

Debt Crowdfunding Growth and MSME Credit Risk in Indonesia's Sustainable Digital Economy

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ABSTRACT

Micro, Small and Medium Enterprises (MSMEs) in Indonesia often lack the collateral that banks require, and Peer-to-Peer (P2P) lending, the debt form of crowdfunding, has become a channel through which they raise capital in the digital economy. Lending now grows fastest outside Java, where platforms hold the shortest records on their borrowers. **This study** builds a monthly panel of 34 provinces from official statistics of the Financial Services Authority (*Otoritas Jasa Keuangan / OJK*) for December 2023 to December 2024 and estimates two-way fixed-effects models with standard errors clustered by province. **The models test** whether faster growth of outstanding loans is followed by a higher share of loans more than 90 days overdue (*Tingkat Wanprestasi 90 Hari / TWP90*) and whether this link differs between Java and the other regions. **Outstanding loans rose** by 29.1% to Rp 77.02 trillion, by 20.5% in Java and by 57.8% elsewhere, and MSMEs held 36.7% of the stock at the end of 2024. Current growth shows no significant link with TWP90. Growth three months earlier is followed by a lower TWP90 in Java, with a coefficient of -0.084 ($p < 0.01$), while outside Java the coefficient is only -0.011 ($p = 0.079$), and the gap between the two regions is significant ($p < 0.01$). **Rapid P2P expansion** was not associated with higher TWP90 during the study period, while the observed negative relationship between earlier loan growth and TWP90 in Java was substantially weaker outside Java. Platforms and regulators therefore need closer credit assessment where lending grows fastest if debt crowdfunding is to support MSME capital formation and the targets of Sustainable Development Goals 8 and 9. The evidence is associational and covers thirteen months, so longer panels with data specific to MSMEs are needed.

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1. INTRODUCTION

Micro, Small, and Medium Enterprises (MSMEs) make up most firms in Indonesia, but many lack the collateral and the financial records that banks require. Studies of Indonesian MSMEs link their growth to information technology, e-commerce and digital transformation [1, 2, 3], and they trace financial distress among small producers to both digital and financial factors [4]. Digital resilience is also proposed as a condition for MSMEs to withstand volatile markets [5]. Tighter monetary policy after 2022 raised borrowing costs and made

bank lending conditions more restrictive across close to 50 countries, and small firms feel such tightening first [6]. Crowdfunding offers another route. In its debt form, known as Peer to Peer (P2P) lending, an online platform matches many lenders with individual or business borrowers and assesses them with digital data in place of collateral [7, 8]. Indonesian research describes fintech as a financing solution for MSMEs [9], discusses its integration with crowdfunding and blockchain [10], and proposes big data analytics to widen access to digital microcredit [11, 12]. Indonesia regulates this activity as Information Technology-Based Joint Funding Services (*Layanan Pendanaan Bersama Berbasis Teknologi Informasi / LPBBTI*), under Regulation 10/POJK.05/2022 of the Financial Services Authority (*Otoritas Jasa Keuangan / OJK*) [13].

Evidence from other countries shows that digital lending can widen access to credit. In the United States, fintech lenders and finance companies replaced much of the small business lending that banks withdrew after 2008 [14]. In France, small firms that received unsecured fintech loans later obtained more bank credit and used it to buy new assets [15]. In Indonesia, P2P lending is associated with higher output growth in the provinces of Java [16], and the entry of fintech lenders has intensified competition among banks [17]. Other studies examine how financial technology changes the quality of banking services [18], how P2P lending startups adjust their business strategy [19], and how digital micro entrepreneurship programs support growth in underserved communities [20].

The same expansion also carries risk. Fintech lenders in the United States first served riskier borrowers, whose default rates were higher than those of comparable bank borrowers [21]. In Indonesia, provinces with low outstanding P2P loans can still show very high default rates [22]. Research on fintech further points to regulatory risk [23] and cybersecurity risk [24], and Indonesian banks have adopted risk management models for their digital operations [25]. If lending grows fastest where borrowers are least known to platforms, rapid growth today may produce more defaults later, and that would weaken the channel just where it is most needed.

