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APPRAISAL PROCEDURES, FIRM SIZE AND NON-PERFORMING LOANS AMONG DIGITAL LENDERS IN KENYA

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Abstract

Digital credit providers have transformed access to finance in Kenya by using technology-driven appraisal systems to assess borrowers and deliver credit rapidly. However, non-performing loans (NPLs) remain a concern, raising questions about whether organizational scale strengthens the ability of digital lenders to translate credit appraisal practices into improved loan performance. This study examined the moderating role of firm size in the relationship between credit appraisal procedures and NPLs among digital credit providers in Kenya. Guided by the Theory of Asymmetric Information and Market Power Theory, the study adopted a positivist philosophy and explanatory cross-sectional design. A census of all 85 digital credit providers licensed by the Central Bank of Kenya in 2024 was conducted. Primary data on appraisal procedures were collected through structured questionnaires administered to credit officers and risk managers, while secondary data on firm size and NPLs were obtained from audited financial statements, regulatory filings and Central Bank of Kenya reports covering 2021–2024.

Data were analyzed using descriptive statistics and moderated regression analysis. The findings showed that appraisal procedures had no significant effect on NPLs ($B = 0.475$, $p = 0.445$). Firm size also had a negative but insignificant effect ($B = -0.077$, $p = 0.559$), while the moderation model explained only 1.1% of NPL variation ($R^2 = 0.011$; $F = 0.458$, $p = 0.634$). The study concludes that organizational scale does not significantly strengthen the appraisal–NPL relationship. Digital lenders should therefore prioritize effective risk-management capabilities and continuous portfolio monitoring rather than assuming that greater organizational scale necessarily improves credit outcomes.

Keywords: Credit Appraisal, Digital Credit Providers, Firm Size, Non-Performing Loans, Organizational Scale, Credit Risk, Kenya

INTRODUCTION

Digital lending has become an important part of Kenya's financial system, supported by the widespread use of mobile technology, digital payments and alternative approaches to assessing creditworthiness. Unlike conventional financial institutions that often depend on collateral, formal income records and face-to-face interactions, digital credit providers (DCPs) use technology-enabled platforms to receive loan applications, evaluate borrowers and disburse credit within relatively short periods. Credit-scoring algorithms, Credit Reference Bureau (CRB) information, transaction histories and other digital information have made it possible to extend credit to individuals who may have limited conventional financial records (Björkegren & Grissen, 2018; Djeundje et al. 2021). This development has contributed to financial inclusion, but it has also increased the importance of effective credit-risk management as lenders seek to balance rapid credit access with sustainable loan portfolios.

Credit appraisal is central to this balancing process because lending decisions are made under conditions of uncertainty. Borrowers normally possess more information about their financial circumstances and repayment intentions than lenders, creating the problems of adverse selection and moral hazard described by Asymmetric Information Theory (Akerlof, 1970; Stiglitz & Weiss, 1981). Digital lenders attempt to reduce these information gaps through automated scoring, CRB reports, manual verification and third-party scoring systems. In principle, stronger appraisal procedures should improve borrower selection and reduce the likelihood of loans becoming non-performing. However, evidence from financial institutions suggests that appraisal practices do not always translate directly into lower NPLs, particularly when repayment outcomes are influenced by factors that emerge after loan disbursement (Mburu et al., 2020; Mutai & Opuodho, 2023).

An important but less understood issue is whether the effectiveness of credit appraisal depends on the organizational scale of the lender. Firms differ considerably in their financial resources, customer bases, technological infrastructure and ability to invest in sophisticated risk-management systems. Larger financial institutions may have greater capacity to acquire data, employ specialized risk personnel, develop advanced scoring models and diversify credit risk across larger loan portfolios. Market Power Theory similarly suggests that larger firms can benefit from resource advantages and economies of scale that may strengthen their competitive and operational capabilities (Bain, 1956). Empirical studies have consequently associated firm size with differences in credit-risk outcomes in conventional financial institutions (Haruna et al., 2023; Salas et al., 2024).

