.028	0.071	0.064	0.085	0.041	1		
Collateral	-0.006	0.074	0.061	0.025	0.051	0.037	0.007	0.066	0.083	0.058	0.088	0.063	-0.078	0.106	0.028	0.079	1	
Benchmark Interest Rate	0.126	0.088	0.061	0.090	0.035	0.106	0.036	0.077	0.036	0.079	0.053	0.017	0.070	0.066	0.056	0.031	0.083	1

5.2 Empirical Results

Days Past Due

Table 4 shows the regression results of factors affecting days past due for all types of loans, samples for working capital loans, consumer loans, and other loans.

Table 4. Days Past Due Estimation

	1	2	3	4
	All Sample	Working Capital	Consumption	Other
(Intercept)	2.0714***	1.9293***	2.0844***	1.6982***
	(5.1585)	(5.1519)	(5.0586)	(4.9311)
Lending Rate	3.1462***	2.9546***	3.3043**	3.5093**
	(2.6679)	(2.8080)	(2.5468)	(2.4594)
Loan Amount	3.8193	3.8023	4.1826	3.5864
	(1.3066)	(1.3641)	(1.4844)	(1.1595)
Lending Cap Policy	-1.7636**	-1.8033**	-1.7978**	-1.7967**
	(-2.3364)	(-2.3860)	(-2.5594)	(-2.4976)
Term Loan	-2.3988	-2.2944	-2.6628	-2.2504
	(-0.9508)	(-0.8409)	(-0.8396)	(-1.1014)
Gender	2.9662	3.4127	2.7708	2.9238
	(1.3832)	(1.1483)	(1.3076)	(1.4576)
Marital Status	1.1959	0.8318	1.0688	1.2127
	(1.2488)	(1.4168)	(1.4296)	(1.0769)
Age	2.2305	1.7826	2.4786	1.9680
	(1.3357)	(1.1522)	(1.1750)	(1.3374)
Education	2.0813	1.8674	1.9650	2.3962
	(1.5029)	(1.4857)	(1.5541)	(1.5938)
Income	-6.4731*	-6.7221*	-6.2071*	2.4364*
	(-1.8184)	(-1.8107)	(-1.8275)	(1.7722)
Residential Ownership	0.9356	1.1021	0.9073	0.7000
	(0.6543)	(0.5204)	(0.8713)	(0.5365)
Financial Institution Loan	0.4215	0.6068	0.5482	0.0829*
	(1.4276)	(1.3934)	(1.4812)	(1.8499)
Default Loan	0.9058**	0.5419**	0.6824*	0.9250**
	(1.9966)	(1.8997)	(1.8659)	(2.0920)
Authentication	1.6572	1.3374	1.6473	2.0487
	(0.7974)	(0.6754)	(0.7900)	(0.8557)
Loan Purpose (Multi)	1.7426	1.4518	1.6333	2.0276
	(0.7793)	(0.5799)	(0.9050)	(0.9019)
Loan Purpose (Financing)	1.8861	1.4620	1.4259	2.1630
	(0.9749)	(0.8788)	(0.7495)	(0.7548)
Insurance	1.8554	2.0130	2.1433	1.5316
	(1.4509)	(1.5262)	(1.3516)	(1.3934)
Collateral	1.3434	0.9948	1.5507	0.9932
	(1.4551)	(1.5407)	(1.4800)	(1.5774)
Benchmark Lending Rate (7DRR)	1.6902	1.7294	1.6798	1.4891
	(1.3726)	(1.4158)	(1.1720)	(1.1643)
Number of Observations	5873689	822336	3056080	1995273
Pseudo R^2	0.3331	0.3364	0.3472	0.3468

Days past due is estimated with Tobit regression, while lending rates and loan amounts are ordinary least square (OLS). Value in the bracket shows robust t-statistic. * is significant in 0.1, ** is significant in 0.05, and *** is significant in 0.01.

For all types of loans, loan lending rates are significant at the 1% level affecting days past due with a positive coefficient. On the other hand, lending rate restrictions are also significant at the negative 1% level. A higher lending rate will result in a larger total refund amount, so the possibility of repayment past the due date is relatively higher. Meanwhile, the appropriate lending rate restrictions imposed by the association also effectively reduced the DPD. The next factor is income and the frequency of non-performing loans, which are significant at the 10% level. In line with Santoso et al. (2020), this study finds that income is negatively associated with borrower days past due. Furthermore, consistent with Santoso et al. (2020) and Chen et al. (2016), the frequency of non-performing loans increases the days past due. It suggests that a borrower's previous credit quality can affect his current repayment ability. The factors that affect the days past due are consistent across all the samples, consumer loans, working capital loans, and other loans.