Two gaps remain in this literature. Studies of fintech credit risk rely mostly on loan level or platform data from a single country [21], while the Indonesian studies either relate P2P lending to regional output [16] or group provinces at one point in time [22]. None of them follows provinces month by month to see whether faster lending is followed by more loans in arrears. OJK reports the share of loans more than 90 days overdue, known as TWP90, for every province each month, so the question can be tested with public data [26].

The study makes three contributions. It builds a monthly provincial panel from official statistics, so the evidence rests entirely on public government data. It separates the immediate effect of new lending on TWP90 from the effect that appears after loans have had time to season, by including both current and lagged loan growth. It also tests whether the lagged effect differs between Java, where most lending is concentrated, and the rest of the country, where lending is growing faster. The findings bear on Sustainable Development Goals (SDGs) 8 and 9, whose Targets 8.3 and 9.3 call for better access of small enterprises to financial services [27].

2. LITERATURE REVIEW

2.1. Debt Crowdfunding and Small Firm Finance

Capital structure theory explains why small firms turn to crowdfunding. Pecking order theory holds that firms use internal funds first and borrow next, because outside investors know less than owners about the quality of the firm. For MSMEs this information gap is wide, so banks ask for collateral that many cannot offer. Credit rationing theory adds that lenders with imperfect information may refuse loans instead of raising prices, since higher rates attract riskier borrowers. In Indonesia, bank lending to small business under the People's Business Credit program is related to the financial performance of banks [28], and leverage and working capital turnover shape firm profitability [29]. Entrepreneurs tied to distressed banks are more likely to raise money from the crowd [30], and firms that raise crowd equity tend to add new debt soon afterwards [31]. Equity crowdfunding raises the growth opportunities of small firms [32], and P2P business loans serve established small firms that need medium term funds which banks do not readily provide [33]. Sharia crowdfunding has been proposed for MSME supply chain finance [34], and young Indonesian investors show a clear intention to fund firms through securities crowdfunding [35]. Crowdfunded finance thus enters the balance sheet of small firms where bank finance falls short.

Platforms also change how information about small borrowers is produced. Fintech lenders combine automated credit scoring, transaction data and other alternative data to assess borrowers that banks find too opaque [7]. Soft information shared through investor networks shapes funding decisions on platforms [36], and

market feedback gathered during a campaign helps entrepreneurs persist and perform [37]. These tools lower screening costs, so digital credit can reach borrowers that banks do not serve. Big data are now used widely across the digital economy [38], and blockchain is examined as a base for cashless investment and transactions [39]. On the demand side, financial literacy shapes the digital loan decisions of women [40] and, together with risk perception, the intention of individuals to invest in new digital assets [41]. The adoption of digital banking in Indonesia also differs across generational cohorts [42]. Whether such credit complements or substitutes for bank lending depends on the banking system. Global data show that fintech credit grows faster where bank markups are high and tends to complement bank credit [43], while a study of 78 countries finds substitution in concentrated and fragile banking systems [44]. Platform lending also held up better than bank lending during the first months of the COVID 19 pandemic [45].

2.2. Loan Growth and Credit Quality

Research on banks shows that fast loan growth often comes before weaker credit quality. Banks that expand loans faster than their peers later report higher loan losses, and lending booms tend to coincide with looser standards when lenders know little about new borrowers. Lending standards also drift as lenders lose the memory of past losses, and a review of commercial banks relates sustainable lending to the value chain and environmental, social and governance performance of the lender [46]. The common point in these studies is that growth brings in borrowers who are less well known to the lender, and the cost of that gap in information appears with a delay.

The fintech evidence points the same way. Fintech lenders that grow quickly by serving riskier borrowers see higher default rates among them [21], and provincial data from Indonesia show that outstanding volume and default rates do not move together [22].

The ratio that OJK reports as TWP90 reacts to growth in two ways. New loans enlarge the denominator at once, before any of them can be 90 days overdue, which lowers the ratio. Once these loans season, weaker borrowers start to miss payments, which raises the ratio if growth came from riskier lending. Research on crowdfunding has called for more evidence on what happens after funds are raised and not only on the fundraising itself [47, 48], and the default experience of crowdfunded debt is a central part of that evidence.