The relationship may nevertheless operate differently in digital lending. Financial technology can reduce some of the costs and infrastructure requirements traditionally associated with financial intermediation by improving information processing, borrower screening, verification and service delivery (Thakor, 2020). FinTech lending similarly enables technology-based screening and monitoring mechanisms that may alter the resource requirements traditionally associated with credit provision (Berg et al., 2022). Consequently, organizational scale may be less decisive in determining the effectiveness of credit appraisal in a technology-driven lending environment than in conventional banking. This possibility makes firm size an important contextual factor rather than simply another independent determinant of NPLs.

The Kenyan digital credit market provides an appropriate setting for examining this question. Licensed DCPs operate at different scales, serve different numbers of borrowers and possess varying levels of financial and technological capacity. Despite increasing adoption of structured appraisal procedures, loan performance remains an important concern. In the thesis data underlying this paper, the average NPL ratio increased from 5.3% in 2021 to 6.1% in 2024. This trend raises an important practical question: if digital lenders are increasingly using technology-supported appraisal procedures, does being a larger firm strengthen their ability to translate those procedures into better loan performance? Understanding this relationship is important for lenders deciding whether organizational expansion and greater resource capacity necessarily improve credit-risk management.

Existing empirical literature leaves this question unresolved. Studies have examined the direct relationship between credit appraisal and loan performance, while another body of research has considered firm size as an independent determinant of NPLs. For example, Mburu et al. (2020) found that client appraisal considered independently did not significantly influence NPLs among Kenyan commercial banks, whereas Mutai and Opuodho (2023) demonstrated the broader importance of credit-risk management practices among microfinance banks. Studies examining organizational scale have generally suggested that larger institutions may benefit from diversification, capital resources and stronger risk-management capabilities (Haruna et al., 2023; Salas et al., 2024). However, these relationships have largely been examined separately.

A clear gap therefore exists regarding the moderating role of firm size. Treating firm size simply as a direct predictor does not establish whether organizational scale changes the effectiveness of another credit-risk management practice. Moderation addresses a different question: whether the relationship between appraisal procedures and NPLs becomes stronger or weaker depending on the size of the lender. This distinction is particularly relevant in digital lending because technology may either strengthen the advantages enjoyed by larger firms through greater investment capacity or reduce those advantages by making sophisticated credit technologies accessible to smaller providers (Bain, 1956; Sanya & Wolfe, 2022).

The study therefore examined whether firm size moderates the relationship between credit appraisal procedures and non-performing loans among digital credit providers in Kenya. Specifically, it assessed the effect of appraisal procedures on NPLs and determined whether organizational scale significantly changed this relationship. Firm size was operationalized using the natural logarithm of annual revenue, while appraisal procedures captured the extent of implementation of credit-scoring algorithms, CRB information, manual verification and third-party scoring systems.

The study contributes to digital finance and credit-risk literature by moving beyond the assumption that organizational scale necessarily produces better lending outcomes. Rather than asking only whether larger firms experience fewer NPLs, the study investigates whether being larger improves a lender's ability to convert appraisal practices into better portfolio performance. This distinction has practical implications for digital credit providers because investments in organizational growth may have limited value for credit-risk outcomes unless they translate into stronger decision capabilities. It also contributes to the application of Market Power and Asymmetric Information theories by examining whether resource advantages associated with firm size meaningfully alter the effectiveness of borrower screening in Kenya's technology-driven credit market (Akerlof, 1970; Bain, 1956; Stiglitz & Weiss, 1981).