Lending Rate

Table 5 shows the results of the regression of factors that affect lending rates for all types of loans, samples for working capital loans, consumer loans, and other loans. In general, the influencing factors are restrictions on lending rates, tenors, age, and income. In contrast to Santoso et al. (2020), which does not test the limits of the maximum amount of lending rates, this study finds that the policy of limiting lending rates reduces loan lending rates.

Table 5. Lending Rate Estimation

	1	2	3	4
	All Sample	Working Capital	Consumption	Other
(Intercept)	2.7011***	2.9496***	2.6574***	3.1216***
	(4.5288)	(4.3925)	(4.3601)	(4.3126)
Loan Amount	2.9836	2.8468	3.2202	3.2117
	(1.5604)	(1.4249)	(1.6394)	(1.4821)
Lending Cap Policy	-0.6944**	-0.7274**	-0.6637**	-0.8488**
	(-2.2264)	(-2.1376)	(-2.3076)	(-2.3357)
Term Loan	-3.0641***	-2.7003***	-3.1868***	-2.6580***
	(-2.8126)	(-2.7920)	(-2.9164)	(-2.8068)
Gender	2.8064	3.0497	2.7208	3.1076
	(1.2504)	(1.0463)	(1.1129)	(1.1506)
Marital Status	1.0744	1.3104	1.4755	0.7402
	(1.4305)	(1.4139)	(1.4025)	(1.4620)
Age	1.8871*	1.7182*	2.1694*	1.7753*
	(1.8216)	(1.8576)	(1.9296)	(1.7601)
Education	-2.2566	-2.2237	-2.4143	-2.5391
	(-1.1345)	(-1.1625)	(-1.0615)	(-1.0469)
Income	-2.3183**	-1.8592**	-2.5672**	-2.5418**
	(-2.3244)	(-2.2833)	(-2.1809)	(-2.2843)
Residential Ownership	2.3533	2.3903	2.7045	2.6910
	(1.4294)	(1.4148)	(1.2791)	(1.5009)
Financial Institution Loan	0.3102	0.6617*	0.4362	0.1991*
	(1.5083)	(1.6516)	(1.4100)	(1.6942)
Default Loan	3.1599	2.9536	3.0823	3.1805
	(1.1696)	(1.2029)	(1.1336)	(1.3590)
Authentication	2.3198	2.1792	2.3637	2.2548
	(1.4084)	(1.2551)	(1.3242)	(1.4387)

Loan Purpose (multi)	2.6122	2.7499	2.2106	2.7640
	(1.3236)	(1.3645)	(1.3536)	(1.3244)
Loan Purpose (financing)	3.0431	3.3387	2.8756	1.0724*
	(1.4817)	(1.5691)	(1.3432)	(1.6759)
Insurance	3.0937	3.1282	3.4362	2.7775
	(1.2447)	(1.1368)	(1.0455)	(1.2115)
Collateral	-1.2737	-1.4979	-1.1065	-1.1365
	(-1.2562)	(-1.3126)	(-1.0432)	(-1.0748)
Benchmark Lending Rate (7DRR)	1.8786	2.2710	2.1644	1.6778
	(1.0054)	(1.1385)	(0.9093)	(0.9642)
Number of Observations	5873689	822336	3056080	1995273
R^2	0.3109	0.3917	0.4234	0.2665

Days past due is estimated with Tobit regression, while lending rates and loan amounts are ordinary least square (OLS). Value in the bracket shows robust t-statistic. * is significant in 0.1, ** is significant in 0.05, and *** is significant in 0.01.

This study finds that the loan tenor has a negative relationship with lending rates. It could be because certain loans, such as productive loans with longer tenors, do not use standard daily lending rates but have much lower monthly or annual lending rates. The same findings were also found by Santoso et al. (2020). For income, the coefficient is negative or in line with DPD, where borrowers with higher incomes are considered to have lower credit risk, thus earning lower lending rates. The significance results with the sample for working capital purposes, consumption purposes, and other purposes are consistent, with a difference in significant financial institutions loan at the 10% level in the sample for working capital purposes and other purposes.

Loan Amount

Table 6 shows the regression results of the factors that affect loan size for all types of loans, working capital loans, consumer loans, and other loans. The influencing factors are tenor, age, and income. Lending rate restrictions are significant at the 1% level, significant income at the 5% level, and significant age at the 10% level. The coefficients of the three are positive, which means that lending rate restrictions effectively increase the loan amount.