2.3. Hypothesis Development

New loans cannot be 90 days overdue in the month they are made, so they enlarge the denominator of TWP90 before they can add to its numerator. Current growth should therefore dilute the ratio.

H1. The current monthly growth of outstanding P2P loans in a province is negatively associated with its TWP90.

Loans made during an expansion need time to season. If growth draws in weaker borrowers, part of these loans should fall into arrears once they have aged beyond 90 days, which would match the delayed losses reported for banks [49].

H2. Growth of outstanding P2P loans three months earlier is positively associated with TWP90.

Platforms know less about borrowers in regions where they have operated for a shorter time. Expansion there resembles the lending booms in which information on new borrowers is thin [50], so the later quality of loans should be weaker than in Java, where platforms hold longer records.

H3. The association between lagged loan growth and TWP90 is more positive in provinces outside Java than in Java.

Figure 1 shows how these hypotheses connect loan growth, the region of the borrower and loan quality.

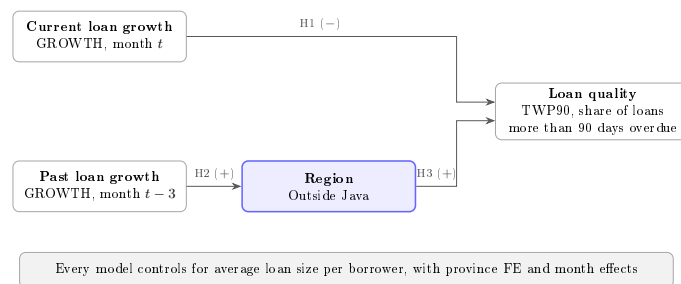


Figure 1. Conceptual framework and hypotheses.

As Figure 1 shows, current growth acts on loan quality directly, while past growth acts through a path whose strength may depend on the region.

3. METHODOLOGY

This section describes the data, the construction of the variables, the model and the tests used to check it. The official statistics report province level totals and not individual loans, and this shapes every choice below.

3.1. Data and Variables

All data come from one official source, the LPBBTI statistics published by the Department of Data Management and Statistics of OJK for December 2024 [26]. This edition reports thirteen monthly observations from December 2023 to December 2024 and covers every provider licensed by OJK, including Sharia providers. Table 1 lists the four tables of the publication that the study uses, under the Indonesian label Tabel that OJK applies.

Table 1. Data sources in the OJK LPBBTI statistics.

OJK Table	Content	Use in This Study
Table 9	Active borrower accounts, outstanding loans and TWP90 by province of borrower, monthly	Dependent variable, loan growth and loan size
Table 6	Number of borrowers and amount disbursed by province of borrower, monthly	Description of lending flows
Table 10	Outstanding loans by borrower category, separating MSME and other borrowers, monthly	Share of MSMEs in outstanding loans
Table 7	Loans disbursed to productive sectors and their share of total disbursement, monthly	Share of productive lending

The provincial data in Table 1 follow the 34 provinces that existed at the start of the period. OJK began to report the four new provinces of Papua separately in mid 2024, so their figures are added back to Papua and Papua Barat, with TWP90 recombined as a weighted average that uses outstanding loans as weights. This step keeps each province comparable across all months. Table 2 defines the variables.

Table 2. Definition of variables.

Symbol	Measurement	Role and Expected Sign
TWP90	Loans more than 90 days overdue divided by outstanding loans, percent	Dependent
GROWTH	Monthly growth of outstanding loans, 100 times the change in its natural logarithm	Negative (H1)
$GROWTH_{t-3}$	GROWTH three months earlier	Positive (H2)
OUTSIDE	1 for provinces outside Java, 0 for the six provinces of Java	Moderator
$GROWTH_{t-3} \times OUTSIDE$	Product of $GROWTH_{t-3}$ and OUTSIDE	Positive (H3)
LNSIZE	Natural logarithm of outstanding loans per active borrower account, Rp million	Control

As Table 2 shows, all variables are ratios or growth rates, so they do not depend on the size of a province. A lag of three months is used because a loan counts as overdue beyond 90 days only after about three monthly reporting dates, so three months is the shortest horizon at which the loans made in an expansion can appear in TWP90. The lag requires growth from January 2024 onwards, so the estimation sample runs from April 2024 to December 2024 and contains 306 province month observations. Continuous variables are winsorized at the 1st and 99th percentiles to limit the influence of extreme values.