LITERATURE REVIEW AND THEORETICAL FRAMEWORK

Literature Review

Credit appraisal is a critical component of credit-risk management because it enables lenders to assess borrowers before committing financial resources. In digital lending, appraisal increasingly involves credit-scoring algorithms, Credit Reference Bureau (CRB) information, identity verification and third-party scoring platforms. These approaches allow lenders to process applications rapidly and evaluate customers who may lack conventional credit histories. Digital information can reduce some of the information gaps between borrowers and lenders, although access to more data does not necessarily eliminate uncertainty regarding future repayment behaviour (Björkegren & Grissen, 2018; Djeundje et al., 2021).

Effective appraisal is generally expected to reduce non-performing loans (NPLs) by helping lenders identify applicants with higher probabilities of default. Empirical evidence, however, is mixed. Sharifi et al. (2019) associated effective credit-risk identification and assessment with improved management of non-performing assets, while Mutai and Opuodho (2023) found that credit-granting procedures, monitoring and internal controls improved loan performance among Kenyan microfinance banks. Conversely, Mburu et al. (2020) found that client appraisal considered independently did not significantly influence NPLs among commercial banks in Kenya. These differences suggest that the effectiveness of appraisal may depend partly on the institutional environment and the lender's capacity to use appraisal information effectively.

Firm size is one organizational characteristic that may shape this capacity. Larger financial institutions generally possess greater capital resources, larger customer databases, specialized personnel and greater capacity to invest in sophisticated credit-risk technologies. They may also diversify lending across a wider portfolio, reducing exposure to individual borrower or market risks. Evidence from conventional financial institutions generally supports this argument. Haruna et al. (2023) reported a negative relationship between bank size and NPLs among Nigerian deposit-money banks, while Salas et al. (2024) showed that institutional characteristics, including size, were relevant to differences in NPL behaviour across banks internationally. Mukuru and Thuo (2023) similarly associated firm size with credit-risk management among financial institutions.

Nevertheless, organizational scale may operate differently within digital lending. Technology can reduce the infrastructure traditionally required to conduct credit appraisal. Smaller lenders can access external scoring systems, digital platforms and third-party technologies without developing all these capabilities internally. Consequently, the traditional advantage enjoyed by larger institutions may be weakened in a digital environment. Size alone may therefore be less important than how effectively technological and financial resources are converted into credit-risk management capabilities (Sanya & Wolfe, 2022).

Most existing studies have examined either the direct relationship between appraisal and loan performance or the direct effect of firm size on NPLs. Less attention has been given to whether firm size changes the strength of the relationship between appraisal procedures and

NPLs. This represents an important gap because moderation addresses whether appraisal works differently across firms of different organizational scales. The present study therefore examines firm size as a moderator rather than merely another predictor, providing evidence on whether larger digital lenders are better positioned to translate appraisal procedures into improved loan performance (Mburu et al., 2020; Mukuru & Thuo, 2023).

Theoretical Framework

The study is principally anchored on the Theory of Asymmetric Information and Market Power Theory. The two theories provide complementary explanations for the proposed relationship between appraisal procedures, firm size and NPLs. Asymmetric Information Theory explains why lenders require effective appraisal mechanisms, while Market Power Theory provides a basis for understanding why organizational scale may influence the capacity of firms to implement those mechanisms effectively (Akerlof, 1970; Bain, 1956).

The Theory of Asymmetric Information originates from Akerlof (1970) and was extended to credit markets by Stiglitz and Weiss (1981). The theory argues that parties involved in economic transactions may possess unequal information. In credit markets, borrowers normally know more about their financial circumstances, intentions and repayment ability than lenders. This imbalance creates adverse selection before lending and moral hazard after credit has been advanced. Lenders therefore require screening and monitoring mechanisms to reduce uncertainty and improve borrower selection (Akerlof, 1970; Stiglitz & Weiss, 1981).

Credit appraisal provides a practical response to this information problem. Digital lenders use scoring algorithms, CRB reports, verification procedures and other information to estimate borrower risk before approving loans. Better appraisal should theoretically improve borrower selection and reduce NPLs. However, Asymmetric Information Theory also recognizes that screening cannot completely remove uncertainty because lenders cannot perfectly observe future borrower behaviour. Consequently, even sophisticated digital appraisal systems may fail to capture all circumstances affecting repayment after disbursement (Björkegren & Grissen, 2018; Stiglitz & Weiss, 1981).