Table 6. Loan Amount Estimation

	1	2	3	4
	All Sample	Working Capital	Consumption	Other
(Intercept)	4.1464***	3.8880***	4.0446***	3.9165***
	(3.7169)	(3.8297)	(3.5083)	(3.7706)
Lending Cap Policy	0.4643	0.1384	0.1584	0.4344
	(1.0720)	(1.2328)	(1.2125)	(1.0436)
Term Loan	1.7404**	1.4176***	1.8341**	1.5212**
	(2.3846)	(2.6105)	(2.2194)	(2.4050)
Gender	1.2444	1.2526	1.3229	1.6886
	(1.4755)	(1.3101)	(1.4188)	(1.4194)
Marital Status	2.2405	2.3073	2.4020	1.8421
	(1.5078)	(1.4233)	(1.5967)	(1.3822)
Age	2.9434*	2.6960*	2.6175**	3.0127*
	(1.8659)	(1.8624)	(2.0515)	(1.7064)
Education	3.7605	3.6731	3.9564	4.0653

	(1.3583)	(1.4076)	(1.3691)	(1.3341)
Income	2.9772**	3.1927**	2.8480**	3.2615**
	(2.3192)	(2.3755)	(2.3762)	(2.1804)
Residential Ownership	-1.6442	-1.2981	-1.8945	-1.5823
	(-1.3269)	(-1.4532)	(-1.4375)	(-1.5026)
Financial Institution Loan	1.5031	1.5101	1.3752	1.4305
	(1.2626)	(1.2671)	(1.1303)	(1.0673)
Default Loan	2.2532	2.1891	2.2944	2.4887
	(1.2515)	(1.1445)	(1.2078)	(1.4312)
Authentication	2.2540	1.9797	2.4684	2.5000
	(1.0209)	(1.0917)	(0.8034)	(0.8783)
Loan Purpose (multi)	2.2547	2.3608	2.1710	1.9738
	(1.3726)	(1.1948)	(1.5074)	(1.1939)
Loan Purpose (financing)	1.7375	1.3017	1.5401	1.3557
	(1.3159)	(1.2766)	(1.4913)	(1.5058)
Insurance	2.3391	2.7504	2.5043	2.5709
	(0.8265)	(1.0136)	(0.7512)	(0.9030)
Collateral	2.6810	3.0608	2.9037	2.8679
	(1.3150)	(1.4291)	(1.1832)	(1.3341)
Policy Interest Rate	1.1993	1.4247	0.8956	0.9734
	(0.7497)	(0.8479)	(0.6820)	(0.7988)
Benchmark Lending Rate (7DRR)	5873689	822336	3056080	1995273
R^2	0.3284	0.2358	0.2658	0.2115

Days past due is estimated with Tobit regression, while lending rates and loan amounts are ordinary least square (OLS).

Value in the bracket shows robust t-statistic. * is significant in 0.1, ** is significant in 0.05, and *** is significant in 0.01.

6. Conclusion

In line with the significant growth of the P2PL industry, policy adjustments are needed to support the soundness and the optimal growth of the industry. In line with the spirit to improve the effectiveness of P2PL regulation in emerging countries, including in Indonesia, this study aims to determine factors that affect borrowers' days past due, lending rate, and loan amount. To achieve those purposes, this research is the first study to employ a very large loan database from 20 P2P Lending platforms in Indonesia with a market share of 71.10% of the entire industry.

Using the day past due model from Brezigar-Masten et al. (2021) to estimate loan risk, this study shows that lending rates, lending rate cap policy, and income affect the number of days in arrears on loans. This is in line with Santoso et al. (2020), which uses the probability of default. However, we did not find the impact of loan size on borrowers' TKB. Furthermore, loan lending rates are also influenced by restrictions on lending rates, tenors, and income. Correspondingly, the size of the loan is also influenced by the tenor and income. However, in contrast to lending rates which have a negative relationship with tenors, the relationship between loan amount and tenor has a positive relationship or means that loans with long tenors generally have a larger amount. This study could not find any relationship between macroeconomic indicators of policy lending rates with days past due, lending rates, and the loan amount.

Regarding the lending rate restrictions, this study found that lending rates and maximum lending rate restrictions significantly affect borrower loan risk. Specifically, this study finds that limiting the maximum lending rate reduces the number of days past due, so this study supports the regulation to cap the loan lending rate in the Indonesia P2PL industry.

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