3.2. Model and Estimation

The study uses a panel model with province and month effects, since provinces differ in stable ways that influence both lending and default, and since national events affect all provinces in the same month. The

full model is written as follows.

$$TWP90_{it} = \beta_1 GROWTH_{it} + \beta_2 GROWTH_{i,t-3} + \beta_3 (GROWTH_{i,t-3} \times OUTSIDE_i) + \gamma LNSIZE_{it} + \alpha_i + \lambda_t + \varepsilon_{it} \quad (1)$$

In Equation (1), i indexes provinces and t indexes months. Province effects α_i remove stable differences such as the local mix of platforms and borrowers, and month effects λ_t remove shocks common to all provinces, including national changes in regulation and seasonal patterns. Together they define the two way fixed effects (FE) model. The coefficient β_1 tests H1. The coefficient β_2 measures the link between past growth and TWP90 in Java and tests H2 in the model without the interaction, and β_3 tests H3. The sum $\beta_2 + \beta_3$ gives the link for provinces outside Java. OUTSIDE does not change over time and is therefore absorbed by the province effects, which is why it enters only through the interaction.

Standard errors are clustered by province, which allows for unequal variance and for serial correlation within each province. With 34 clusters inference is reasonable but not generous, so p values close to conventional thresholds should be read with care. Diagnostic tests check multicollinearity with Variance Inflation Factors (VIF), the choice between fixed and random effects with the Hausman test, serial correlation with the Wooldridge test, groupwise unequal variance with the modified Wald test and cross sectional dependence with the Pesaran test [51].

The lagged growth term reduces the risk that defaults drive growth, but the design remains observational and does not exclude local shocks that affect both [52]. Every province has P2P lending in every month, so there is no untreated group and a staggered difference in differences design is not available [53].

Five robustness checks repeat the full model with Driscoll and Kraay standard errors, without DKI Jakarta, without Papua and Papua Barat, without May and June 2024, which OJK revised, and with a two month lag in place of three. The Driscoll and Kraay estimator was built for panels with many time periods, so with nine months it serves only as a supplementary check. All estimates come from one open Python script that reads the OJK workbook directly and writes every table and figure in this paper. Figure 2 summarizes the research flow.

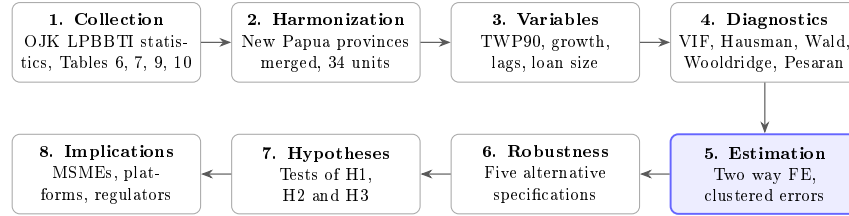


Figure 2. Research Flowchart

Figure 2 shows that the merger of the new Papua provinces and the construction of the variables come before any test or estimate.

4. RESULT AND DISCUSSION

This section first presents descriptive evidence and the diagnostic tests. It then reports the main estimates and the robustness checks, and it ends with a discussion of what the results mean for debt crowdfunding and MSME finance.

4.1. Descriptive Evidence and Diagnostics

Outstanding P2P loans grew from Rp 59.64 trillion in December 2023 to Rp 77.02 trillion in December 2024, an increase of 29.1 percent, and the number of active borrower accounts reached 22.3 million. Lending remains concentrated in Java, which held 71.6 percent of outstanding loans at the end of the period, but it grew much faster elsewhere. Outstanding loans rose by 20.5 percent in Java and by 57.8 percent in the other provinces, and the fastest growth was in Sulawesi Tenggara at 157.1 percent. Figure 3 shows how much of this lending reached MSMEs and productive activities.