Market Power Theory, associated with Bain (1956), provides the basis for introducing firm size into this relationship. The theory suggests that larger organizations may enjoy advantages arising from greater resources, economies of scale and stronger market positions. Applied to digital lending, larger providers may have greater financial capacity to invest in sophisticated scoring systems, acquire extensive borrower information, employ specialized risk personnel and maintain advanced technological infrastructure. They may therefore be better positioned to convert appraisal information into effective credit decisions (Bain, 1956; Salas et al., 2024).

However, digitalization challenges the assumption that organizational size automatically creates superior decision capability. Cloud-based systems, third-party scoring platforms and other digital services can make sophisticated technologies available to relatively small lenders. Accordingly, the benefit of organizational scale may depend on whether additional resources actually strengthen the effectiveness of appraisal. This makes moderation theoretically important: firm size may strengthen, weaken or have no meaningful influence on the appraisal–NPL relationship (Mukuru & Thuo, 2023; Sanya & Wolfe, 2022).

Integrating the two theories produces the conceptual argument tested in this paper. Appraisal procedures constitute the independent variable, NPLs the dependent variable, and firm size, measured through the natural logarithm of annual revenue, the moderating variable. The study consequently tests the null hypothesis:

H_0: Firm size does not significantly moderate the relationship between credit appraisal procedures and non-performing loans among digital credit providers in Kenya.

The framework therefore determines whether the resource advantages associated with organizational scale actually strengthen the ability of digital lenders to translate borrower appraisal into better credit outcomes (Akerlof, 1970; Bain, 1956).

METHODOLOGY

The study was guided by a positivist research philosophy and adopted an explanatory cross-sectional research design to examine whether firm size moderates the relationship between credit appraisal procedures and non-performing loans (NPLs) among digital credit providers in Kenya. The target population comprised all 85 Digital Credit Providers licensed by the Central Bank of Kenya in 2024. Given the relatively small and accessible population, a census approach was adopted, allowing all licensed firms to participate. The digital credit provider constituted the unit of analysis, while credit officers and risk managers served as respondents. Primary data on appraisal procedures were collected using structured questionnaires, whereas secondary data on firm size and NPLs covering 2021–2024 were obtained from audited financial statements, regulatory filings and Central Bank of Kenya reports. Data were coded and analyzed using the Statistical Package for the Social Sciences (SPSS). Appraisal procedures were measured using a composite score covering credit-scoring algorithms, CRB information, manual verification and third-party scoring systems. Firm size was measured as the natural logarithm of annual revenue, while NPLs were measured as the percentage of non-performing loans relative to total loans. Descriptive statistics summarized the study variables, while diagnostic tests assessed normality, linearity, multicollinearity and heteroscedasticity before inferential analysis. Simple regression was first used to determine the direct relationship between appraisal procedures and NPLs. Moderated regression analysis was subsequently conducted to determine whether organizational scale significantly changed this relationship. The moderating effect of firm size was evaluated at the 5% level of statistical significance (α = .05).

RESULTS

Response Rate

The study targeted all 85 digital credit providers licensed by the Central Bank of Kenya and used a census approach. All 85 questionnaires administered electronically were returned and verified as complete, giving a 100% valid response rate. The complete response ensured that the analysis represented the entire targeted population of licensed digital lenders.

Table 1: Questionnaire Response Rate

Response category	Frequency	Percentage (%)
Completed questionnaires	85	100.0
Non-response	0	0.0
Total	85	100.0

Validity and Reliability Tests

Ensuring that research instruments are both reliable and valid is a fundamental requirement for producing credible and high-quality research outcomes (Saunders et al., 2013). The reliability, accuracy, and validity of the study findings are directly related to how efficiently and effectively the data collection tools utilized in the research process measure the constructs that are intended to be measured. Reliability and validity assessment increases the level of trust in the research findings, increases methodological soundness, and reduces measurement errors. On the other hand, failure to evaluate reliability and validity may conceal measurement errors that could distort or weaken the theoretical relationships being examined in the study (Cooper & Schindler, 2014).