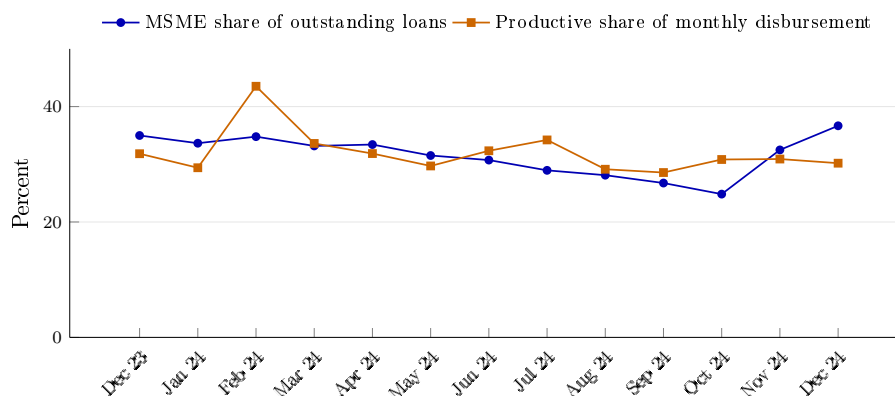


Figure 3. MSME share of outstanding P2P loans and productive share of monthly disbursement, Indonesia, December 2023 to December 2024.

Figure 3 shows that MSMEs held 35.0 percent of outstanding loans in December 2023 and 36.7 percent in December 2024, equal to Rp 28.25 trillion at the end of the period. The share fell to 24.8 percent in October 2024 before recovering, so monthly movements should be read with care. On average 32.0 percent of monthly disbursement went to productive sectors, ranging from 28.6 percent in September 2024 to 43.5 percent in February 2024. Roughly one third of P2P credit therefore finances MSMEs and productive activity, so its quality bears directly on MSME capital formation. Table 3 reports the provincial variables used in the regressions.

Table 3. Descriptive statistics, province month observations.

Variable	N	Mean	Std. dev.	Min	Median	Max
TWP90 (percent)	306	1.80	0.91	0.58	1.54	5.26
GROWTH (percent per month)	306	3.66	3.39	-2.91	3.32	16.49
GROWTH _{t-3} (percent per month)	306	4.21	3.06	-2.82	3.99	16.38
LNSIZE	306	1.19	0.17	0.75	1.18	1.63
Outstanding loans (Rp billion)	306	2083.80	3847.06	65.25	699.74	19558.81
Active borrowers (thousand)	306	584.11	1053.08	22.11	216.88	6097.88
OUTSIDE	306	0.82	0.38	0.00	1.00	1.00

Table 3 shows an average TWP90 of 1.80 percent across province months, with a standard deviation of 0.91 and a maximum of 5.26 percent, so default rates differ widely across provinces and months. In December 2024 the national TWP90 stood at 2.60 percent, with the highest provincial rate in Jawa Barat at 3.30 percent and the lowest in Maluku at 0.78 percent. The national rate is weighted by outstanding loans while the provincial mean gives each province the same weight, so higher rates in the large provinces of Java most likely explain why the national figure is above the average. Default risk is therefore not limited to small or remote markets.

The correlations among the regressors are low. Growth three months earlier has the strongest simple correlation with TWP90 at -0.31 , the largest absolute correlation among the regressors is 0.23, and the largest variance inflation factor is 1.06, far below the usual threshold of 10, so multicollinearity does not affect the estimates. Table 4 reports the panel diagnostic tests for the full model.

Table 4. Panel diagnostic tests for the full model.

Test	Null Hypothesis	Statistic	p-value
Hausman	Random effects consistent	$\chi^2 = 18.69$	$p < 0.01$
Wooldridge	No first order serial correlation	$F = 39.31$	$p < 0.01$
Modified Wald	Homoskedastic errors across provinces	$\chi^2 = 28537.45$	$p < 0.01$
Pesaran CD	No cross sectional dependence	$z = -0.65$	$p = 0.519$

The Hausman test in Table 4 rejects random effects, which supports province effects. The Wooldridge test detects serial correlation, and the modified Wald test detects unequal error variance across provinces, so all models use standard errors clustered by province, which remain valid under both. The Pesaran test does not detect cross sectional dependence once month effects are included.

4.2. Main Estimates and Robustness

Table 5 presents the main estimates. Column 1 includes current growth alone, Column 2 adds growth three months earlier, and Column 3 adds the interaction with OUTSIDE.

Table 5. Two way FE regressions of TWP90 on P2P loan growth.

Variable	(1)	(2)	(3)
GROWTH	−0.007 (0.005)	−0.006 (0.005)	−0.007 (0.005)
GROWTH _{t−3}		−0.014** (0.006)	−0.084*** (0.014)
GROWTH _{t−3} × OUTSIDE			0.074*** (0.014)
LNSIZE	−1.202*** (0.362)	−1.136*** (0.343)	−1.178*** (0.340)
GROWTH _{t−3} for provinces outside Java			−0.011* (0.006)
Province FE	Yes	Yes	Yes
Month effects	Yes	Yes	Yes
Observations	306	306	306
Provinces	34	34	34
Within R^2	0.189	0.207	0.234

Note. Dependent variable TWP90 in percent. Standard errors clustered by province in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Column 1 of Table 5 does not support H1. The coefficient on current growth is -0.007 with $p = 0.158$, so a rise in monthly growth of one standard deviation, equal to 3.39 percentage points, changes TWP90 by only -0.024 percentage points. New lending in a given month is too small relative to the existing loan book to move the default ratio noticeably.

Column 2 does not support H2. Growth three months earlier enters with a coefficient of -0.014 and $p = 0.026$, which is significant but negative and not positive. Provinces where lending expanded faster saw lower default ratios three months later. Two explanations fit this pattern. Loans made three months earlier may have only just reached the 90 day threshold, so they still enlarge the denominator of TWP90 more than they add to its numerator. Alternatively, growth in this period may have come mainly from borrowers whom platforms could assess well, which is the cream skimming pattern and not the lax screening pattern.

Column 3 shows that this result holds mainly in Java, and it supports H3. In Java the coefficient on past growth is -0.084 with $p < 0.01$. The interaction with OUTSIDE is 0.074 with $p < 0.01$, so outside Java the combined coefficient is only -0.011 with $p = 0.079$. Past growth outside Java is therefore not followed by the same fall in default ratios. The control for loan size also matters, since provinces where the average loan per borrower rose saw lower default ratios, with a coefficient of -1.178 and $p < 0.01$. Larger average loans may reflect more business borrowers and more established customers, who tend to repay more reliably.

The size of these associations can be judged against the spread of the data. In Java, growth three months earlier that is one standard deviation higher, equal to 3.06 percentage points, goes with a TWP90 that is 0.26 percentage points lower, or about 14 percent of the sample mean of 1.80. Outside Java the same difference in growth goes with a change of only 0.03 percentage points. A rise of one standard deviation in LNSIZE, equal to 0.17, goes with a TWP90 that is 0.20 percentage points lower. Figure 4 plots the pooled estimate and the two regional estimates with their confidence intervals.

Figure 4 compares the relationship between loan growth three months earlier and TWP90 across regions. The pooled estimate is close to zero, but the regional results show a clear difference. In Java, the estimated relationship is negative, with a 95% confidence interval entirely below zero. Outside Java, the estimate is much closer to zero, and its confidence interval includes zero. These findings indicate that the pooled estimate does not fully reflect the differences between regions.