Validity Test

In order to ensure validity of the research tool, three types of validity have been examined in this study, which include content validity, face validity, and construct validity. Content validity was determined with the help of experts in digital finance and credit risk management by reviewing the questionnaire. Their recommendations on revising wording, restructuring questions, and incorporating additional relevant items helped improve the instrument and ensured that the questionnaire adequately addressed the study objectives and captured all relevant dimensions of the variables under investigation.

Face validity was also achieved through engagement with the same experts, who assessed whether the questionnaire items appeared appropriate and relevant for measuring the intended concepts. Their evaluation confirmed that the instrument was suitable for the study and capable of capturing the targeted constructs effectively.

Construct validity was established by designing questionnaire items that were closely aligned with the theoretical concepts underpinning the study variables. For example, appraisal procedures were measured using indicators based on widely accepted digital credit evaluation practices, including credit scoring algorithms, Credit Reference Bureau (CRB) records, and the use of alternative borrower information during credit assessment. Interest rates and firm size were measured using internationally accepted financial indicators and organizational performance measures, whereas non-performing loans (NPLs) were operationalized through financial ratios consistent with central bank reporting guidelines and previous empirical research. Each construct was measured using multiple-item scales adapted from established studies and refined to suit the specific objectives of the present research, thereby ensuring that the instrument accurately represented the underlying theoretical constructs.

Reliability Test

Reliability refers to the capability of a research tool to yield reliable, stable, and consistent results during repeated administrations under similar circumstances (Mugenda & Mugenda, 2003). In the current research, reliability was determined in order to show that the questionnaire reliably measured the main study variables including appraisal process, interest rates, firm size, and NPLs. Internal reliability was checked through determination of Cronbach's alpha coefficients for the Likert scale items that were used to measure the extent of adoption of the study variables. According to DeVellis (2017), a Cronbach's alpha coefficient of 0.70 or higher was considered a good indication of acceptable reliability. Additionally, test–retest reliability was assessed through administration of the questionnaire to a selected group of respondents twice with an interval of two weeks between the two administrations. The scores obtained through the two administrations were correlated in order to check the consistency of the test over time. High correlations between the two administrations were considered a clear indication of reliability.

Inter-item reliability was also assessed to determine whether the items within each construct consistently measured the same underlying concept. Additionally, inter-rater reliability was considered for items requiring professional judgment to ensure that respondents interpreted the questionnaire uniformly. A pilot study involving 10 percent of the target sample was undertaken using respondents drawn from microfinance institutions (MFIs). These institutions were selected because they operate within a comparable lending environment and utilize credit appraisal practices similar to those employed by digital lending firms (Kiplimo & Kalio, 2021). Although the pilot study primarily enhanced the clarity, relevance, and comprehensibility of the questionnaire, it was not regarded as sufficient evidence of instrument reliability on its own.

Regarding the construct of appraisal procedures, which was measured using four different indicators in terms of implementation of credit appraisal systems such as credit scoring models, CRB, manual identity verification, and third party credit scoring systems, the Cronbach's alpha values showed high level of internal consistency with values higher than the recommended value of 0.70. This indicated that the items measured the construct of appraisal procedures in digital lending companies. Generally, reliability results show that the measurement tool was suitable for the study and could produce consistent data.

Table 2: Reliability Test Results for Appraisal Procedures Construct

No	Appraisal Practice Statement	Alpha
1	Use of credit scoring algorithms (AI/ML-based models)	0.905
2	Use of Credit Reference Bureau (CRB) reports during appraisal	0.907
3	Manual verification of customer identity (ID documents, utility bills)	0.910
4	Use of third-party credit scoring platforms or APIs	0.908

The appraisal procedures construct was assessed using four items that captured the extent to which credit appraisal practices were implemented and exhibited a high level of internal consistency. The Cronbach's alpha coefficients for each of the items were above the recommended threshold of 0.70, demonstrating that the measurement scale possessed strong reliability. These results indicate that the four indicators consistently represented the underlying appraisal procedures construct among digital lending firms operating in Kenya.

Descriptive Findings

Firm size was measured as the natural logarithm of annual revenue. The results show a gradual increase in mean firm size from 17.8 in 2021 to 18.5 in 2024, with an aggregate mean of 18.2. The minimum and maximum values also demonstrate substantial variation in organizational scale across the firms. Skewness values were close to zero and kurtosis values were negative, indicating an approximately symmetrical but relatively flat distribution.

Table 3: Firm Size (Natural Log of Annual Revenue, KES)

Year	N	Min	Max	Mean	SD	Skewness	Kurtosis
2021	85	12.5	22.3	17.8	2.35	0.15	-0.78
2022	85	12.7	22.8	18.1	2.40	0.12	-0.74
2023	85	12.6	23.0	18.3	2.42	0.10	-0.71
2024	85	12.8	23.2	18.5	2.45	0.08	-0.69
Aggregate	85	12.5	23.2	18.2	2.41	0.11	-0.73

N = number of observations; SD = standard deviation.

Note: based on estimated annual revenue ranges of digital lenders

Non-performing loans (NPLs), measured as a percentage of total loans, increased gradually over the study period. The mean NPL ratio rose from 5.3% in 2021 to 6.1% in 2024, producing an aggregate mean of 5.75%. The results indicate that portfolio credit risk remained present across firms and increased modestly over the four-year period.

Table 4: Non-Performing Loans (Percentage of Total Loans)

Year	N	Min (%)	Max (%)	Mean (%)	SD	Skewness	Kurtosis
2021	85	0.5	12.8	5.3	2.85	0.72	-0.42
2022	85	0.6	13.5	5.7	2.92	0.68	-0.37
2023	85	0.7	14.2	5.9	3.01	0.64	-0.35
2024	85	0.8	14.8	6.1	3.08	0.61	-0.32
Aggregate	85	0.5	14.8	5.75	2.97	0.66	-0.36

N = number of observations; SD = standard deviation.

Note: based on estimated digital lender NPL ranges

Diagnostic Tests

Regression assumptions were examined before hypothesis testing. Skewness and kurtosis values were within the thresholds used in the study, supporting approximate normality. The residual scatter plots showed no systematic curvature, indicating linearity. Tolerance values were above 0.10 and VIF values were close to 1, showing no serious multicollinearity. The Breusch-Pagan test was also insignificant ($\chi^2 = 2.47$, $p = 0.29$), supporting homoscedasticity.

Table 5: Normality Test Results

Variable	Skewness	Kurtosis
Appraisal procedures	-0.48	0.07
Firm size	0.11	-0.73
NPLs	0.66	-0.36
Standardized residuals	-0.12	-0.28

Table 6: Selected Regression Diagnostic Results

Diagnostic	Variable/Test	Result	Decision
Multicollinearity	Appraisal procedures	Tolerance = 0.983; VIF = 1.017	No multicollinearity
Multicollinearity	Firm size	Tolerance = 0.984; VIF = 1.016	No multicollinearity
Heteroscedasticity	Breusch-Pagan test	$\chi^2 = 2.47$; $p = 0.29$	Homoscedasticity supported
Linearity	Residual scatter plot	Random dispersion around zero	Linearity supported

Direct Effect of Credit Appraisal Procedures on NPLs

A simple regression was first estimated to establish the direct relationship between credit appraisal procedures and NPLs. The model produced $R = 0.083$ and $R^2 = 0.007$, indicating that appraisal procedures explained only 0.7% of the variation in NPLs. The model was not statistically significant, $F(1, 83) = 0.575$, $p = 0.445$. Appraisal procedures had a positive but statistically insignificant coefficient ($B = 0.475$, $\beta = 0.083$, $p = 0.445$).