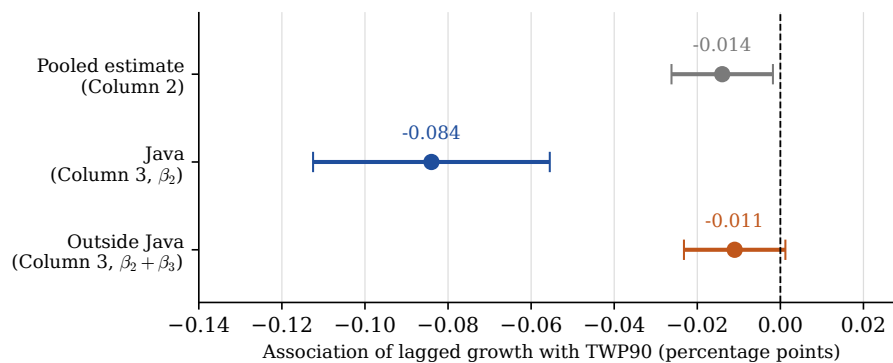


Figure 4. Association of growth three months earlier with TWP90 by region. Bars show 95 percent intervals based on the clustered standard errors in Table 5 and the t distribution with 33 degrees of freedom.

The results in Figure 4 suggest that the negative association between past loan growth and TWP90 is stronger in Java than outside Java. To examine whether these findings remain consistent under different model specifications and sample restrictions, Table 6 presents a series of robustness checks.

Table 6. Robustness checks for the full model.

Specification	GROWTH	Lagged GROWTH	Lagged GROWTH $\times$ OUTSIDE
Driscoll and Kraay standard errors	-0.007 (0.005)	-0.084*** (0.020)	0.074*** (0.019)
Excluding DKI Jakarta	-0.006 (0.005)	-0.083*** (0.020)	0.072*** (0.019)
Excluding Papua and Papua Barat	-0.007 (0.006)	-0.084*** (0.015)	0.071*** (0.014)
Excluding May and June 2024 (revised by OJK)	-0.010 (0.007)	-0.089*** (0.013)	0.086*** (0.013)
Two month lag instead of three	-0.007 (0.005)	-0.035 (0.034)	0.032 (0.034)

Note. Each cell reports the coefficient with its standard error in parentheses. Lagged GROWTH refers to a three month lag except in the last row, where it refers to a two month lag.

Table 6 shows that the three-month lagged growth coefficient remains negative and statistically significant across the first four robustness checks, while its interaction with OUTSIDE remains positive and significant. These results remain consistent when using Driscoll–Kraay standard errors, excluding DKI Jakarta, excluding Papua and West Papua, and removing the months revised by OJK. However, when the lag is shortened to two months, both coefficients retain their signs but are no longer statistically significant. This suggests that the observed relationship is more evident at a three-month lag than at a two-month lag.

4.3. Discussion

The evidence supports H3 but not H1 or H2, and the failure of H1 and H2 is informative in its own right. Current growth is too small relative to the loan book to dilute TWP90 in a visible way, and the lagged effect has the opposite sign to the one expected from the lax screening argument. In Java, faster growth was followed by lower default ratios, which fits the cream skimming pattern in which expansion reaches borrowers that platforms already know how to assess.

These results point to a gap between Java and the other provinces. Lending outside Java grew almost three times as fast as in Java, but without the improvement in loan quality that followed growth in Java. Platforms have operated longer in Java, hold more repayment data there and face more competition from banks, so they can expand with better information. Outside Java the same growth reaches borrowers who are newer to platforms, and that information advantage is weaker. The pattern does not show that lending outside Java is unsafe, since its default rates are not uniformly higher. It shows that growth there is not yet self correcting in the way it is in Java.

The findings add to theory by carrying the lending boom argument developed for banks to digital platforms and to a regional setting, since the information a lender holds on its borrowers appears to condition the risk of fast growth. They also suggest that the delayed losses reported for banks need not show up within

a short window for lenders that screen with data. A longer panel is needed to see whether losses emerge later. One caution applies to the lagged result. TWP90 is a ratio, and growth three months earlier raises the stock of loans in the denominator at time t , so a negative coefficient is partly mechanical and cannot by itself prove that loan quality improved. The contrast between Java and the other provinces remains informative because the same mechanical effect operates in both regions.