Table 7: Direct Effect of Credit Appraisal Procedures on NPLs

Predictor	**B**	**SE**	**β**	**t**	**p**	**95% CI**
Appraisal procedures	0.475	0.631	0.083	0.759	0.445	[-0.776, 1.733]

Model: $R = 0.083$; $R^2 = 0.007$; Adjusted $R^2 = -0.005$; $F = 0.575$; $p = 0.445$. Dependent variable: NPLs.

Moderating Role of Firm Size

The study reported a moderated regression analysis to determine whether firm size changes the relationship between appraisal procedures and NPLs. The model yielded $R = 0.105$ and $R^2 = 0.011$, meaning that appraisal procedures and firm size explained only 1.1% of the variation in NPLs. The adjusted R^2 was -0.013, indicating very limited explanatory power after adjustment.

Table 8: Moderated Regression Model Summary

Model	R	R^2	Adjusted R^2	Std. Error of Estimate
1	0.105	0.011	-0.013	1.46121

Table 9: ANOVA for the Moderated Regression Model

Source	Sum of Squares	df	Mean Square	F	p
Regression	1.955	2	0.977	0.458	0.634
Residual	175.082	82	2.135		
Total	177.037	84			

Dependent variable: NPLs.

The overall model was not statistically significant, $F(2, 82) = 0.458$, $p = 0.634$. Appraisal procedures remained positive but insignificant ($B = 0.444$, $p = 0.487$), while firm size had a small negative and statistically insignificant coefficient ($B = -0.077$, $p = 0.559$). The confidence intervals for both coefficients included zero.

Table 10: Regression Coefficients for Appraisal Procedures and Firm Size

Variable	B	SE	β	t	p	95% CI Lower	95% CI Upper
Constant	5.740	3.525	—	1.628	0.107	-1.273	12.752
Appraisal procedures	0.444	0.636	0.077	0.698	0.487	-0.822	1.709
Firm size	-0.077	0.131	-0.065	-0.580	0.559	-0.336	0.183

Dependent variable: NPLs.

Hypothesis Decision

The results did not provide statistically significant evidence that organizational scale strengthened or weakened the relationship between appraisal procedures and NPLs. The study therefore failed to reject the null hypothesis that firm size does not significantly moderate the relationship between credit appraisal procedures and non-performing loans among digital credit providers in Kenya. The findings imply that larger and smaller digital lenders did not exhibit systematically different appraisal-related NPL outcomes within the model reported in the study.

Table 11: Summary of Hypothesis Testing

Hypothesis	Key statistical evidence	Decision
H_0: Firm size does not significantly moderate the relationship between appraisal procedures and NPLs.	$R^2 = 0.011$; F = 0.458; model p = 0.634; firm size B = -0.077, p = 0.559	Fail to reject H_0

DISCUSSION

The findings show that firm size did not significantly influence non-performing loans (NPLs) among digital credit providers in Kenya and did not provide meaningful evidence of strengthening the relationship between credit appraisal procedures and loan performance. The moderated regression model explained only 1.1% of the variation in NPLs ($R^2 = 0.011$) and was statistically insignificant ($F = 0.458$, $p = 0.634$). Firm size had a small negative coefficient ($B = -0.077$, $p = 0.559$), suggesting that larger digital lenders tended to record slightly lower NPLs, but the relationship was too weak to establish a statistically meaningful effect.

This finding challenges the assumption that organizational scale automatically provides digital lenders with superior credit-risk management capabilities. Market Power Theory suggests that larger firms should benefit from greater financial resources, technological investment, specialized personnel and economies of scale (Bain, 1956). Such advantages could theoretically enable larger lenders to develop more sophisticated appraisal systems and manage credit portfolios more effectively. However, the present findings indicate that these potential resource advantages did not translate into significantly different NPL outcomes. The wide variation in firm size observed among the lenders, with an aggregate mean of 18.2 and values ranging from 12.5 to 23.2 on the natural logarithm of annual revenue, further suggests that differences in organizational scale existed but were not sufficient to explain loan performance.

The results also have implications for understanding credit appraisal in technology-driven lending. Appraisal procedures remained statistically insignificant after firm size was introduced into the model ($B = 0.444$, $p = 0.487$). This suggests that having greater organizational resources does not necessarily make conventional appraisal procedures more effective in controlling default risk. Digital technologies may partly reduce the advantages traditionally associated with organizational size because smaller lenders can also access automated credit scoring, CRB information and third-party digital risk-assessment systems. Consequently, the quality of credit decisions may depend more on how effectively available information is interpreted, updated and incorporated into lending decisions than on the scale of the organization itself.

From the perspective of Asymmetric Information Theory, the findings further suggest that organizational growth cannot completely eliminate uncertainty surrounding borrower repayment behaviour (Akerlof, 1970; Stiglitz & Weiss, 1981). Even well-resourced digital lenders may experience adverse selection and moral hazard where appraisal data do not adequately capture changes in borrowers' circumstances after loan disbursement. The gradual increase in mean NPLs from 5.3% in 2021 to 6.1% in 2024 reinforces the importance of looking beyond organizational size when explaining credit risk. Digital lenders should therefore focus not simply on expanding their scale, but on strengthening the capabilities through which borrower information is converted into effective lending, monitoring and repayment decisions.

CONCLUSION AND RECOMMENDATIONS

The study concludes that firm size does not significantly explain differences in non-performing loans among digital credit providers in Kenya and, based on the moderation model reported in the thesis, does not provide evidence of strengthening the relationship between credit appraisal procedures and NPLs. The model explained only 1.1% of the variation in NPLs ($R^2 = 0.011$) and was not statistically significant ($F = 0.458$, $p = 0.634$). Firm size recorded a negative but insignificant coefficient ($B = -0.077$, $p = 0.559$), while appraisal procedures were similarly insignificant ($B = 0.444$, $p = 0.487$). These results suggest that organizational scale, by itself, is not sufficient to produce better credit-risk outcomes among digital lenders.

The findings have an important implication for the assumption derived from Market Power Theory that larger firms benefit from superior resources, economies of scale and greater operational capabilities (Bain, 1956). Although such advantages may exist, they do not automatically translate into lower NPLs. Digitalization may partly reduce traditional scale advantages because credit-scoring systems, CRB information and third-party technological services can also be accessed by smaller providers. Digital lenders should therefore focus on the quality and effectiveness of their credit-risk capabilities rather than organizational expansion alone. Investment in technology should be accompanied by appropriate use of borrower information, effective risk analytics and continuous review of credit decisions.

The study further recommends that digital lenders strengthen post-disbursement monitoring and dynamic borrower-risk assessment. Credit appraisal should not end once a loan has been approved. Lenders should continuously evaluate repayment patterns and identify emerging signs of repayment difficulty. This is particularly important because Asymmetric Information Theory recognizes that borrower screening cannot completely eliminate adverse selection and moral hazard. The increase in mean NPLs from 5.3% in 2021 to 6.1% in 2024 further demonstrates the need for continued attention to portfolio quality.

For regulators and industry stakeholders, the findings suggest that assessments of digital lenders should not assume that larger providers necessarily possess stronger credit-risk management systems. Regulatory oversight should emphasize the quality of appraisal, risk-management processes, responsible lending practices and portfolio performance across firms of all sizes. Future research should also examine organizational characteristics beyond revenue-based firm size, including technological capability, quality of risk personnel, data-management capacity and portfolio diversification, to establish whether these factors better explain differences in the effectiveness of credit appraisal among digital lenders.

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