For MSME capital formation, these findings matter because roughly a third of P2P credit reaches MSMEs and productive sectors. Debt crowdfunding can support investment by small firms over time only if loans are repaid and lenders keep funding the platforms. Expansion that lowers default ratios in Java strengthens this channel, while expansion outside Java needs closer attention to borrower screening to avoid weakening it. Several features of the data limit these conclusions. OJK reports provincial loans for all borrowers and not for MSMEs alone, so the provincial panel mixes consumer and productive lending. The panel covers thirteen months, which captures the seasoning of short P2P loans but not a full credit cycle. The estimates are associations, so local shocks that affect both growth and repayment cannot be ruled out.

5. MANAGERIAL IMPLICATIONS

The results carry practical lessons for three groups. Each follows from the finding that growth is followed by better loan quality in Java but not outside it, and from the link between larger average loans and lower default.

For MSME owners, P2P loans are a practical source of working capital and small equipment finance, but they are short and priced for risk. Owners should borrow for assets or stock that pay back within the loan term and should treat timely repayment as an investment in their credit record. Larger loans were associated with lower default rates in this study, which suggests that owners gain from presenting complete business information and borrowing an amount that fits their needs, and not from taking small amounts repeatedly.

For platforms. Platforms that expand outside Java should match the pace of growth to the quality of the data they hold on new borrowers. Growth outside Java was much faster than in Java but did not lower default ratios afterwards, so new regions call for tighter initial limits, gradual increases for borrowers who repay, and partnerships with local cooperatives or regional banks that already know the borrowers. Platforms should also report productive and MSME lending separately for each province.

For OJK and regional governments. OJK already publishes default rates by province every month, which makes it possible to monitor whether growth in a region is followed by rising arrears. Supervisors could use the link between past growth and later TWP90 in each province as an early warning measure, with closer attention to provinces where growth is high and platforms are new. Publishing provincial data on lending to MSMEs and productive sectors would allow a direct assessment of how debt crowdfunding supports small firm investment. Regional governments outside Java can support safe expansion through financial literacy programs and by promoting licensed platforms.

6. CONCLUSION

This study examined how the growth of P2P lending, the debt form of crowdfunding, relates to loan quality across 34 Indonesian provinces, using official monthly OJK statistics from December 2023 to December 2024. Outstanding loans grew by 29.1 percent, much faster outside Java than in Java, and MSMEs held 36.7 percent of the outstanding stock at the end of 2024. Current growth shows no significant link with TWP90, so the evidence does not support H1. Growth three months earlier is followed by lower and not higher default ratios, so the evidence does not support H2. This favorable link appears in Java but is much weaker outside Java, and the evidence supports H3.

The study has limits that shape how the results should be used. The provincial data cover all borrowers and not MSMEs alone, so the link to MSME capital formation rests on national shares and not on provincial MSME data. The panel spans thirteen months and cannot show how the pattern behaves over a full credit cycle. The estimates are associations, and because TWP90 is a ratio the lagged result is partly mechanical.

Future research can extend this work in several directions. Combining several December editions of the OJK statistics would give a longer panel, and using the amount of overdue loans as a separate outcome would remove the ambiguity of the ratio. Linking provincial data with regional accounts on fixed investment would test whether debt crowdfunding raises MSME capital formation, and borrower level data would show whether the weaker link outside Java reflects new borrowers, different loan purposes or different platforms.

7. DECLARATIONS

7.1. About Authors

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7.2. Author Contributions

Conceptualization: RG and TS; Methodology: MM, RG, and TS; Software: TS; Validation: MM and RG; Formal Analysis: TS and MM; Investigation: RG and TS; Resources: MM; Data Curation: RG and TS; Writing Original Draft Preparation: MM and RG; Writing Review and Editing: TG, MM, and RG; Visualization: TS and MM; Visualization: MM; All authors (RG, TS, MM) have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

7.4. Funding

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7.5. Declaration of Conflicting Interest

The authors declare that there are no financial or personal conflicts of interest that could have influenced the findings or conclusions presented in this study.

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